

**In the Matter of:**

**10th Annual FTC Microeconomics Conference**

*November 2, 2017*  
*Day 1*

**Condensed Transcript with Word Index**



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1 FEDERAL TRADE COMMISSION	1 P R O C E E D I N G S
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3	3 WELCOME AND OPENING REMARKS
4	4 MR. VITA: My name is Mike Vita. I am the
5	5 Deputy Director for Research and Management, as well
6	6 as currently Acting Director here at the FTC's Bureau
7	7 of Economics, and I just want to welcome everybody to
8 THE TENTH ANNUAL	8 the -- this is now the Tenth Annual Micro Conference
9	9 we have held here, and it's hard to believe it's been
10 FEDERAL TRADE COMMISSION	10 that long.
11 MICROECONOMICS CONFERENCE	11 The purpose of this conference, like all of our
12	12 conferences, is an attempt to combine, you know,
13	13 cutting-edge academic research with discussions of
14 DAY 1	14 real-world policy problems, and I think if you look at
15	15 the agenda, I think, you know, it promises to do that
16	16 this year like it has in the past.
17 Thursday, November 2, 2017	17 Before the first panel gets started, just a few
18 9:00 a.m.	18 announcements and a few acknowledgments. First of
19	19 all, I want to express our gratitude to Northwestern
20	20 University and the Searle Center for their continued
21 Federal Trade Commission	21 cosponsorship of this conference.
22 Washington, D.C.	22 Let me also acknowledge, you know, some of the
23	23 work of the FTC people who -- first of all, the
24	24 Scientific Committee that helped us put this together.
25	25 That's Steve Berry from Yale, Jonathan Zinman from
2	4
1 FEDERAL TRADE COMMISSION	1 Dartmouth, and Igal Hendel from Northwestern. Thanks.
2	2 You know, as usual, really great work in selecting a
3 Welcome/Opening Remarks	3 great selection of papers to be presented.
4	4 Just a few words about us, I mean, and some of
5 Paper Session	5 the people in the group -- in the audience might not
6	6 be overly familiar with the FTC and what we do here.
7 Keynote Address	7 We're an independent agency that, along with the
8	8 Department of Justice, enforces the antitrust laws,
9 Panel Discussion	9 but we also have -- unlike Justice, we also have an
10	10 additional enforcement mission, which is consumer
11 Paper Session	11 protection law.
12	12 So these enforcement missions are supported by
13 Keynote Address	13 the FTC Bureau of Economics, which is about 80 Ph.D.
14	14 economists, and so it makes it one of the largest
15	15 applied microeconomics groups in the Federal
16	16 Government. We think -- you know, those of us at the
17	17 FTC think that these twin enforcement missions
18	18 reinforce and complement each other. Competition is
19	19 most effective when consumers are making well-informed
20	20 decisions and free choices, and consumer protection
21	21 works best when consumers have real alternatives.
22	22 So the purpose of today's conference, like its
23	23 predecessors, is to help ensure that the FTC's actions
24	24 are informed and guided by the best possible economic
25	25 analysis. So in addition to the normal papers, you

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1 know, the paper sessions -- which one will be starting  
 2 in just a few minutes -- we also have two panel  
 3 discussions that focus more on policy issues. The  
 4 panel discussion today is antitrust-focused. It's on  
 5 cross market hospital and healthcare provider mergers.  
 6 Tomorrow, there will be a panel discussion on privacy  
 7 and data security. So, you know, both of -- you know,  
 8 those each addressing the two -- the twin enforcement  
 9 missions of the FTC.

10 So I thanked our scientific panel, and let me  
 11 also thank the FTC economists who, you know, helped  
 12 organize this, Ted Rosenbaum and Nathan Wilson, and  
 13 Peter Nguon of the Bureau of Economics, one of our RAs  
 14 who really did great work in helping put this  
 15 together. And also our admin team which works -- does  
 16 incredibly hard work behind the scenes to make sure  
 17 that this comes off. So Maria Villafior, Kevin  
 18 Richardson, Neal Reed, Constance Harrison, Priscilla  
 19 Thompson, Tammy John, and Chrystal Meadows.

20 Before I turn this over to the -- to Jonathan  
 21 Zinman and the first panel, let me call your attention  
 22 to two calls for research that recently were issued by  
 23 the FTC just in the last couple of days. The first is  
 24 a request for empirical research and public comments  
 25 on the effects of certificates of public advantage and

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1 other kinds of state-based regulatory approaches  
 2 intended to control healthcare prices and quality.

3 COPAs have turned out to be pretty important  
 4 for the FTC, especially our hospital merger  
 5 enforcement mission. Basically, if two hospitals that  
 6 are -- you know, that are close rivals propose to  
 7 merge and it would ordinarily attract the attention of  
 8 possibly an enforcement action with the FTC, that can  
 9 be avoided by obtaining something called a COPA  
 10 from -- it's awarded by the individual state, and that  
 11 can immunize the transaction from antitrust scrutiny,  
 12 and that's come up in a couple of recent cases. So  
 13 it's an important issue for us, and we would like to  
 14 know more about you know, how these things work and  
 15 what their effects are.

16 So if you go to the FTC's website and also, you  
 17 know, out on the table where the papers are, you'll  
 18 see the actual call for research. There's going to be  
 19 a public workshop in 2018 where -- you know, where  
 20 researchers can, you know, present the results of  
 21 their findings, and we can, you know, help maybe, you  
 22 know, guide further policy actions by the FTC. So,  
 23 again, you can find a discussion of that -- you know,  
 24 the call for papers is out, and there's a copy of it  
 25 up on the table out there with the papers, but it's

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1 also on the FTC's main website, on the homepage.  
 2 Second, Economic Inquiry has just announced a  
 3 symposium on the economics of consumer protection.  
 4 The goal of the symposium is to create a unique  
 5 reference on consumer protection economics that would  
 6 synthesize what we know about the current state of  
 7 economic analysis, of consumer protection law, and  
 8 enforcement policy, identify what consumer policy  
 9 questions are in need of more analysis, and advance  
 10 the application of economics to consumer protection  
 11 policy analysis and law enforcement.

12 The symposium -- which there will actually be a  
 13 symposium next year, next December here at the FTC --  
 14 celebrates the 40th anniversary of the 1978 founding  
 15 of the Division of Consumer Protection in the Bureau  
 16 of Economics. So up until 1978, the Bureau of  
 17 Economics really only was directly involved in the  
 18 antitrust enforcement mission. By the time the late  
 19 seventies rolled around and the enforcement mission  
 20 was picking up steam, it was realized, you know, that  
 21 there needed to be a role for economics there, too.  
 22 So next year is the 40th anniversary.

23 So I think there will be a special issue of the  
 24 journal where selected papers are -- you know, are  
 25 published and then the symposium in December. The

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1 editors of the symposium are Wesley Wilson, he's one  
 2 of the editors -- I guess he is the lead editor of  
 3 Economic Inquiry -- and Jan Pappalardo, who's our  
 4 Assistant Director for Consumer Protection here at the  
 5 FTC. And, again, that call for papers, a copy of it's  
 6 out at the desk, but I think it will be also posted on  
 7 our website.

8 Okay, I think that's all the things I wanted to  
 9 announce. Oh, just, you know, I am supposed to make  
 10 announcements about exits and things like that. So if  
 11 there is a fire or something, follow the exit sign.  
 12 You guys are all Ph.D.s. I'm sure you can figure that  
 13 out. There's a cafeteria over here -- there is going  
 14 to be lunch, but there's a cafeteria over here if you  
 15 want to get something to eat this morning, you know,  
 16 you can go over there, and we also have coffee and  
 17 other refreshments back there. And I think that is  
 18 it.

19 So, Jonathan I think is running the first  
 20 session. Is that -- is that right? Okay, you want to  
 21 do the -- okay, so I will hand it over to Nathan  
 22 Wilson. Thanks.

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## PAPER SESSION

MR. WILSON: Thanks a ton, Mike.

All right. Our first paper session will kick off with Charlie Murry speaking on middlemen as information intermediaries. Before Charlie takes over, I wanted to pass on one last important announcement, which is the restrooms are directly behind me. The men's room is on the left as you're facing this wall. The women's room is on the right. All right. And if you have questions, please just let us know.

Charlie?

MR. MURRY: Okay. So this paper has a title, and the title is on the first slide. So this paper is about middlemen or intermediaries. It's with Gary Biglaiser, who's here today, and Fei Li at UNC, and Yiyi Zhou who's at Stony Brook. So the next slide, please.

Okay. So middlemen, intermediaries are everywhere in the economy. Just kind of from a very broad perspective, there's kind of a public debate of whether middlemen or intermediaries are of value to society. So think about, like, you know, in different industries like financial institutions or different kind of used goods industries.

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Our paper is going to be about used cars, okay, and we all might have a particular thought or vision about a used car intermediary or a used car dealer, all right? And so -- the next slide, yeah -- so this may or may not be your kind of picture of what a used car dealer is, but we're going to provide some framework to think about the services this type of intermediary provides in his marketplace. Okay, next slide.

Okay, so there's kind of two things that the literature is focused on for the role of intermediaries. The first is that intermediaries facilitate search and matching by potential buyers, okay? So there's a large literature, a theoretical literature on the role of intermediaries fulfilling search and matching. There is also a very nice empirical literature documenting this feature of different industries.

We're going to take a different view of the role of intermediaries. We're going to view intermediaries as being information certifiers, okay? So there is some theoretical work on the role of intermediaries as certifying information in markets -- Biglaiser '93 and Lizzeri '99 -- but there is very limited empirical work documenting or testing the role

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of intermediaries of relieving informational problems and certifying goods in markets.

So what we're going to do is examine the role of used car dealers in relieving asymmetric information. So specifically we're going to present a model of dealer experts motivated by features of the used car market, and then we're going to empirically test two key assumptions of our model.

The first assumption is that -- it has to do with the role or the value of dealers in this market, okay? What we find from the model, what we predict from the model is that there's a price premium that the dealer can charge over the private party market, and so you can -- as a consumer, you can go to the dealer to buy a used car, right, or you can do an off-dealer transaction with an individual. And so there's a price premium that the dealers can charge in this market, and this price premium is correlated with the age of the car.

In particular, we find that the price premium is increasing in the age of the car, and the important thing about the age of the car is that it's a -- is the age of the car is correlated itself with the fact that the car might be a lemon or not, okay, and I am going to go over that in detail.

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The second way we bring the model to the data is kind of more of a classical test of asymmetric information. So the model predicts that cars sold from private parties turn over more quickly, so they're resold more quickly than cars sold from dealers. That's because cars sold from private parties are more likely to be lemons, okay, and the people purchasing those cars are going to want to shed those cars, get rid of those cars.

Okay. So why do we care about this? So why do we care about used cars? Why do we care in general about this question? So there's kind of two reasons, big picture reasons. One is kind of from an academic perspective. Used cars are a very classic example of kind of Akerlof's lemons problem. In particular, we're suggesting that dealers here, as an information certifier, act as a counteracting institution in the parlance of Akerlof 1970, okay? So these guys are -- they come in and they make the market work.

More practically, why do we care about used cars or why do we care about this question? Well, there has been a lot of recent research on online markets and the role of information certification in online markets -- so, for example, you know, the star rating on eBay -- yet a significant amount of trade

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1 still happens offline. So how do these offline  
2 markets function without these kind of mechanisms that  
3 we've grown accustomed to in online markets, like a  
4 star rating, right? You cannot go to your friend  
5 who's selling a car and ask him for his star rating,  
6 right? He's never sold a car before. No one's rated  
7 him, okay?

8 In particular, the used car market is quite a  
9 relevant market when thinking about asymmetric  
10 information problems. So, first of all, it's a huge  
11 market. These numbers are kind of good guesses.  
12 We've done a lot of work to figure out how big the  
13 used car market is, but there is not a lot of great  
14 information. But the total sales of used cars in a  
15 year is roughly 300 to 400 billion dollars, okay?  
16 This is roughly three to four times the gross  
17 merchandise volume for eBay in a year. So this is a  
18 very large market.

19 Cars are kind of the classic example of  
20 asymmetric information. They're complicated machines  
21 that require specialized care. And so we think this  
22 market is ripe for asymmetries. In our sample, the  
23 sample of transactions we have, about two-thirds of  
24 used car transactions happen through a dealer, and  
25 there are kind of institutional features that we think

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1 make this market kind of natural to study this kind of  
2 information certification problem.

3 That is that dealers are quite regulated by  
4 U.S. states. They might have reputation concerns that  
5 are different than private parties that are  
6 transacting in this market, and they do things to kind  
7 of explicitly try to resolve asymmetric information  
8 problems, which is offer warranties and guarantees.

9 Okay, so what I'm going to do is I'm going to  
10 present a model very briefly. I'm not going to use  
11 any notation, so I am just going to give you the  
12 intuition for our model and then give you the  
13 intuition for the predictions of the model. Then I'm  
14 going to bring the model to the data and show you how  
15 we test these two predictions with our data.

16 Okay, so let me set up the model here. So in  
17 the model we have different agents interacting. The  
18 first type is an owner of a car or a seller of a car,  
19 okay? The owner of a car has a used car. That car  
20 can have two potential states. So that car can either  
21 be high quality or low quality. The car can either be  
22 not a lemon or a lemon. This state of quality is  
23 private information to the owner of the car.

24 With some probability, a quality shock  
25 arrives -- this is a continuous time model, so a

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1 quality shock to the car arrives at some rate that  
2 changes the state of the car, that takes the car from  
3 a high state to a low state, so a nonlemon to a lemon,  
4 okay? Also, there's a liquidity shock that arrives to  
5 the owner of the car so that the owner is forced to  
6 sell this car at some point in time.

7 When the owner receives this liquidity shock or  
8 the seller receives this liquidity shock, they can  
9 visit a dealer with some exogenous probability, okay?  
10 So they are basically allowed to visit a dealer with  
11 some probability, okay? So let me talk about what  
12 happens if they visit a dealer.

13 If the owner of the car visits a dealer, the  
14 dealer can run a test to discover the true quality of  
15 the car. So the dealer in this market is an expert,  
16 okay? Other private individuals in this market are  
17 not an expert, so they cannot run the same test. The  
18 dealer then makes a take-it-or-leave-it offer to the  
19 owner of the car, and this could potentially be a  
20 losing offer. For example, if the dealer finds out  
21 this is a lemon, then the dealer might not want to  
22 take possession of the car.

23 Okay, then if the dealer takes possession of  
24 the car, they set a selling price to the market, and  
25 they earn some profit, the selling price they set

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1 minus the cost that they paid for the car from the  
2 original owner. And then also the dealer has some  
3 cost of selling a lemon, okay? So if the dealer takes  
4 possession of a lemon and decides to sell it on the  
5 market and sells it, there's some cost there, okay?  
6 And I'll talk more about that cost, but this makes it  
7 kind of -- this makes it so that the dealer has a  
8 distaste for selling a lemon to the market.

9 Okay, there's two more -- okay, there's one  
10 more agent in the model that's interacting with the  
11 dealers and the owners, and that is the buyer, okay?  
12 So we assume that there's at least two buyers for any  
13 given car in the market, and the buyer receives  
14 some -- like a single unit of utility from a car until  
15 it turns bad, okay? So they continue to receive this  
16 flow utility from the car until the car becomes a  
17 lemon, and then they receive no utility from the car.

18 The two or more than two buyers simultaneously  
19 bid on the car, whether -- if it's from a private  
20 market or whether it's from a dealer. And what does  
21 the buyer know? Okay, so the buyer observes the  
22 vintage of the car, observes how old the car is. This  
23 is important because we have this kind of -- this  
24 quality shock arriving at the car at some random rate,  
25 okay? So with an older car, it will more likely be a

17	<p>1 lemon, all right?</p> <p>2 But the potential buyer does not observe the</p> <p>3 true quality of the car, and also, the potential buyer</p> <p>4 does not observe whether the original owner has taken</p> <p>5 the car to the dealer to be inspected and tried to</p> <p>6 sell the car to the dealer, okay? So the only thing</p> <p>7 this buyer knows is the age of the car.</p> <p>8 Okay. And then there's one more thing that can</p> <p>9 happen in the model, that after this stage where these</p> <p>10 buyers bid on a car and potentially transactions</p> <p>11 happen, there's a second stage where the new owner of</p> <p>12 the car can resell the car, okay? So these new owners</p> <p>13 of the cars receive another liquidity shock with some</p> <p>14 probability, and when they receive that liquidity</p> <p>15 shock, they must sell the car.</p> <p>16 Okay, if you're a new owner of the car, you can</p> <p>17 also just sell your car anyway. So, for example, if</p> <p>18 you took possession of a lemon and you realized it was</p> <p>19 a lemon, you can also go in the market and try to get</p> <p>20 rid of this lemon, okay? And in the resale market, it</p> <p>21 works very similar to the original market, and that is</p> <p>22 in the resale market, the new buyers observe the</p> <p>23 vintage of the car, how old the car is, but they do</p> <p>24 not know the selling motive of the new seller of the</p> <p>25 car. So they don't observe if the car was purchased</p>	19	<p>1 the market to go. So this is our mechanism to get</p> <p>2 this market to go.</p> <p>3 We can actually allow -- the model is very</p> <p>4 simple if you don't allow for endogenous</p> <p>5 self-selection, but we can actually allow for some</p> <p>6 endogenous self-selection -- so for some guys who have</p> <p>7 a lemon to endogenously go to the market and sell this</p> <p>8 lemon -- but we need some high type cars in the</p> <p>9 market.</p> <p>10 The second important assumption is the value of</p> <p>11 a high car versus the value of a low car. The key</p> <p>12 assumption here is that the utility that a consumer</p> <p>13 gets from a high car is greater than from a lemon.</p> <p>14 Both types' value depreciation with age, so as the car</p> <p>15 gets older, the flow utility you receive from a car</p> <p>16 depreciates, and the difference between a high car and</p> <p>17 a low car goes to zero as the age goes to infinity,</p> <p>18 okay? So at some point your car just is a POS, and it</p> <p>19 doesn't really matter if it's a lemon or not. You</p> <p>20 don't really want to be driving it.</p> <p>21 Also, the third kind of assumption I want to</p> <p>22 point out is that the dealer has some sort of cost of</p> <p>23 selling a lemon. This is kind of a way to model the</p> <p>24 fact that dealers are less myopic than private</p> <p>25 sellers, okay? For example, dealers might have --</p>
18	<p>1 originally from a dealer or a private party, and they</p> <p>2 don't observe the private information of that car,</p> <p>3 what state it's in.</p> <p>4 Okay, so there are some key assumptions we've</p> <p>5 made in this model, and I just want to briefly kind of</p> <p>6 go over them. One is that there's an exogenous</p> <p>7 liquidity shock, so basically I have a car and I have</p> <p>8 to sell it for some reason. Then I can only go to the</p> <p>9 dealer with a certain probability. What does this do</p> <p>10 in our model?</p> <p>11 Well, this kind of forces there to be a mixing</p> <p>12 between high and low cars in the private market, okay?</p> <p>13 So the consumers will know for sure that there's some</p> <p>14 probability that a high car will exist in the private</p> <p>15 market. Okay, why is this important? Well, we need</p> <p>16 some sort of, in Akerlof's term, counteracting</p> <p>17 institution to kind of make this market go, okay?</p> <p>18 Otherwise, the consumers, all right, would believe</p> <p>19 that the only cars being sold are lemons, and the</p> <p>20 market would unravel like Akerlof 1970.</p> <p>21 So another example of this is in a nice paper</p> <p>22 by Igal Hendel and Alessandro Lizzeri, where they</p> <p>23 basically tranche up the market into different -- into</p> <p>24 new cars and used cars, and they create distribution</p> <p>25 evaluations, and this is another kind of way to get</p>	20	<p>1 dealers are going to this market day-in and day-out,</p> <p>2 whereas private sellers go to this market typically</p> <p>3 once and don't go back, okay? And so dealers might be</p> <p>4 concerned about their reputation and so they might not</p> <p>5 want to sell a lemon for some reason.</p> <p>6 Okay. In the model, buyers will bid their</p> <p>7 expected quality in the private market. A seller will</p> <p>8 accept a dealer's offer if it's greater than the</p> <p>9 outside option. It turns out that dealers will only</p> <p>10 trade in high types of cars, and the price that they</p> <p>11 set equals the buyer's utility, so the flow utility</p> <p>12 for this high type of car, and that the resale --</p> <p>13 there is action in the resale market.</p> <p>14 Okay. So the model predicts kind of two things</p> <p>15 that we're going to take to the data. One is that the</p> <p>16 dealer's price premium in price terms is humped</p> <p>17 shaped -- and I'll show you this in a second -- and</p> <p>18 that the dealer's price premium in percentage terms is</p> <p>19 greater than one. So there is always a dealer</p> <p>20 premium, and it's increasing in the age. So in</p> <p>21 percentage terms, there's an increasing dealer</p> <p>22 premium.</p> <p>23 Okay. The intuition here is that older cars</p> <p>24 are more likely to be lemons. Buyers value the</p> <p>25 dealer's kind of certainty. Buyers value the fact</p>

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1 that the dealers are screening these cars and  
2 providing them certainty of whether this car is a  
3 lemon or not, okay? But as the car gets really old,  
4 the depreciation wins out, and really old cars are  
5 worth nothing anyway, and so that's why this is humped  
6 shaped in dollar terms.

7 The other prediction we're going to take to the  
8 data is that -- it has to do with car resales. So a  
9 buyer is less likely to resell a car if originally  
10 purchased from a dealer, okay? The intuition here is  
11 that all lemons, when -- if you are in this resale  
12 market and you've found a lemon, you want to get rid  
13 of it, okay? But the only way you are going to get  
14 rid of a car that's not a lemon in this resale market  
15 is if you receive a liquidity shock. So it's more  
16 likely for cars to be resold if they were bought  
17 originally in the private party market as opposed to  
18 the dealer market.

19 Okay. So to test these assumptions, we  
20 gathered data on the universe of used car transactions  
21 in the states of Pennsylvania and Virginia, and the  
22 nature of these data are the following: We have the  
23 transaction date, we have something about the vehicle  
24 identification number, we have the odometer reading,  
25 we have the zip code of the buyer, we have the seller

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1 identity. So whether it's a dealer or not, who the  
2 dealer is, and if it's a private party, we know the  
3 zip code of the individual.

4 For the Virginia data, which we used to test  
5 the dealer premium story, we observe a -- kind of a  
6 long panel, 2007 to 2014, and we observed a squish  
7 VIN, which is like the first 11 digits of the VIN. So  
8 we don't know the exact car being sold, but we know  
9 everything else about the car, so what -- the exact  
10 trim, the specifications of the car.

11 For the Pennsylvania data, we have a much  
12 shorter panel, so 2014 to 2016, but we observe the  
13 entire VIN of the car. So we know exactly which car  
14 is being sold, and so we can link the same car over  
15 time, subsequent resales.

16 Okay. So just to point out some moments from  
17 the data, this is from the Virginia data, it's clear  
18 that there is a dealer premium. Not conditioned on  
19 anything, there is a dealer premium. So, on average,  
20 the price of a private party transaction is about  
21 \$4,000 in our data set. The price of a dealer  
22 transaction is about \$13,000.

23 Dealer transactions are younger, six years as  
24 compared to 11 years, and they have lower mileage on  
25 them, okay? This is not surprising. About 60 percent

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1 of our sales go through dealers, okay? So this is  
2 what the dealer premium looks like in the Virginia  
3 data. This top line is the average price -- is the  
4 price -- the average price of a dealer sale. This  
5 bottom line is the average price of a private party  
6 sale at different ages, okay? So it's clear that  
7 prices are going down as the age of a car gets  
8 greater, okay?

9 There is this hump -- you can't really see it  
10 here, but there is this humped shaped in the dollar  
11 terms of the dealer premium, so it starts out pretty  
12 small and then gets bigger, the difference between  
13 these two lines, and then goes down again. And then  
14 this line here is the dealer premium in terms of a  
15 ratio of the dealer price to -- the average dealer  
16 price to the average private party price.

17 Okay, but these patterns could exist because  
18 there's some kind of sorting in these markets based on  
19 observed characteristics of the car; for example, the  
20 make or model of the car, okay? So we are going to do  
21 a little bit more serious job about testing this idea  
22 that there's a dealer premium and that it's increasing  
23 in age.

24 So we are going to run a Hedonic price  
25 regression, and the important thing about this

24

1 regression is we're going to be able to add a  
2 make/model/MY/trim/fix effect, so this is going to  
3 condition on basically everything observable in terms  
4 of characteristics about each car.

5 We are going to include a seller type and car  
6 age dummy interactions, okay, and so we're going to be  
7 able to predict the dealer premium for any given  
8 model/make/ MY/trim for any given age, okay? And I am  
9 going to show you what these -- the basically  
10 expectation of these prices look like, conditional on  
11 these controls, on the next page. I won't go into the  
12 different samples we used.

13 Here's the predictions from this kind of price  
14 Hedonics regression, okay? So this is the predictions  
15 of the -- this is the predicted price premium for a  
16 dealer by age, okay? And so you can see that young  
17 cars have a low price premium. For example,  
18 one-year-old cars have about a \$1,000 price premium,  
19 on average, and it certainly is hump-shaped, and it  
20 peaks at about six years, okay, and then it  
21 depreciates, right? So this is consistent with the  
22 prediction of our model, that in dollar terms, the  
23 price premium for dealer cars is hump-shaped, okay,  
24 and depreciates as the car gets older.

25 Okay, the other prediction from the model about

25

1 price premium is that, in ratio terms, it's  
 2 increasing, and so this is the predictions in terms of  
 3 the predicted price premium in terms of ratios from  
 4 this kind of Hedonic pricing model, okay? And so for  
 5 one-year-old cars, the price premium is about 15  
 6 percent, and this increases until about age eight or  
 7 nine and then kind of levels off or slightly decreases  
 8 to age 20. Okay, so these two features of the data  
 9 are consistent with the predictions of the model about  
 10 the dealer price premium.

11 The other thing we test is this bit about car  
 12 resale. So the implication is that a buyer is less  
 13 likely to resell his car if the car was purchased from  
 14 a dealer. Okay, we used the Pennsylvania data where  
 15 we can link cars over time, so we take all cars that  
 16 we observed transacted in 2014 and follow them until  
 17 2016, and this is just the moments from the data here.

18 One percent of dealer sales are resold within a  
 19 quarter, 2.2 of private sales are resold within a  
 20 quarter, and these patterns continue to exist as we  
 21 think about longer resale terms, so two quarters,  
 22 three quarters, four quarters. So it's always the  
 23 case that private sales are kind of more likely to  
 24 turn over within any of these resale bins.

25 So, again, this could be because there's kind

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1 of mixing and types of cars that are being resold, so  
 2 we -- let's see, this guy -- can you move the slide  
 3 deck one forward? Yeah, okay, so we do a little  
 4 better job here. We look at resale rates by  
 5 three-month intervals, controlling for the same  
 6 model/make/MY/trim/trim/fixed effect, and we're worried  
 7 that there might be some reason -- unobserved to us --  
 8 why you buy a car from the dealer in the first place  
 9 and you are going to sell it quickly. For example,  
 10 maybe you're a transient person who's just in town for  
 11 three months. So we are going to instrument for  
 12 seller type by using data we have on the inventory  
 13 holdings of dealers in local markets.

14 And we run a logit model with fixed effects,  
 15 and when we do instrumenting, we use a control  
 16 function to instrument for the -- whether the car was  
 17 bought from a dealer or not, and our results here are  
 18 consistent with the patterns in the data, which is  
 19 that if the car was bought from a dealer, it's more  
 20 likely to be resold in one quarter than a car bought  
 21 from a -- I'm sorry, it's less likely to be resold  
 22 after one quarter than a car bought from a private  
 23 party, and in two quarters, and in three quarters, and  
 24 in four quarters.

25 And actually, this kind of probability that you

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1 resold within this time frame is decreasing in the  
 2 time frame, which, you know, kind of is suggestive  
 3 evidence that this asymmetric information problem is  
 4 kind of going away over time. And this is the results  
 5 with the instruments, but they tell the same story.

6 Okay, so my time is almost out. Kind of one  
 7 important thing, though, that might be going on in  
 8 this market that we haven't talked about, although I  
 9 mentioned it briefly at the beginning, is that we  
 10 could observe this dealer premium because of a search  
 11 and matching role for dealers, and so in the paper we  
 12 spend some time talking about the predictions of a  
 13 search and matching story in our model, and we show  
 14 that it's not quite consistent with these particular  
 15 patterns that we find; specifically, the fact that the  
 16 dealer premium is increasing in car age.

17 But I'm out of time, so I won't go over that in  
 18 detail, and I will leave it at that. So, thank you  
 19 again.

20 (Applause.)

21 MR. WILSON: Thanks very much.

22 Discussing this paper will be Tobias Salz of  
 23 Columbia University.

24 MR. SALZ: Thank you.

25 So thanks to the organizers for allowing me to

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1 discuss this paper. I like the topic. I like the  
 2 paper. It was a lot of fun to think about it.  
 3 So I want to start out with this quote that I  
 4 found, and I'm sure many people out here are familiar  
 5 with the story behind this. The reason I thought it  
 6 was fitting is that if you are sort of in the trenches  
 7 of day-to-day work and, you know, you kind of look at  
 8 other papers and you feel everything is pretty  
 9 incremental and the process comes very slowly, and  
 10 then you compare sort of how we nowadays think about  
 11 the interplay between theory and data to -- you know,  
 12 what this referee must have thought when he was  
 13 rejecting the original lemons paper, you can't help  
 14 but think that, well, actually, we have made a lot of  
 15 progress, and I think this paper is a nice example of  
 16 sort of how we use data in a more nuanced way to  
 17 inform theory.

18 So as the authors have already highlighted,  
 19 intermediation is a big part of the economy. I think  
 20 there's more empirical work to be done. And something  
 21 to appreciate about this paper is that it's really  
 22 hard to pin down these informational stories without  
 23 observing sort of what people know exactly, and what  
 24 this paper does, it leverages the intertemporal  
 25 dimension of this market a lot, and basically it gets



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1 a lot of qualitative prediction just out of that from  
2 a very, very simple model, okay?

3 The paper has great data. I think I learned  
4 many new facts. The model is parsimonious in a good  
5 way and yet it gives all these predictions. And then  
6 something else to highlight, I think I -- and I know  
7 we have studied car markets a lot, so it's one of  
8 those markets that, you know, we think we know very  
9 well, and yet there's a lot more to be learned here,  
10 which I think is nice, and it's a big and an important  
11 market.

12 So let me quickly recap the model. I'm using  
13 notation, so I should have coordinated a bit better,  
14 but -- so the model basically has cars that are aging,  
15 and everybody can condition on age, so there's a  
16 depreciation effect that everybody can condition on,  
17 and then there is a quality that's only -- a binary  
18 quality value that only the seller can condition on.  
19 And so over time the car becomes sort of obsolete just  
20 because it -- you know, it depreciates but also  
21 because the chance is getting higher that it becomes  
22 of low quality.

23 And the sellers of the car, they exogenously  
24 meet either a party in a bilateral market or a dealer,  
25 and dealers will only sell high-quality cars. So this

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1 is -- in the middle, I think -- in the main text it's  
2 pretty much assumed, but then in the appendix, it's  
3 derived from a little cost that the dealer has to  
4 maintain reputation.

5 And so over time, the market -- the bilateral  
6 market becomes more and more select -- adversely  
7 selected because dealers, they are -- they are  
8 confronted with a car, they turn it down, and so more  
9 and more low-quality cars will be traded in the  
10 bilateral market.

11 So one thing that's also important which makes  
12 the model sort of much simpler is that the sellers in  
13 this market can basically extract all the rents, okay?  
14 So buyers engage in Bertrand competition for cars.

15 So I think that you can pretty much get three  
16 out of four predictions from the model by just looking  
17 at these two equations. So as I said, dealers will  
18 only sell high-quality cars, and they offer a warranty  
19 with these cars, so that buyers know that they get  
20 high-quality cars, and so dealers are charging the  
21 value -- the high utility value.

22 And in the bilateral market, you have this  
23 ratio of good cars, the mass of good cars that are  
24 being traded in the bilateral market, times the  
25 utility value for a high-quality car. The low-quality

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1 value cancels out because it's normalized to zero.

2 And so what you can nicely see from this  
3 expression is that because over time the high-quality  
4 cars -- the mass of high-quality cars is shrinking,  
5 that the ratio of bilaterally traded cars is going to  
6 one. And then if you look at the ratio between the  
7 price and this -- what buyers paid in the bilateral  
8 market, you'll see that the depreciation effect, which  
9 comes through you, cancels out, and so you are left  
10 with the selection effect, and it's then pretty easy  
11 to see that the percentage premium in this market  
12 increases over time.

13 And then lastly, if you take the difference  
14 between these two, so if you subtract the bid for a  
15 car in the bilateral market from the price that a  
16 dealer is charging, you have both the depreciation  
17 effect and the selection effect, and this leads to  
18 this hump-shaped pattern that the authors are  
19 documenting.

20 And then lastly, there's an  
21 additional prediction which comes from an extension of  
22 the model in which sellers are able to resell.

23 So I want to make two main comments here. The  
24 first comment is that dealers and bilateral sellers  
25 are engaging in a slightly different business. So

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1 dealers, they're negotiating with the customers over a  
2 bundle, over a bunch of products at the same time.  
3 They're negotiating over the car, financing and  
4 insurance, trade-in value, add-ons, and so on.

5 So one thing I was wondering is whether the car  
6 that we observe for dealer -- sorry, the price that we  
7 observe for dealer-traded cars is the price that you  
8 would get if you only negotiate over that part of the  
9 bundle, okay?

10 And so just to sort of give you one piece of  
11 evidence, this is borrowing something from a paper  
12 that I'm working on which is looking at how dealers  
13 price the financial aspect of the deal and the car  
14 price jointly. So what this shows here is a  
15 regression of prices of financial charges and the  
16 total price, which includes both financial charges and  
17 the car price, on a bunch of controls.

18 So, again, we have model controls and a bunch  
19 of other controls for the buyer, and then the key  
20 variable of interest here is an indicator that's  
21 called subvented. So this is whether or not a loan is  
22 subvented. So what is a subvented loan? It's  
23 basically when the vertically integrated lender of the  
24 manufacturer -- so Honda Finance -- ties the dealer's  
25 hands and says, well, you have to offer this loan as

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1 zero percent finance, okay?

2 And so this is -- you know, you should take  
3 this with a grain of salt, because this is not -- you  
4 know, subvented is not randomly assigned here, but I  
5 think there's some descriptive evidence from these  
6 subvented loans that this is a joint pricing problem  
7 and that, in fact, as you can see, the car price goes  
8 up conditional on the model if the dealer can no  
9 longer get this markup from the financial aspect of  
10 the deal, okay?

11 And so, of course, mechanically, financial  
12 charges go down, and it actually turns out that the  
13 total price is going up for these subvented deals. So  
14 this is just saying, well, there might be some other  
15 aspect of the bundle that is not included in this  
16 price here, and so I'm not even sure I would  
17 necessarily go against the authors, because it depends  
18 a lot on sort of, you know, where in the age  
19 distribution of cars are financial services offered  
20 and sort of how are these relative markups assigned,  
21 but I think one thing to sort of dig into a bit more  
22 is sort of what -- you know, what kind of price are we  
23 looking at here?

24 So then the other thing that I wanted to  
25 explore a bit more -- and this is sort of going back

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1 to I think a debate that, you know, is a long debate  
2 in the schooling literature. You know, it's either  
3 all information and selection and signaling, or it  
4 could be, you know, added value, and here it could be  
5 that dealers are, in fact, you know, adding value or  
6 recovering some of the value of low-quality cars.

7 And so I'm proposing a very simple model. This  
8 is exactly -- pretty much exactly like the one that  
9 the authors are looking at except that now the quality  
10 of the car is also observable to everyone, and dealers  
11 can recoup some of the lost value of a low-quality car  
12 at some fixed cost.

13 So they pay a mechanic for a few hours, and  
14 then there's sort of a random shock with which they  
15 can recover some of the value, and then I'm sort of  
16 playing around with the fixed cost for this -- for the  
17 mechanic, and on top of that, you might think there is  
18 a fixed cost for inventory, for dealer inventory,  
19 okay? Then we can kind of see how, over the time  
20 of or over the age distribution, these patterns that  
21 the authors are documenting look like, okay?

22 So I am going through a few cases now. So the  
23 first case is where there's a repair cost but no fixed  
24 cost. So the dealers basically repair the car if the  
25 fixed cost of the repair is smaller than the value

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1 that they can recover. And what you can see is we  
2 basically are totally wrong on the market share. The  
3 market share of dealers is flat because they're always  
4 selling all cars, because quality is observed, right,  
5 and they can extract all the rents.

6 Then we get that both the percentage premium  
7 and the absolute premium has this hump-shaped pattern.  
8 So basically we get one out of the three prediction of  
9 the model without the extension, right, so that's not  
10 going to give it to us. Ah, here we go.

11 So now the case where we have a fixed cost but  
12 not a repair cost. So what you can see here is that  
13 now dealers are turning away cars that no longer --  
14 whose value is no longer larger than their fixed cost  
15 of holding, so over time they are actually losing  
16 market share because they are more likely to send  
17 these low-quality cars back to the bilateral market.

18 We also see that the dealer percentage premium  
19 is increasing, but the absolute dealer premium is also  
20 increasing, and this comes due to selection on  
21 varieties. So at the very end of the age  
22 distribution, you only want to hold expensive  
23 varieties. And so, again, we get this time two out of  
24 three right, and it's not going to give it to us.

25 Okay. So now both of these patterns combined

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1 give you sort of a similar picture. We have  
2 decreasing market share, we have increase in  
3 percentage premium, but we also have increasing dollar  
4 premium. So the only case that I could find -- the  
5 only case that gets all three of those patterns right  
6 in the unextended model is the following case, and you  
7 can sort of think for yourself whether you think  
8 that's a plausible model.

9 So dealers have this repair cost, and they take  
10 a low-quality car only if they can repair it, and they  
11 send it back to the bilateral market otherwise, okay?  
12 Remember, this is a bit of a funny -- this would be a  
13 bit of a funny case because quality is observable. So  
14 I could still sell the car at the low value, so there  
15 must be some other reason, and so maybe I don't want  
16 to have shabby-looking cars on my lot.

17 So this might be one reason I send -- send away  
18 cars that are of -- that I can't repair, and then you  
19 get basically all three of those patterns, and I would  
20 just basically urge the authors to sort of maybe  
21 discuss a bit more what can be done with this  
22 alternative. I think a plausible explanation is that  
23 the dealer is actually adding some value.

24 So then I have a few more other smaller  
25 comments. I think the model in this resale extension

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1 makes also a sharp prediction on whom resales go to;  
2 namely, they should not go to dealers, because sellers  
3 know that dealers know the quality. So there should  
4 basically be an additional prediction that the model  
5 makes, that the authors can test for.

6 This is maybe bickering a bit, but, like, you  
7 could also look at more types than -- at least in  
8 these equations that I showed you, these -- the -- you  
9 don't -- you no longer get the depreciation effect, so  
10 cancel out nicely. I think things are still going  
11 through, but that would be something to look for.

12 Then I was wondering about spatial controls, so  
13 where are dealers located and does this correlate with  
14 the types of cars that are being sold in some way that  
15 could give rise to some of these patterns.

16 In terms of model specification, you could  
17 think that sometimes the bilateral market gives you  
18 all these guarantees or warranties that the dealers in  
19 this market are providing. So, for example, if I'm  
20 selling to my brother-in-law, then, you know, I don't  
21 want to sell him a lemon necessarily, so there might  
22 be some sort of repeated play that enforces this or  
23 has this reputation effect.

24 So something I was wondering about, what about  
25 age versus mileage? So basically the model is all

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1 done in terms of the age of the car, but you could  
2 think that -- you could sort of rephrase all of this  
3 and say, well, the observable dimension is actually  
4 the mileage of the car. We instead control for age,  
5 and I was wondering whether all of these things sort  
6 of look similar if we instead do it the other way  
7 around.

8 And then something I'm always interested in is  
9 sort of the distribution of prices. So we see these  
10 are all mean effects, but, you know, if you sort of  
11 see the price distribution for dealers in the  
12 bilateral market, how do they look like? Is it driven  
13 by the tails? That would be something to look at.

14 And that's all I have.

15 MR. WILSON: Thanks very much. We have got  
16 time for a couple of questions for Charlie. If you do  
17 have a question, please wait for the microphone to  
18 assist our stenographer.

19 Charlie, do you want to come up?

20 Jonathan?

21 MR. ZINMAN: This may be a question for FTC  
22 folks as much as for Charlie. I'm wondering if there  
23 are any efforts under way, public sector and/or  
24 private sector, to bring more data to bear in this  
25 market against the asymmetric information problem. It

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1 seems like there's a lot of data that could, in  
2 principle, be captured about vehicle history.

3 So, for example, it seems like many cars these  
4 days know what's wrong with them on an automated  
5 basis. Is there any interest in helping or forcing  
6 manufacturers to capture and share that data to build  
7 vehicle histories that would be more observable?

8 MR. MURRY: So I can't really answer that  
9 question too well. One resource available to kind of  
10 researchers -- not in the Government -- there's more  
11 research sources, like, for example, CARFAX reports.  
12 Those are, in practice, accessible to researchers.  
13 The problem is CARFAX reports are not very good  
14 actually, so you shouldn't really trust a CARFAX  
15 report.

16 And so maybe there is a role to kind of  
17 regulate CARFAX reports or something else, but I  
18 can't -- yeah, I don't know if anybody from the FTC  
19 wants to take that or not.

20 MALE AUDIENCE MEMBER: Thank you for that  
21 paper. I really wish my good friend and colleague Jim  
22 Lacko were here, because I don't know if you're aware  
23 of his research -- it's 30 years old now -- but he had  
24 research from a survey of used car buyers, and I would  
25 just encourage you to look back at his paper from, I

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1 think, 1985, where one of the differences with his  
2 data from your data was he was able to get more  
3 information on the private sales -- was it to a  
4 brother-in-law, as the discussant mentioned, or was it  
5 to a stranger -- to see whether that factor influenced  
6 the quality of the car being traded.

7 I don't know his research well enough to do  
8 more than that, but I would just encourage you to look  
9 back at that report. We'll be happy to get it to you.  
10 I'm here at the FTC, but it's a really, really fine  
11 piece of work with a different -- a different approach  
12 to the data.

13 MR. MURRY: Yeah, so one thing to kind of -- on  
14 that point and something that Tobias mentioned, we do  
15 see the zip codes of the buyer and the seller in the  
16 private party transactions, and so we do have one  
17 specification that maybe not was in the paper that you  
18 saw, where we control for the zip codes of the buyer  
19 and seller.

20 And you might think in rural areas there might  
21 be a reputation effect of selling to somebody in the  
22 same zip code, but in urban areas, there isn't. So  
23 we -- but thank you for the suggestion, yeah.

24 FEMALE AUDIENCE MEMBER: I wanted to follow up  
25 on Tim's comment and question because I was thinking

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1 along the same lines. In Jim's work, I believe that  
2 he found that there was a distinction between the  
3 outcome if the dealer sold new cars and used cars or  
4 only used cars, and I'm wondering if you were able to  
5 investigate that.

6 MR. MURRY: Yeah, we do know the -- who the  
7 dealer is, so we do -- we do the same analysis for  
8 just the subset of dealers who also sell new cars and  
9 just -- and for the subset of dealers who only sell  
10 used cars. And the patterns that I showed exist for  
11 both types of sellers, but they're kind of shifted up  
12 for the used-only cars, but we do some of that in the  
13 paper, where we've split the sample into these two  
14 types of sellers, yeah. Thank you.

15 MR. WILSON: Thanks very much.

16 Now we're on to our next paper by Maryam Saaedi  
17 of Carnegie Mellon. She will be speaking about  
18 certification, reputation, and entry.

19 MS. SAEEDI: Okay. So this is a paper with my  
20 student, Xiang Hui, who is on the market now,  
21 Giancarlo Spagnolo, and Steve Tadelis. So in other  
22 sessions that we just saw, there exist in many  
23 markets, online and offline. If you want to buy  
24 something on eBay, you -- the seller will know more  
25 about the item that you know. If you want to get

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1 something on Airbnb, you know, the host knows much  
2 more about the noise level in the neighborhood, and  
3 actually, as I found out last night, this is true for  
4 the hotels as well. There might be a train outside  
5 your hotel that goes every 15 minutes from 5:00 a.m.  
6 So I have been awake since 5:00.

7 And then, like, if you want to hire someone on  
8 Upwork, they know much better about their knowledge,  
9 their experience, or even if there are offline  
10 markets, you are hiring a procurement contractor, they  
11 know much more about the quality of their work than  
12 you do. And we know that from Akerlof, that there can  
13 be a lot of inefficiency and a lot of low-quality  
14 trade or sellers in the market as a result of that.

15 So there is a common solution for this problem,  
16 is having a reputation mechanism. So eBay, since its  
17 site has these feedback rating and other system has  
18 started, there are like Better Business Bureau, there  
19 are like restaurant ratings, Yelp reviews, all  
20 different kind of feedback ratings that can help  
21 overcome this problem.

22 So here in this paper we are actually focusing  
23 more on other kind of mechanisms, not exactly, but  
24 something that is related to feedback rating that can  
25 mitigate some of this asymmetric information problem.

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1 Okay.

2 So one standard solution that is similar to  
3 what we just saw is certification. So the  
4 certification can be that marketplace can be using  
5 data or some kind of process to certify the quality of  
6 their existing sellers. So the problem with doing  
7 this kind of licensing is that it can be some kind of  
8 barrier for the new sellers to enter in the market.

9 And this kind of certification is actually very  
10 common in online markets. So eBay has eBay Top-Rated  
11 Seller. Airbnb has super -- Airbnb Superhost. Upwork  
12 has its top-rated freelancers.

13 So these badges sort of show that there is --  
14 shows to the buyers that these sellers have passed  
15 some bar. And, for example, on eBay, when you're  
16 searching for something -- so this is from the time  
17 that we have the data on -- we're searching at that  
18 time when iPod still was traded heavily on eBay, and  
19 when you were searching on eBay, you would see that  
20 there is, like, some sellers that are top-rated, so --  
21 and you could see that on the search page, and then  
22 after you click on them, you would see more  
23 information on the listing page about the fact that  
24 this seller is top-rated and more information about  
25 this seller as well.

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1 Okay. So the good thing about the badges is  
2 that it mitigates some of the asymmetric information,  
3 but the problem is that it can be a barrier to entry.  
4 And what we want to do here in this paper is, what  
5 will happen if you actually make this certification to  
6 be harder to get? You want to see what's the  
7 incentive for the new sellers entering into the market  
8 and what is the quality distribution of these sellers  
9 and sellers in the market.

10 And we are going to use a study -- a policy  
11 change on eBay to answer these questions. So I will  
12 skip the literature review. So I will give you some  
13 stylized model that can help you think about what we  
14 have in mind. It's a very simple model. It's  
15 actually based on a paper that I have with Ugal  
16 Oppenheim (phonetic) here.

17 So we are assuming here that -- the paper is --  
18 so sellers are competing in a competitive market. So  
19 it's quite -- not a very bad assumption for eBay.  
20 There are hundreds of sellers, if not thousands, that  
21 are selling the same product. So we are assuming that  
22 it's a competitive market.

23 And then firms differ in two dimensions, either  
24 in their quality or entry cost. So their quality,  
25 they're assuming they can have three levels of quality

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1 here,  $z_1$ ,  $z_2$ , and  $z_3$ , and they have an entry cost that  
2 is independently distributed from a function  $G$ .

3 And the buyers observe certification badge.

4 They care about the quality, but they don't see  $z_1$ ,  
5  $z_2$ , or  $z_3$ . They see only the certification badge, and  
6 the certification badge signals if the quality is  
7 weakly above a threshold.

8 So we are assuming that there is a baseline  
9 demand function, which is  $P(Q)$ , which would be the  
10 demand for the lowest quality, and the demand for  
11 equality with expected quality,  $\bar{z}$ , is going to be  
12 additive to that demand function. So it would be  $P(Q)$   
13 plus  $\bar{z}$ .

14 So the policy change is going to be having this  
15 format. So at the beginning, before the policy  
16 change, group of  $z_2$  and  $z_3$  sellers were getting badge,  
17 they -- and they would show that they have a badge,  
18 but afterwards, only  $z_3$  sellers would show that they  
19 have a badge. So we change the threshold from  $z_2$  to  
20  $z_3$ .

21 Okay, so the impact on the entry depends on the  
22 changes in the prices. So we can prove that the price  
23 for  $z_2$  guys is going to drop, so these are the people  
24 who were getting the badge before, now they are not  
25 getting the badge. And they are losing the premium,

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1 and as a result, the price will go down, and there  
2 would be fewer of these sellers in the market  
3 afterwards.

4 And -- but for  $z_3$  and  $z_1$ , we can't prove that  
5 the price would go up for them for sure, but we can  
6 prove that at least one of the prices go up, but it  
7 can be both of them. So if, for example, for  $z_3$   
8 types, if the price is going up, it's because now they  
9 can get a more informative signal that they are of the  
10 highest level of quality, and then they would be  
11 entering into the market more.

12 And for  $z_1$  type, if the price is going up for  
13 them, it's because now they are pooled with  $z_2$  guys,  
14 and they can get the higher prices, and they would be  
15 entering into the market more.

16 Okay. So I am now going to the data. So we  
17 have proprietary data from eBay, and we have a lot of  
18 information about all the transactions that happen and  
19 what has happened afterwards. So we see everything  
20 that the buyer can see, and we can see everything  
21 about the history of the seller and the history of the  
22 buyers.

23 And one thing about the eBay product catalog  
24 that we are using is that eBay has this catalog  
25 formation that is about 400-plus categories that will

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1 include everything that is sold on eBay. So one  
2 category is fiction and literature, another one is  
3 fresh-cut flowers, and I will explain how we are going  
4 to use that.

5 Also, we have these product IDs that we are  
6 going to be using that is looking at very homogenous  
7 goods, like iPhone 6, black, 32-gigabyte, unlocked.  
8 So it would be very specific about the product that is  
9 sold. And we will have information about when the  
10 sellers enter the market in each of these categories.

11 Okay. So what was the policy change? So eBay  
12 used to have another badge called eBay Powerseller,  
13 and they have changed that badge and made it harder to  
14 get. So nowadays, if you want to become a badge,  
15 which is now called eBay Top-Rated Seller, you have to  
16 meet all the requirements for Powerseller, and then  
17 you have to meet some additional requirements.

18 And here -- and also, then, you cannot see if  
19 someone has a Powerseller status but not eBay  
20 Top-Rated Seller. So the only thing that you can see  
21 is the new badge. You don't -- the previous badge is  
22 completely obsolete.

23 Okay. So the impact on the percentage of  
24 people, percentage of sellers who were badged after  
25 this change was quite stark. So about 10 percent of

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1 the sellers had badge before, but afterwards, it  
2 dropped to about 4 percent, and then you see there is  
3 a growing in the number of sellers who have badge  
4 afterwards.

5 Okay. So what is our empirical strategy?  
6 Okay, so we can't be just using what has happened and  
7 just state the averages and say that's the impact of  
8 this policy, given that there's many things that are  
9 going on on eBay and also the fact that it's -- we are  
10 in the middle of financial crisis when this change has  
11 happened.

12 So what we are going to be using or doing -- we  
13 are going to do a two-stage approach. The first stage  
14 is we are going to be looking at the categories that I  
15 mentioned, the 400-plus categories that we have, and  
16 we are going to see which of them were more impacted  
17 by the policy than the others.

18 So here we run this simple regression, and we  
19 are looking at the share of badged sellers in each  
20 category over time, and we had a dummy for policy and  
21 some fixed effects and some time trend. And so this  
22 identification is based on assuming that these  
23 different markets were affected differentially, and it  
24 was exogenous why they were affected differentially.

25 We would run a placebo test to make sure that

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1 this doesn't just show some correlation that is  
2 driving other results as well. I will go over that by  
3 the end of the presentation.

4 Okay. So the second stage, we are going to use  
5 the results from the first stage and then look at  
6 different variables of interest, like number of  
7 entrants, quality and performance of entrants, and  
8 also quality of incumbents, and see if they were  
9 affected more with the policy or not. So we are  
10 multiplying this Gamma by that Beta-hat-C, and then we  
11 do also some other controls.

12 Okay. So the first stage result, we can see  
13 that this is the Beta-C, see how different categories  
14 were affected. So this is showing the whole 400 of  
15 them, just writing a few of the numbers. You can see  
16 that almost, other than one category, everything else  
17 had fewer badge sellers, few badge sellers afterwards,  
18 and you can see that the effect is very different from  
19 one category to the other. We have a good  
20 distribution, variation in the effects of the policy  
21 in these categories.

22 Okay. And now let's look at the results for  
23 the second stage. So now we are using that  
24 Beta-hat-C, so this Beta-hat-C is negative, so more  
25 affected categories have a bigger negative number. So

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1 Gamma less than zero means that there would be more  
2 entrants in more affected categories.

3 So here the Y, the first Y we have is entrant  
4 ratio, so it's the number of entrants at time t  
5 divided by the number of sellers at time t minus 1.  
6 And what we can see here is that there are more  
7 entrants into the more affected categories, and -- if  
8 we are looking at three months before and after, six  
9 months before and after, but if we are looking at the  
10 months seven to twelve afterwards, we don't see a  
11 significant impact. It seems that the entry happens  
12 very early on for the first three to six months, and  
13 then it doesn't, at least, continue as much as we move  
14 on.

15 Okay. So then we want to also see what -- the  
16 impact on the quality of the entrants. To look at the  
17 quality of the entrants, instead of looking at  
18 feedback ratings, which is usually 100 percent  
19 positive for all the sellers, we are using this  
20 effective positive rating measure, which is based on  
21 the paper by Chris Nosko and Steve, that they are  
22 looking at the number of positive feedbacks over the  
23 number of transactions instead of the number of  
24 feedbacks received, and they show in their paper that  
25 that's much better measure of quality, and they can

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1 see what buyers do afterwards, and they can say this  
2 sort of predicts how happy buyers are about the  
3 transaction, than just looking at the feedback  
4 positive rating.

5 And what we see here is that there is a  
6 positive impact, so there is -- the more affected  
7 categories have, on average, better quality entrants  
8 into the market. If you are looking at six-month  
9 window, twelve-month window, and also -- which is  
10 plus/minus three, plus/minus six, and actually, for  
11 this one, even if we are looking for longer time  
12 periods, we still see an impact on more higher quality  
13 entrants entering into those markets.

14 So this study shows us the average -- that on  
15 average higher quality entrants entering into this  
16 market, but you might also ask, so, what about the  
17 distribution of entrants? So that's what we want to  
18 do now. So we want to see how was the distribution of  
19 the entrants.

20 So to do that, we are going to divide the  
21 entrants in each of these subcategories into deciles  
22 based on their EPP in the first year after their  
23 entry. And then for each decile, we will run this  
24 regression again.

25 So for each decile, we will consider -- so this

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1 would be their Betas for that categories, but then for  
2 each decile, we are going to look at what was the  
3 impact of the EPP of that decile. This is the result  
4 for that Gammas. So this decile one is the lowest  
5 quality item. Decile ten is the highest quality  
6 sellers.

7 So here, the decile ten, which is the highest  
8 quality entrants, we have a negative coefficient,  
9 which means that they're higher EPP in more affected  
10 markets. So it sort of shows you that the -- if you  
11 were considering the distribution of the entrants, if  
12 you are looking at the highest decile, it has moved  
13 more to the right -- yes, okay, that's right, to the  
14 right.

15 And on the decile one, which is the lowest  
16 quality entrants, a positive coefficient -- we have a  
17 positive coefficient. Even though it's not  
18 significant, it shows that the letter EPP on the more  
19 affected markets, so the other tail, the left tail,  
20 also move more to the left.

21 So we have higher raise in the tails and a bit  
22 less in the middle. So it seems that even though we  
23 get average higher quality, it's sort of coming from  
24 the very highest decile, which makes sense, because  
25 those are the only people who have a chance of getting

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1 a badge. Not everyone can get a badge. It's a very  
2 small percentage of people who can get a badge.  
3 Okay. So we also -- so this was strange  
4 effects for the incumbents -- for entrants. We wanted  
5 to see what's the impact on incumbents, because it  
6 also can tell you that maybe these are not better  
7 sellers who are entering into these categories. It's  
8 just that these sellers who enter, after they enter,  
9 they start acting better because of the change that  
10 has happened in the market.

11 So we want to see what's the impact on the  
12 sellers who stay -- who were there before -- before  
13 the policy, and we actually -- when we are looking at  
14 these EPP measures, we don't see much of impact right  
15 after the policy change. So this is -- zero is when  
16 the policy change has happened. So the blue one, the  
17 blue circles are showing the average EPP for the  
18 entrants who entered in this month, this month, and so  
19 on.

20 You can see that the average EPP for the  
21 entrants afterwards is much higher than before, but  
22 when you are looking at incumbents, there's not that  
23 much of, at least, noticeable change. And we did  
24 different kind of slices of the data. So here we are  
25 looking at incumbents in top EPP quartiles and various

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1 different kind of cut, and we don't see much of  
2 impact.

3 So here we are looking at -- the blue one is  
4 the year of the policy, the green is the year after,  
5 and the red is the year before, and we don't see much  
6 of impact for -- if we are looking at different  
7 quartiles. And we also run regressions, we don't see  
8 much of impact for incumbents.

9 So the best that we could come up why that has  
10 happened is that maybe the sellers on eBay are doing  
11 the best that they can already and there's not that  
12 much room for improvements for them, but we don't --  
13 we were surprised that we didn't find any results  
14 here. So that was at least surprising for us.

15 Okay. So we also look at the impact on prices.  
16 So we are looking at group -- so BB is the sellers  
17 that are badged before and after; BN, sellers are  
18 badged before and not after; not badged before and  
19 badged after. So this NB group is surprising for many  
20 people. So the thing is that on eBay, they check the  
21 badge requirements once in a month, so it might have  
22 been that you were getting your badge no matter what,  
23 and even now that the badge becomes harder, you're  
24 still getting a badge. So that's why you have some  
25 people who don't have a badge but have badge after.

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1 And then you have people who didn't have badge before  
2 and after.

3 So we are looking at relative prices, so --  
4 because you can have a lot of stories about sellers  
5 after they become badged, they are going to sell  
6 better items. So we are going to look at the listing  
7 price divided by product value, and then we find the  
8 product value to be the average price of the product  
9 in the posted price format for that product ID. So  
10 the product ID, for example, again, would be iPhone 6,  
11 64 gigabyte, black, unlocked. It would be very  
12 specific.

13 And we also look at sales probability, so  
14 what's the chance that they can sell an item and  
15 what's the number of items they can sell and what was  
16 their market share. So, in general, this is what we  
17 find if we combine everything together, that the  
18 best -- so the guys that were not badged and after --  
19 even though there are not that many of them, they are  
20 the most affected, obviously, but then you have the  
21 people who were badged before and after, they have a  
22 positive impact, and then sellers who were not badged  
23 before and after, they also see a positive impact, and  
24 these people who lost their badge, they see a negative  
25 impact.

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1 And so these are the regressions for  
2 different -- so I will skip that, it will take a long  
3 time, and for the last four minutes I talk a little  
4 bit about this placebo test that we run.

5 So this is a big concern that maybe our result  
6 is driven by some serially correlated subcategory  
7 heterogeneity that is simultaneously correlated with  
8 the Beta-hat-C and Y, the variable of interest and  
9 number of entrants, the quality of entrants, and so  
10 on.

11 So we were -- so if we assume that this kind of  
12 correlation would persist over time, so if it says  
13 something about these categories that will have more  
14 entrants or higher quality entrants coming to their  
15 market, we should be able to predict the number of  
16 entrants if we are going to look at the number of  
17 entrants or quality of entrants two months, three  
18 months, a year before, and so on.

19 So we don't -- we have done this for different  
20 time periods, for three months, six months, and a year  
21 before, to just looking at September, that was the  
22 policy change year, and we run all these regressions  
23 one more time for the number of entrants, the quality  
24 of entrants, and so on, and none of the variables that  
25 we find is statistically significant.

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1 And it's not proved that this is -- that this  
2 is not a problem, but at least it's reassuring that if  
3 you are looking at some other time period, you don't  
4 see any correlations, only at the policy time that you  
5 see some correlation happening in other categories.  
6 Okay.

7 So another interesting thing here to show that  
8 is also related to our model is that -- so the  
9 entrants that we looked at, we sort of lumped two  
10 different type of entrants into one. So if a seller  
11 for the first time starts selling in a new category  
12 that they haven't been selling at before, we consider  
13 them to be a new seller, but then you can also have  
14 very brand new sellers who were not on eBay at all and  
15 then they entered into the market.

16 So in these regressions, we are going to divide  
17 them. So we are calling this new sellers versus  
18 existing sellers who were entering into the market and  
19 also enter into eBay completely or entering into new  
20 categories. So the result that we find is actually  
21 very interesting. So here, when we are looking at the  
22 number of entrants, we see that -- so both of the --  
23 so the signs are all the same, so they are all  
24 negative, and that's what we had for -- when we were  
25 combining them together, but the magnitudes are

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1 different, and actually, they -- it speaks to our  
2 model.

3 So when we are looking at these numbers, these  
4 numbers are smaller than this, so it sort of shows  
5 that for the new sellers, the very brand new sellers,  
6 it's not as easy to enter even when they changed the  
7 policy change, but when you are looking at the effects  
8 on their quality, you can see that these numbers are  
9 much bigger than these. So you can think of that  
10 fixed cost of entry into eBay is higher if you are a  
11 new -- a completely brand new seller, but entering  
12 into new categories, it still has a fixed cost, but  
13 it's not as high.

14 So you would see more entry for these guys who  
15 have lower fixed costs, but on average, even though  
16 they are higher quality, they are not as high quality  
17 as these guys, which they would be entering with  
18 smaller numbers, but when they enter, they have much  
19 higher qualities, on average. Okay.

20 So I -- we run a bunch of other robustness  
21 checks, look at the percentile of Beta, different kind  
22 of -- looking into the -- looking at shares, looking  
23 at the numbers, and everything -- the signs of  
24 everything will stay the same, so -- I don't have much  
25 more time -- and also for the prices, we're looking at

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1 differing kind of -- and also, we're looking at exit  
2 behavior. What we see is that this BN group, people  
3 shrink in the size, and they exit the market with  
4 higher percentage.

5 And that's -- that's -- ah, okay, here. So  
6 this is what we have done. So that was our question,  
7 how does more demanding certification affect entry?  
8 We find that we will get more entrants into the market  
9 and higher quality with fatter tails, and quality  
10 change for -- from -- mostly from improved selection.  
11 Not much has changed in the behavior of sellers.

12 And it has some kind of implication for digital  
13 platforms, so the -- this certification can impact the  
14 rate and quality of the entrants, and -- but the other  
15 finding that we have is that they can impact quality  
16 mostly through selection and behavior of the sellers.

17 Thank you.

18 (Applause.)

19 MR. WILSON: Thanks very much.

20 Our discussant is going to be Peter Newberry of  
21 Penn State.

22 MR. NEWBERRY: All right, thanks.

23 So it's good to be here. Twelve years ago I  
24 was an RA at the FTC, and I helped organize I think  
25 what was the prequel of this conference, which was a

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1 conference on Ecommerce with Chris Adams. So it's  
2 good to be here. I enjoyed reading the paper. It was  
3 fun.

4 So, yeah, as far as big picture goes, both  
5 these papers that we've seen are motivated by  
6 information problems. So we know Akerlof tells us  
7 about the lemons problem, where if sellers or if  
8 buyers can't -- or if consumers can't identify low-  
9 and high-quality sellers, then only the lowest quality  
10 goods will sell.

11 So we had an example of used cars, but the kind  
12 of rise of e-commerce has made us think a little bit  
13 even more about this, because presumably the  
14 information asymmetries are worse in online markets  
15 because you can't touch the goods and you can't really  
16 interact with the sellers as easily as you can in  
17 offline markets.

18 So we have seen some institutions that are  
19 introduced to try to help with these problems. We  
20 have warranties and seller guarantees or return  
21 policies, dynamic reputation, and what both these  
22 papers have focused on is certification, right? So --  
23 but what Maryam and coauthors do is think about this  
24 also as a barrier to entry, and specifically, if you  
25 think about dynamic reputation and certification in



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1 these markets, this is going to be a barrier to entry  
2 as -- especially if you think about dynamic  
3 reputation, it's hard to get stars and recommendations  
4 without selling anything, right?

5 So -- and when you first arrive to the market,  
6 everyone might think you're bad and you're not going  
7 to sell anything, right? Okay. So we're going to  
8 think about these institutions as -- or at least  
9 certification as also a barrier to entry.

10 Okay. So what does this paper do? I would say  
11 the way I think about it, what are the long-run  
12 effects of introducing or changing a certification  
13 program, and specifically on eBay? So if we think  
14 about entry, so the trade-off here kind of is do the  
15 incentives from higher prices for sellers outweigh  
16 these barriers to entry? So we will see more entry.  
17 And then what happens to the distribution of quality?  
18 How does overall quality change?

19 And when you think about the entrants, like,  
20 are there higher or lower quality entrants? And what  
21 happens to the incumbents? And then they also think  
22 about prices and market shares.

23 So the strategy, as we saw, is to utilize a  
24 policy change that occurred on eBay in 2009 that  
25 actually made certification more difficult for the

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1 sellers to reach, and evidence suggests that this  
2 policy had heterogenous impact across product  
3 categories. So we see that stricter certification,  
4 qualifications led to more entry. This entry was from  
5 the top and the bottom of the quality distribution,  
6 and we saw this result that it didn't seem like  
7 incumbents were responding.

8 Okay. So my opinions, what do I like? So this  
9 paper is really well motivated. I think reputation  
10 mechanisms are really important in these markets,  
11 especially as they continue to grow. So solving these  
12 information problems are very important. There's  
13 clear policy implications here for these platforms.  
14 How should we organize the platform as to solve these  
15 problems, right?

16 And I like the idea -- a lot of papers --  
17 empirical papers on information asymmetries are  
18 looking at are information asymmetries a problem, you  
19 know, how do consumers react to this information,  
20 where here we're thinking about more of an equilibrium  
21 entry model, which I really appreciate.

22 And the data is obviously great. I mean, you  
23 have proprietary data from eBay. You observe  
24 everything, basically. Then you have this nice --  
25 this nice policy change that occurred on eBay.

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1 All right. Where I think there's some more  
2 work to be done, so the model I know is very stylized  
3 and it's from another paper, but I would have  
4 preferred it be more posed as a puzzle, when does  
5 entry increase and when -- like, under what conditions  
6 would we see it actually decrease when those middle  
7 guys, right -- and, you know, under what conditions  
8 will we see quality change and quality not change? So  
9 I would have preferred -- maybe that's in the other  
10 paper.

11 I also -- this assumption of the perfect  
12 competition, I -- you know, I buy it, but at the same  
13 time, there's still price dispersion for the same  
14 products on eBay, I'm guessing, so where -- you know,  
15 where does that come from? And you never really talk  
16 about exit in the paper, so I'm wondering -- you know,  
17 in the model, you could think about exit, and even in  
18 the data.

19 The results, can we say something about what  
20 happens to concentration? Like, you look at market  
21 shares of individual sellers but not really how the  
22 market overall is concentrated before and after the  
23 policy. You talk about prices but never really, like,  
24 how -- you know, overall price levels, what's going to  
25 affect -- how is this going to affect consumers? Is

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1 it making consumers better off? But it could also  
2 make them worse off.

3 And then eBay's incentives, like, you know,  
4 what are their -- are they trying to align incentives  
5 between them and the sellers or -- you know, what's  
6 the impact of eBay's bottom line on these platforms?

7 So what I am going to focus on for the rest is  
8 this empirical strategy. So I'm still worried  
9 about -- I know about the placebo test, but I'm still  
10 worried about the exogeneity of your instrument, and  
11 I'll talk about that.

12 Okay. So the primary analysis uses this --  
13 this is the second stage, right, where you have the  
14 outcome on left-hand side and then the policy on the  
15 right, interacted with some measure of what I'm going  
16 to call exposure to the policy, right? So the  
17 intuition here is it's kind of a continuous treatment,  
18 where if you're more exposed to the policy, that's the  
19 treatment group, and the less exposed groups are the  
20 control.

21 So this is, I think, you know, related to  
22 what's called a Bartik instrument, which is, you know,  
23 you basically are -- have this interaction with a  
24 policy variable on how exposed -- it's in the labor --  
25 it started in the labor literature, but a really good

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1 example is in this QJE paper that's looking at the  
2 effect of Cash for Clunkers on sales for cars, and  
3 they actually use -- in a local market, the exposure  
4 is how many clunkers are there in that market when the  
5 policy -- the day the policy gets enacted, okay? So  
6 this is kind of an ex ante measure of exposure to the  
7 policy, okay?

8 So a key assumption -- obviously we know this.  
9 So where do I think the policy -- where do I think the  
10 problem is? Okay, so in order to calculate their  
11 exposure, they run -- you know, they run this  
12 regression, where the Beta-hat is their measure of  
13 exposure, but my -- I think what's going on here is  
14 the problem is this is actually an ex post measure of  
15 exposure. After the policy happened, how did -- you  
16 know, which categories were more affected, right? So  
17 this is an ex post measure of exposure rather than an  
18 ex ante measure of exposure.

19 So, for example, so share badged is actually an  
20 equilibrium outcome which is a function of your  
21 left-hand side variable. So, for example, just if you  
22 think the change in the share badged simply could just  
23 be written as this, so the change in the share badged  
24 is a function of entry, right? If this category saw  
25 more entrants, that's actually going to change the

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1 share badged. So the result of this is actually this  
2 is a mechanical relationship between entry and the  
3 policy -- the policy -- the policy estimate that  
4 you're estimating.

5 Okay. However, so, fortunately, I think this  
6 is actually solved pretty easily. Think about this  
7 Cash for Clunkers paper. My suggestion is to use a  
8 measure of ex post exposure in a given category. So  
9 on the day the policy was enacted, how many sellers  
10 would have become badged that day, right? So this is  
11 a measure of exposure within a given category.

12 You could also just determine categories ex  
13 ante yourself and say this category is probably  
14 affected more because it has more high-volume sellers  
15 or the quality of the goods may be less salient, so  
16 they sell more new and used goods, and so you could,  
17 ex ante, just choose categories that you think are  
18 better control groups and then use maybe that first  
19 regression as evidence that that's true.

20 And then you could also -- I know you said this  
21 maybe isn't great, but you could just take an event  
22 study approach and assume that the policy was  
23 exogenous and then see, within a category, you know,  
24 what happened to -- what happened to entry and  
25 quality.

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1 Okay. So I have one minute left. So that's my  
2 main comment, and I think, you know, try these things  
3 and see what happens. I just have a couple other  
4 things.

5 So other suggestions, could you think about the  
6 effect of the policy on other signals of quality? So  
7 are sellers reacting in some other way, like are they  
8 showing more photographs? Are they -- is their  
9 description a lot bigger, the guys who don't get  
10 badged?

11 Are they changing their products within a  
12 category? Are they selling more new versus used  
13 goods? Like I said earlier, what happened to overall  
14 price levels? And then concentration.

15 Another one of your main results is  
16 this quality dispersion, and I worry that that's also  
17 somewhat mechanical, maybe not completely, but my  
18 suggestion here is why not just run your definitive  
19 estimation on some measure of quality dispersion, like  
20 the distribution of -- like the variants of quality or  
21 some, you know, measure of distribution of quality,  
22 rather than break these guys up into these bins,  
23 right?

24 Yeah, so I just have, like, random other  
25 thoughts that were supposed to be or that we'll talk

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1 about offline and I'll send you, but those are my  
2 main -- my main -- my main comments. So thanks for  
3 listening.

4 MR. WILSON: Thanks very much. And, again, we  
5 have a few minutes for questions from the audience.

6 MALE AUDIENCE MEMBER: Hi. I realize there's a  
7 public face and maybe a private face, but what is  
8 eBay's public justification for increasing the sort of  
9 stringency of the certification?

10 MS. SAEEDI: So I guess -- so I wasn't in any  
11 kind of committees who are deciding these things, and  
12 it's very hard -- we tried to actually get them to  
13 answer for this. We were not successful in finding  
14 what they actually thought about. So something that  
15 they told us, like, they found is that the number of  
16 people who were badged were too many. They just  
17 wanted to reduce that. And a lot of times, they  
18 never -- actually, they never go back to see what was  
19 the result of what they have done. They usually see  
20 that -- so they give some benefits to people who are  
21 badged, and they were thinking that the money that  
22 they have to spend on that is too much, and they  
23 wanted to reduce the number of people who have the  
24 benefit. Yeah.

25 MALE AUDIENCE MEMBER: I don't know if you have

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1 already done a little bit of this, so this is either a  
2 question or a suggestion, but I think the -- what  
3 Peter suggested along the lines of looking at  
4 different categories and characteristics of different  
5 categories is just super interesting, both for the  
6 identification purposes he's suggested, but also just  
7 kind of validating the theory testing --

8 MS. SAEEDI: Right.

9 MALE AUDIENCE MEMBER: -- and also thinking  
10 about, you know, future policy implications, if they  
11 were to do a -- you know, a kind of more refined sort  
12 of policy that was more targeted.

13 MS. SAEEDI: Yes. So I will be talking with  
14 you guys afterwards, so say exactly what was -- so one  
15 thing along the -- the lines of what Peter was saying,  
16 so what we have done, we've looked at, for example,  
17 very short period of one week before and after to find  
18 out -- so we don't have that much entrants or exiters  
19 during that time, but your suggestion is great.

20 We will -- we can just look at the sellers who  
21 were active in months before and see how many of them  
22 would have lost their badge or not, and we can just  
23 look at all their, like, qualification, the way that  
24 eBay decides for them if they are going to get  
25 badge -- be badged or not, use that, and that would be

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1 much cleaner instrument. Yeah.

2 MALE AUDIENCE MEMBER: Yeah. So fascinating  
3 study. I'm wondering -- and this comes back a little  
4 bit to Andrew's question -- to what extent any of you  
5 guys know what was happening in the market generally,  
6 because you have incredibly rich data that comes from  
7 inside a single firm, but, of course, there are lots  
8 of places one could buy an unlocked 32-gig black  
9 iPhone --

10 MS. SAEEDI: Right.

11 MALE AUDIENCE MEMBER: -- kind of thing. And  
12 in thinking about policy, in particular, but even  
13 management, right, it would be really helpful at least  
14 to have some context for what's happening in the  
15 market as a whole. We just don't know what the  
16 equilibrium is.

17 MS. SAEEDI: Yeah. So when we are talking --  
18 like, I guess, what you are -- you mean is the  
19 dynamics across platforms, and unfortunately, we don't  
20 have data on what is happening outside eBay, but  
21 that's very important. Actually, a lot of policies  
22 that eBay is applying is a result -- like, in response  
23 to what Amazon is doing or other type of platforms are  
24 doing. But, yeah, we have to think about that, see if  
25 we can find some kind of connection, yeah. That's a

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1 good...

2 MS. JIN: And for a platform like eBay, the  
3 count of sellers is very different from the volume or  
4 profit contribution from each seller --

5 MS. SAEEDI: Right.

6 MS. JIN: -- and we know the power sellers  
7 contribute a lot more to the platform. So have you  
8 tried to look at other angles, like sort of the  
9 quantity they sell or the fees eBay can get from those  
10 sellers? And that -- I would imagine that probably  
11 will give a different picture.

12 MS. SAEEDI: So when we -- so I went through  
13 that slide for one second. So we looked at the market  
14 share of the sellers, and what we see is that the  
15 sellers who have stayed badged increased their market  
16 share, but the sellers who lost their badge, who were  
17 at the top before, and they're not -- they lost their  
18 market share.

19 So that's another question, I think, Peter also  
20 suggested, so what's the impact on the total quantity  
21 that is sold on eBay, so that can be -- given that one  
22 group has become bigger, one group becomes smaller,  
23 that can have different implications. We have a -- we  
24 don't have that in the paper now, but, yeah, that's a  
25 good point.

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1 So we -- in the theory papers that I have with  
2 Ugal, we are looking at what's the optimal threshold  
3 to be put to increase -- to maximize the total  
4 quantity sold, but we don't look at the (inaudible)  
5 population.

6 MR. WILSON: Thanks, everybody. We are now  
7 moving on to our third paper in this session. That's  
8 going to be by Matthew Mitchell of the University of  
9 Toronto.

10 MR. MITCHELL: Okay. It's great to be here to  
11 talk about a theory paper that I think is directly  
12 relevant to some important FTC policy. So this is  
13 sort of a paper about Twitter, so it is sort of a  
14 theory of people who make recommendations on Twitter.  
15 One of those two people is a meaningful recommender on  
16 Twitter. The other one is not, really.

17 So, broadly, you know, I'm interested in  
18 intermediaries, because there's a lot of stuff to  
19 consume out there, and it's pretty hard to know what  
20 to consume, so you are going to need to ask somebody  
21 their opinion. And so there are a lot of ways to go  
22 on the Internet and get some opinions about what you  
23 ought to consume, okay?

24 Now, I'm going to be focused mostly on a narrow  
25 topic, which is people that get advice on the internet

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1 frequently from something like Twitter, but where the  
2 person giving the advice is getting, at least  
3 sometimes, compensated by someone who wants some  
4 advertisement. So the reason that the title of the  
5 paper is "Free (Ad)vice," with "Ad" in parentheses  
6 there, is because, you know, the advice has some ads  
7 snuck in there.

8 That's actually a relevant policy issue at the  
9 FTC right now. People at the FTC sort of know that.  
10 How people on the internet should be required to  
11 disclose their financial relationships with the things  
12 they recommend is actually an issue that's led to -- I  
13 used to give this talk and I used to say, well, the  
14 FTC has given some guidance, but it's not obvious that  
15 they've actually gone out and fined people yet, but  
16 now they have. So the FTC is actually taking action  
17 on this policy, and I guess I sort of think of this as  
18 broadly related to ideas like fake news.

19 So let me give you an example of what I have in  
20 mind here. This is a recommender or an influencer on  
21 Twitter named Kim France. Kim France is a -- was a  
22 very successful fashion journalist. I'm using her as  
23 an example largely because she had a very successful  
24 career, which she essentially quit to do this instead  
25 because you can make more money doing this. And so

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1 one of the things she does is sort of really  
2 explicitly links people to her own blog where she then  
3 gets a commission for things that people buy through  
4 her blog.

5 I use her also as an example because she has a  
6 nice "Frequently Asked Questions" where she just  
7 explains what it is that she does, and she explains  
8 that, you know, I do sometimes get a commission from  
9 things I sell on my blog, but, of course, she says I'd  
10 never, ever link to anything that I wouldn't think was  
11 a good idea for you to consume, okay? So she's  
12 bundling these links with her recommendations of what  
13 would be good things to consume.

14 Her Twitter feed contains lots of stuff.  
15 Here's another example of something she said on  
16 Twitter. "TheUnbreakableKimmySchmit is a miracle."  
17 Now, I don't know if that's an ad or not. It actually  
18 turns out -- I did a little digging -- and I think The  
19 Unbreakable Kimmy Schmit was doing a viral ad campaign  
20 on Twitter during that period. I'm not trying to get  
21 Kim France into trouble with the FTC, that's a pretty  
22 old tweet, but it's not obvious if that is advice or  
23 an ad for The Unbreakable Kimmy Schmit, okay?

24 So one of the things we want to ask is, if that  
25 is an ad, should she have to disclose that she's

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1 taking money from the TV show? In case you're  
2 wondering, that's a TV show on Netflix. There's so  
3 many TV shows now that you might not even know all of  
4 the TV shows, which is why you need to go to Kim  
5 France and figure that out.

6 Now, so that's -- most of the paper, I'm going  
7 to talk about this, I think, key pillar of the FTC's  
8 mandate, as we were talking about. I do think it's  
9 related to the FTC's other mandate, which is  
10 competition policy. Here's Google. They give advice  
11 on the internet, and this is like the classic picture  
12 of someone Googling Trip Advisor recommendations but  
13 getting Google's recommendations instead, okay? So  
14 that -- the fact that Google has some market power  
15 there might be relevant, but I am going to talk more  
16 about the Twitter-type examples today.

17 So I'm going to just think about a simple model  
18 capable of understanding the basic trade-offs, and in  
19 the middle, there's going to be sort of a question.  
20 Why do you pay attention to these people on the  
21 internet? The answer is going to be because they have  
22 an incentive to build up a good reputation by giving  
23 you some pieces of good advice. That is, if  
24 everything Kim France ever said was useless and she  
25 was just taking money, you'd stop following Kim

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1 France, okay? So it's going to be sort of a pure  
2 reputational model.

3 The model is going to have a lot in common  
4 because there are no transactions of money in the  
5 model between you, the follower, and the influencer,  
6 because that's usually the way these things work. You  
7 don't pay Kim France directly for what Kim France has  
8 to say. And as a result, the model is going to look a  
9 lot like these models from the recent contracting  
10 literature without monetary transfers, especially --  
11 there's a lot of such papers, and I am not going to  
12 talk a lot about the literature, but I do want to  
13 specifically point out Li, et al., and DeMarzo and  
14 Fishman, which are sort of the two most closely  
15 related models to what I'm going to talk about today.

16 And so the thing I want to stress that's going  
17 on here about ads and that's going to be relevant to  
18 what I'm going to have to say about disclosure policy  
19 is that ads are sort of playing two roles here if  
20 you're a consumer. On the one hand, in the current  
21 instant, ads may be a temptation for the influencer to  
22 bias their advice away from what's best for you and  
23 towards what makes them money, but if you weren't  
24 worried about that, then there would be nothing to  
25 worry about with influencers taking money on the

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1 internet.

2 On the other hand, the fact that these

3 influencers can make money by running ads is the way

4 you encourage them to give good advice now. The fact

5 that they will be able to run ads at future instants

6 is the way they want to keep you around, and keeping

7 you around is the motivation for giving good advice at

8 the current instant.

9 So ads are really serving two functions here.

10 They're not just a temptation for the influencer.

11 They're also the way the follower gets incentives from

12 the influencer to behave by sticking around for future

13 ads. Because of that, it's going to turn out the

14 disclosure is not unambiguously good here, and I'm

15 going to propose that in this model there's an idea

16 that's unambiguously better, which I am going to

17 describe in more detail, which is going to be

18 something I am going to call opt-in disclosure, where

19 an influencer can decide and has to state whether or

20 not they're living by, in some sense, the FTC's

21 disclosure rules or not.

22 Okay. So I'm just going to tell you about the

23 basic model. The idea here is to keep the model as

24 stark as possible. So this is going to be a

25 continuous time model with an infinite horizon,

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1 blah-blah-blah. I am going to try to keep the

2 notation as limited as possible, so I am going to

3 normalize the discount rate to one, so these are

4 forward-looking people with some discounting that I'm

5 normalizing.

6 There's going to be two people here, a follower

7 and an influencer. The follower decides whether or

8 not to follow the influencer. That variable is going

9 to be called  $f$ . That's going to be observable. And

10 then good advice arrives to someone who's following an

11 influencer at a rate  $\Lambda$  times one minus the ad

12 level  $a$ . So the idea here is the more is the

13 underlying advertisement level of the advice, the less

14 likely is it to generate good advice for the follower.

15 Now, in the basic model, there's a direct

16 trade-off. If  $a$  is set to its maximum, which I'm

17 taking to be one, there's no good advice. I have an

18 extension where good advice can show up even when

19 you're running the ad technology at maximum, but I

20 want to keep things as stark here as possible to

21 understand how this model works.

22 So the influencer is going to privately choose

23 the ad level. The follower merely observes when they

24 receive good advice. When the follower receives --

25 gets good advice, they get a value -- like a lump of

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1 one unit of value. The influencer gets value  $\Lambda$  times

2 times  $a$  for an ad level  $a$ . So in any given instant,

3 the total surplus from this relationship is  $\Lambda$ , okay?

4 A just decides how that is split up.

5 I'm going to also show you explicitly -- this

6 one I'll get to -- I'm going to explicitly show you

7 what happens if ads generate waste in some sense, that

8 ads lower the total amount of surplus, but for my

9 benchmark model, they don't, okay?

10 The follower has an outside option if they

11 decide not to follow, that's  $s$ . That's what makes

12 following costly. If you decide to follow this person

13 and they're not giving you any good advice, then

14 that's leading to some cost for the follower that you

15 could think of as  $s$ .  $\Lambda$  is bigger than  $s$ , so it's

16 better to follow than not if you're getting good

17 advice.

18 I just want to point out, since  $\Lambda$  is

19 bigger than  $s$ , if we had full information here, we

20 could just trace out the full information Pareto

21 frontier. That would just be all the combinations of

22 the follower's value and the influencer's value. I'm

23 just getting out a little notation here.  $V$  is the

24 follower's value,  $W$  is the influencer's value, where  $V$

25 plus  $W$  equals  $\Lambda$ , okay? But, of course, that's

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1 not what I want to study. I want to study the

2 frontier under the asymmetric information I laid out

3 in the last slide, where the level of the ad is

4 unobserved to the follower.

5 So I'm going to describe this like a dynamic

6 contract. That's not totally critical here, but it's,

7 I think, going to make the construction as simple as

8 possible. So there is going to be no monetary

9 transfers here. The reward comes by a

10 history-dependent choice of  $f$  and  $a$ . Think of that

11 history as a complicated object. It's all the

12 previous periods when you received good advice and

13 whether you followed or not.

14 Of course, I am going to assume that the

15 influencer can't commit to the actions they are going

16 to take in this contract. I am going to assume for

17 the purposes of this talk that the follower can commit

18 to such a sequence of actions. That qualitatively

19 doesn't affect the results here at all. It just makes

20 the math a little simpler. Then I'm going to assume

21 the influencer needs a fixed level to be willing to

22 engage in being an influencer in the first place.

23 This is sort of like a supply of influencers, okay?

24 So that contract's a potentially complicated

25 object. It turns out it can be summarized by

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1 something simple, which is at any instant a  
 2 forward-looking variable that describes in the  
 3 contract for how long the follower will follow the  
 4 influencer in expected discounted terms. I'm going to  
 5 call that variable  $d$ . It lives between zero and one,  
 6 because I normalized the interest rate to one,  
 7 following forever, would mean a  $d$  of one. Giving up  
 8 and never following would be a  $d$  of zero. Durations  
 9 in between reflect different degrees, in some sense,  
 10 of satisfaction with the influencer, because you are  
 11 going to pay attention to them for longer on path.

12 It turns out that describing contracts this way  
 13 -- and not as a function of the total history -- is  
 14 without loss of generality, but if you want to think  
 15 of this as just a restriction on the contracting space  
 16 for now, that's fine.

17 I want to get to the -- to how this model works  
 18 and then describe a little bit about policy. So the  
 19 reason why this variable is very helpful is that the  
 20 total surplus generated by this relationship is a  
 21 simple linear function of duration. When these two  
 22 parties are together, they get  $\Lambda$  divided some way  
 23 depending on the choice of  $a$ . And when they're apart,  
 24 well, then, the follower gets their outside option,  $s$ ,  
 25 and the influencer gets nothing. So that's what that

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1 says up there. The payoff to the influencer,  $W$ , plus  
 2 the follower,  $V$ , adds up to, when they're together,  
 3  $\Lambda$ , and when they're apart,  $s$ .

4 And so the fundamental idea here is that the  
 5 bigger  $d$  grows, the harder it is to get incentives for  
 6 the influencer to keep the ad level low, because the  
 7 reason the influencer keeps the ad level low is to try  
 8 to have these arrivals of good advice so that you're  
 9 convinced to stay in the contract as a follower.

10 I mean, if you want to think about that at the  
 11 extreme case, if  $d$  is equal to zero, surplus is as low  
 12 as it can be, because we're going to have  $s$  forever,  
 13 but the follower gets all of that. If  $d$  is equal to  
 14 one, there will never be any good advice ever again,  
 15 total surplus is as high as possible, but it all goes  
 16 to the influencer. So the follower faces a tension  
 17 between how much surplus they get and the total  
 18 surplus in the relationship.

19 The way I'm going to think about this, like I  
 20 said, is just like a contract. So let's think about  
 21 incentive compatibility of a certain level of  $a$ . So  
 22 the benefit from choosing  $a$  is -- I wish I could --  
 23 there is no way to point here, is there? It says that  
 24 the marginal return to  $a$  is  $\Lambda$  minus some stuff.  
 25 The  $\Lambda$  is the direct benefit of running the ad. I

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1 assume you make revenue equal to  $\Lambda$  times  $a$  from  
 2 running the ad.

3 Whenever good advice arrives, duration, this  $d$   
 4 variable is going to change from what it currently is,  
 5  $d$ , to some future level -- I am going to call it  $d'$ ,  
 6 and the value for the influencer changes from  $W(d)$  to  
 7  $W(d')$ . The more ads you run, the less likely that is  
 8 to happen at rate  $\Lambda$ . So that  $\Lambda$  times  $W(d')$   
 9 minus  $W(d)$  is saying, when you run more ads, it's less  
 10 likely that good advice arrives and the follower is  
 11 happier with you.

12 So if the follower wants to get any good  
 13 advice, they have to pay, in terms of future value, at  
 14 least one unit. The amount that the influencer gets  
 15 after giving good advice has to be one unit higher if  
 16 they are going to not run ads. That's the incentive  
 17 constraint here.

18 I'm going to show you what the value function  
 19 looks like as a function of  $d$ , and then I'm going to  
 20 explain to you why, and then I'm going to talk briefly  
 21 about policy, and then I'm going to be done.

22 Here's the value function as a function of  $d$ .  
 23 I have drawn as a function of  $d$  the dotted line.  
 24 That's the total surplus in this relationship. The  
 25 value function, of course, has to be below that. It's

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1 a concave function. I'm not going to describe to you  
 2 a proof of that here.

3 Of course, I said it starts out at the value  
 4 being equal to  $s$ . It's a concave function where for a  
 5 while it's strictly concave. That's the region where  
 6 the advertiser is not running ads, the influencer is  
 7 not running ads, and then it has a region at the top  
 8 where the influencer is running ads.

9 So in this model, if you want to think of it,  
 10 to the right we have influencers that have been more  
 11 successful. They have given out good advice, and,  
 12 therefore, this duration variable has jumped up to the  
 13 right until we're in the region all the way to the  
 14 right where they become a top influencer and stop  
 15 running ads.

16 During that period, the duration variable is  
 17 going to start to run downwards because they're not  
 18 giving as much good advice -- in my benchmark model,  
 19 they are not giving any good advice -- and for a while  
 20 the duration variable runs down. They live off their  
 21 reputation for a while, and after they live off their  
 22 reputation for a while, we move back into the regime  
 23 where  $a$  equals zero and good advice starts flowing  
 24 again.

25 Again, that's a really extreme version of the

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1 benchmark model I want to show you, but the key  
2 feature that's true in a lot of the versions of the  
3 model that I do in the paper is these cycles for  
4 influencers. Influencers build up a reputation --  
5 think of the low  $d$  as a sort of mediocre reputation --  
6 they build their reputation by not running so many  
7 ads, and then they reap in the future from that  
8 reputation by running ads when  $d$  gets sufficiently  
9 high, okay?

10 I want to show you just a tiny bit more about  
11 how this contract works. Because  $V$  is concave, the  
12 incentive constraint it turns out has to bind, and the  
13 incentive constraint binding, you know in problems  
14 like this, is sort of fundamental to getting things  
15 well understood.

16 Let's think about what the incentive constraint  
17 binding means. It means, from the previous slide,  
18 that the amount by which  $W$  as to go up when there's  
19 good advice is exactly one unit. The amount that the  
20 follower receives every time there's good advice is  
21 exactly one unit. So it's as if, in future value,  
22 you're paying the influencer for exactly the value of  
23 the piece of good advice you received today, and you,  
24 as the follower, receive all the change in total  
25 surplus from the contract moving from  $d$  to  $d'$ . Total

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1 surplus is increasing, and  $d'$  is bigger than  $d$ , so  
2 that's a positive number.

3 So the only reason we're ever in this range  
4 where  $a$  equals one is because you have not enough  
5 duration left, not enough  $d$  left to offer the  
6 influencer to possibly convince them to give you any  
7 good advice. Their reputation is so good that they  
8 have nothing to lose by running ads in the top range.  
9 In other words, we could characterize exactly that  
10 kink point, where you go from  $a$  equals zero to  $a$   
11 equals one, that's exactly where the influencer's  
12 value is exactly one unit less than the maximum it  
13 could possibly be, and the maximum it could possibly  
14 be is  $\Lambda$ .

15 Okay. Now I want to do some sort of policy-  
16 related experiments with that model. So in the model  
17 I assumed that  $a$  doesn't affect total surplus, but  
18 let's suppose it does. For instance, suppose that the  
19 return to the ad technology, instead of being  $\Lambda$   
20 times  $a$ , was  $\Lambda$  times  $a$ .

21 Nothing about this math assumes that  $\tau$  is a  
22 number less than one, but I think that's the idea you  
23 want to have in your head, which is that perhaps  
24 running ads generates some inefficiency, some loss  
25 here, okay? And I want to characterize the contract

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1 where, instead of  $\tau$  being equal to one in what I  
2 showed you up until now,  $\tau$  is a different number,  
3 like think of it as less than one.

4 As a function of  $d$ , this changes nothing about  
5 the contract. In particular, the allocation in terms  
6 of the choices of  $f$  and  $a$  is independent of  $\tau$ . The  
7 only thing that changes is that the influencer gets  
8  $\tau$ -less, because when they run ads, the payoff is  
9 lower. What's the intuition here? Well, when you  
10 make ads have a lower return, you're doing two things:  
11 you're lowering the current temptation to run ads, and  
12 you're lowering the payoff in the future from any ads  
13 you might run if, as an influencer, you build up a  
14 good enough reputation to start running ads. You're  
15 doing those two things in exactly the same proportion.

16 So what I want to stress about this is pure  
17 taxes on ads here -- because that's another way you  
18 can interpret  $\tau$ , is a tax on ads -- have no effect  
19 on the amount of good advice that occurs in this  
20 model. If I was going to give  $a$  -- like, you know, I  
21 only get 25 minutes, so if I wanted, like, one piece  
22 of intuition from this model that's kind of different  
23 from a static model, it's that, because the dynamic  
24 effect of the taxes is exactly offsetting the static  
25 effect of the taxes.

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1 So now I want to think about the FTC in this  
2 model. Igal has seen this paper before because I gave  
3 it at his birthday conference, and, of course, there  
4 were a lot of Minnesota guys there, and the Minnesota  
5 guys said, FTC? I don't know what that is. They  
6 wanted to know, what is the FTC in the model? You  
7 know, I have already got optimal contracts here. What  
8 do I need with the FTC?

9 So the way I'm thinking about the FTC in the  
10 model is that they have an additional technology  
11 that's not available to these two parties, a sort of  
12 auditing technology where they can go look, and if ads  
13 are run that are not disclosed -- I am going to  
14 describe a little bit sort of what I mean by  
15 "disclosed" -- then they can potentially punish  
16 someone who has chosen  $a$  without disclosing that  
17 they're choosing, you know, that level of  $a$ .

18 So it's important that -- I'm assuming, of  
19 course, that the FTC has the access to some technology  
20 that these parties don't. Otherwise, use of that  
21 technology would already be incorporated -- already be  
22 incorporated in my optimal contract.

23 Okay. So here's how I'm going to think about  
24 disclosure rules by the FTC. I'm just going to think  
25 of them like a comparative static on the ad return in

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1 my model. So, first, suppose that the -- that the  
2 contract is calling for a equals zero. Any ads that  
3 are run there are a deviation from what the contract  
4 proposes.

5 Of course, let me just -- that deviation is  
6 relevant because that's what the incentive constraint  
7 is guarding against. So what I'm going to do is I'm  
8 going to make the FTC -- I'm just going to go back to  
9 my benchmark model where the ad technology, you know,  
10 starts from a return of one. They can make the return  
11 from those deviation ads lower, call it  $u$  less than  
12 one, okay?

13 Now, I'm going to assume that when a equals  
14 one, now the ads are on path, and I'm going to give  
15 the influencer a choice between whether or not they  
16 want to disclose or not disclose those ads. If they  
17 don't disclose those ads, the FTC is coming for them,  
18 so the payoff from those ads is  $u$ . If they do  
19 disclose those ads, I am going to allow for the  
20 possibility that those disclosed ads have a lower  
21 return,  $m$ , partially because influencers always say  
22 they do.

23 Also, because there's papers in the economics  
24 literature, like Inderst and Ottaviani, that say these  
25 kind of disclosure rules can lower the total pie

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1 available, the total amount of surplus available to  
2 the two parties, the advisor and the advisee, like my  
3 influencer and follower. So I am going to allow for  
4 the possibility that the disclosure rules have costs  
5 like that, and I am going to think about what  
6 disclosure rules that potentially have costs like that  
7 do in this model. And then I'm going to show you what  
8 a disclosure rule would look like that would work  
9 better in this model, okay?

10 So, first, if the disclosure rules are weak, so  
11 that  $u$  is a number less than one but not as low as  $m$ ,  
12 then nobody discloses any ads because, after all,  
13 they'd rather get  $m$  -- sorry, get  $u$  than get  $m$  by  
14 disclosing the ads. In that case, we know from our  
15 taxation results that disclosure is just a pure  
16 taxation on the influencers. It has no benefit for  
17 the followers.

18 On the other hand, if the disclosure rules are  
19 strict, meaning  $u$  is a smaller number than  $m$ , then  
20 they strictly benefit the followers because they make  
21 the incentive constraint easier to be satisfied. It  
22 shifts out the value function like that. Of course,  
23 what that means is as a function of  $u$ , welfare is not  
24 monotone, and I can't even tell you whether it's  
25 higher at the left end or the -- or the right end.

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1 In the paper, I go into more detail to talk  
2 about where this lower return,  $m$ , might come from from  
3 disclosure, and the place I go is exactly the idea  
4 that there might be some ads that are also good  
5 advice. Kim France might sometimes get a commission  
6 from selling you a bracelet that she also thinks looks  
7 good and that you will think looks good, too, and I  
8 can write down a more specified model of disclosure  
9 where those disclosures can lead to costs because  
10 followers pay less attention to those particular  
11 recommendations. But, of course, in 25 minutes, I  
12 don't have time to do all that.

13 I just want to do one more thing in my last 50  
14 seconds, which is describe what the model says is a  
15 better disclosure rule. The better disclosure rule  
16 here is what I'm going to call opt-in disclosure. So  
17 think of this as an influencer can decide -- just say  
18 on their Twitter bio, they could just say, "I follow  
19 all the FTC disclosure rules," or not say that.

20 Top influencers would want to opt out because  
21 they're in the reap portion of their cycle, and people  
22 who want to build a reputation would want to opt in  
23 because no one would pay any attention to them if they  
24 didn't. So in the model, that kind of opt-in policy  
25 is better than just a pure -- what I might call a pure

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1 disclosure policy, and the reason is because of -- and  
2 I don't have time to talk about extensions -- and the  
3 reason is because sort of the fundamental difference  
4 here is that all the reward for influencers is coming  
5 from future payoffs. And so a way to tighten up the  
6 temptation to run ads when you're building your  
7 reputation, while still leaving the reward as high as  
8 possible when you've built a good reputation, is  
9 generally an improvement.

10 (Applause.)

11 MR. WILSON: Thanks very much. Our discussant  
12 will be Ginger Jin.

13 MS. JIN: Well, thanks for the opportunity to  
14 come back. My time at FTC must give staff impression  
15 that I can read theoretical papers, so they send me a  
16 real one to test out. The challenge is very much  
17 appreciated. I do wish that I had taken the graduate  
18 theoretical course more seriously 20 years ago, but  
19 I'm very grateful that Professor Mitchell has been  
20 very patient and responsive to my emails.

21 So this is a very interesting paper. What I  
22 like most is that it provides a novel framework that  
23 applies to both antitrust and consumer protection.  
24 Those in FTC know that we -- FTC actually run  
25 antitrust and consumer protection separately with very



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1 little overlap, but this theory sort of -- it's  
2 creative for us to think about search engine as an  
3 influencer providing advice to search engine users,  
4 just like social media influencer try to provide  
5 advice to Twitter followers. So I think that's a  
6 creative framework.

7 Actually, this framework could apply to any  
8 advertising-backed media, right? The radio, the  
9 magazines, television, if not all their income, most  
10 all of their income actually coming from advertising,  
11 and they think about the content they provide in order  
12 to generate followers. So I think in that sense this  
13 framework is very general.

14 Academically, it also naturally extend a lot of  
15 the literature in reputation, in paid advice, in  
16 disclosure, in the theory of market power. I would  
17 add to this list the theory of two-sided markets, as  
18 well as media bias.

19 Okay. So I just want to highlight the main  
20 insights in the basic model and probably give a  
21 comment on a few policy implications here. The basic  
22 model has five assumptions. The first is that  
23 influencer engage in an activity that's sort of  
24 disliked by the follower; namely, this advertising,  
25 okay? So here we assume away the influencer can

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1 generate nonadvertising content that could be useful  
2 to the follower. I think that's a useful  
3 simplification, but extending along that direction  
4 might be interesting.

5 The second assumption is that the follower can  
6 only use following as the tool to generate reputation  
7 for the influencer. So the follower cannot say I'm  
8 going to pay more to a good advice if you have a good  
9 history or something like that. So it's unlike the  
10 typical reputation return, that you can get a return  
11 from higher price, and here sort of you can only get a  
12 return from the following behavior, and that following  
13 behavior is based on a noisy signal, which is the  
14 random arrival of good advice.

15 And following is costly, as Professor Mitchell  
16 said. It's because there's an outside option, so you  
17 can think of that as a potential competition with this  
18 technology here. The technology itself, that  
19 technology is exogenously given, okay? And that sets  
20 the total surplus to be fixed. So the tension in the  
21 basic model is how the influencer and the follower  
22 divide the pie rather than how to create a bigger pie.

23 So with those assumptions, the trade-off in  
24 front of the influencer is basically the trade-off  
25 between today and tomorrow. So today there is a pie

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1 for you to grab, which is the advertising revenue,  
2 okay, and that pie might be small if you just have  
3 fewer followers, but it could be really big if you  
4 have a lot of followers, okay? So you can grab this  
5 pie today and leave nothing to the followers, or you  
6 can sort of keep the pie on the table and that's going  
7 to generate future good advice to the follower, and  
8 then the follower can decide what to follow or not,  
9 which determines tomorrow's pie, okay? So you're  
10 trading off between getting more of today's pie or  
11 leave it on the table and generating a bigger  
12 tomorrow's pie.

13 What's interesting here is that today's  
14 follower is actually going to affect the size of both  
15 today's pie and tomorrow's pie, okay? If you have a  
16 lot of followers today, today's pie is very big, but  
17 given that you already have a lot of followers, having  
18 a little advertising going on does not necessarily  
19 completely drain your follower crowd immediately  
20 tomorrow, okay? So your tomorrow's pie still depends  
21 on the good history you have generated so far, plus  
22 some not so good history in a day after today. So  
23 that's the trade-off in front of the influencer.

24 And as a result, we sort of see a cycling  
25 behavior. Okay, so I would call it sow and harvest.

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1 That's the same as what Professor Mitchell call sow  
2 and reap. So from the influencer's point of view,  
3 over time, this reputation indeed is going up and  
4 down. In the down period, the influencer would have  
5 incentive just to, okay, I am going to refrain from  
6 advertising and just the sow the seeds and give good  
7 advice, and once I build up the reputation, I will be  
8 in the harvest mode, okay? I am going to harvest the  
9 advertising income because I have a lot of followers.  
10 That means today's pie is pretty big, okay?

11 From the follower's point of view, the follower  
12 sort of foresee the cycling behavior, but the follower  
13 can only have following as the tool. So the follower  
14 would say, okay, I am going to tolerate it with the  
15 harvest, because that's going to generate incentive  
16 for you to provide the sowing of good advice, but I am  
17 only going to tolerate it to some extent. If it's so  
18 bad, I am going to quit. I am going to quit forever,  
19 okay?

20 And that permanent quit is going to be a threat  
21 to the influencer, and with that threat, the  
22 influencer will not have incentive to overharvest,  
23 okay? So in the equilibrium, you are going to see  
24 this up and down, but the follower would follow. But  
25 the threat of equilibrium past will be important to

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1 ensure that there is a sowing period before the  
2 harvest, okay? So in this sense, the harvest is sort  
3 of providing the incentive for the sowing, so the  
4 harvest is not necessarily bad thing, okay?  
5 Okay. So with that insight, let me talk about  
6 policy implications. Before we get into the exact  
7 policy implications, I want to clarify what's the  
8 objective function we're looking at here. So are we  
9 looking at the follower's payoff as the objective  
10 function or are we looking at the total payoff, okay?  
11 I think that the position the paper takes is we put  
12 more weight on the follower's payoff.

13 In FTC language, that's -- we're maximizing  
14 consumer welfare rather than we're maximizing total  
15 welfare. The basic model set the total pie fixed, so  
16 it's just a redistribution question. The extended  
17 model probably can sort of vary the size of that pie.  
18 So I am going to focus in my discussion assuming that  
19 we are going to maximize the follower's payoff, okay?

20 Okay. So there are several tools to do that.  
21 So you could change the ad technology, including sort  
22 of the size of pie as well as the rule that's dividing  
23 the pie, or you can also restrict the influencer's  
24 behavior directly, like you cannot advertise or you  
25 have to advertise under certain rules, such as

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1 disclosure, or you can raise the follower's outside  
2 option, which is kind of competing with this  
3 influencer in their good advice decision.

4 Okay. So one main result from the paper,  
5 arguing that advertising tax is neutral, the logic is  
6 that advertising tax is going to affect today's pie  
7 and tomorrow's pie proportionately, and your trade-off  
8 is between the two in a relative term, so it shouldn't  
9 matter. The tax should not matter because it's  
10 proportional; however, there is a fixed outside option  
11 there which does not go up or down with this tax. So  
12 my intuition is that when you have a lot of really  
13 high outside options, you would require a lot of good  
14 advice and expectation in this market before you  
15 follow, and that should generate incentive for the  
16 influencer to sort of restrain himself from harvesting  
17 to a greater extent and provide more good advice.

18 So my intuition is that this may not be  
19 completely neutral, because the -- the outside option  
20 is fixed, and then you change the advertising return,  
21 which would change the relative trade-off between  
22 that. So my hunch is that it may not be neutral in  
23 some contexts. So it will be good to see, and maybe  
24 I'm wrong.

25 Another extension is so far the model does not

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1 allow the influencer to create nonadvertising content,  
2 right? But in a lot of social media examples, we see  
3 that they actually create entertaining videos or some  
4 opinion in Twitter, and that's -- that requires some  
5 effort to do, okay? So it will be interesting  
6 extension to see that what if there is a cost to  
7 create those nonadvertising authentic content and that  
8 cost is fixed, when you impose a tax on advertising,  
9 probably going to change the trade-off between  
10 advertising return versus the authentic contents  
11 return, although both may affect following behavior.  
12 So I guess my guess is in that context, the  
13 advertising tax may not be neutral either. So that's  
14 just my hunch.

15 The second comment is on the FTC advertising  
16 disclosure guidance. So I agree with Professor that  
17 the FTC's action going to affect the return to  
18 disclosed ads, as well as return to nondisclosed ads.  
19 I think the paper treat those two as two free  
20 parameters, and in reality, these two are actually  
21 linked because of consumers' belief, right? When you  
22 allow some to be disclosed, it's going to change  
23 people's perception of what is really behind the  
24 nondisclosed ones? So in that sense, the two tools  
25 probably are linked. I think it will be interesting

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1 to explore the connection between those two.

2 Another thing I want to emphasize is that in  
3 the basic model, we sort of assume, okay, here's a  
4 fixed pie, we're just talking about how to divide that  
5 time. While each party may get zero or a positive  
6 fraction of this one, but in reality, the pie that's  
7 available for the influencer to grab is actually  
8 bigger than the real pie. You could sort of pedal up  
9 your advertising so that the followers sort of will  
10 pay higher price to the advertiser, who will kickback  
11 you a higher fraction of advertising revenue, but that  
12 product turns out to be much worse than what you  
13 advertised, so you sort of grab an inflated pie, and  
14 leaving a negative part to the follower, and that is  
15 not allowed in the basic model, but this inflation  
16 from the real pie is something I think really worry by  
17 policymakers, because your action in advertising  
18 generates damage to the followers, not just in the  
19 sense that they do not receive good advice, but also  
20 sort of generated damage negatively and impact them in  
21 terms of higher price or other forms. So I think that  
22 is a -- will be interesting extension. My hunch is  
23 that that is more than just changing outside option,  
24 because this affect the influencer's payoff directly.

25 Okay, about opt-in disclosure, the

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1 recommendation is that FTC only enforce disclosure for  
 2 small influencers. The big influencers, they will  
 3 choose nondisclose, and they will be sort of let be in  
 4 the market, and they -- and I understand the economic  
 5 logic there, because the top influencers are in the  
 6 harvest mode, and harvest is kind of the motivation  
 7 for them to sow good advice beforehand, okay? So I  
 8 understand the hunch that we need to keep the  
 9 incentive there in order to generate good advice.  
 10 However, this is very much against the practice  
 11 I have seen at FTC. For example, FTC has caught Kim  
 12 Kardashian in the Skechers case, where Kim Kardashian  
 13 has been involved in some deceptive advertising for  
 14 Skechers shoes. FTC also send out warning letters to  
 15 21 social media influencers in April 2017. I  
 16 understand there is a new round of warning letters  
 17 going out just recently. So that is targeting big  
 18 influencer rather than small influencer. So this is  
 19 sort of quite opposite from the opt-in disclosure  
 20 recommendation, and that's -- at least on the policy  
 21 ground, it was justified by the potential large damage  
 22 to sort of the negative return to the followers I  
 23 talked before, and I think intuitively, that could be  
 24 better for a big influencer, because they have a lot  
 25 of followers today. So I think it will be good to

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1 reconcile these two, the model recommendation  
 2 versus -- versus the FTC practice.  
 3 And lastly, Professor Mitchell has not talked  
 4 about search engine bias, but in the paper, there is a  
 5 lot of models try to talk about search engine bias. I  
 6 will just talk briefly. The paper models search  
 7 engine bias in two ways. One is that the market power  
 8 would increase the higher -- would mean a higher  
 9 payoff in advertising revenue, which I agree, but it  
 10 also assume the market power would imply a higher sort  
 11 of value of good advice, and that's something I'm not  
 12 sure I follow. So it might be good to sort of justify  
 13 that.  
 14 Another way to model is sort of assuming  
 15 there's additional income coming to the influencer,  
 16 independent of the advertising behavior, which is  
 17 modeled as a constant added to the income to the  
 18 influencer. My question is, I would actually even  
 19 want to think of this V, the constant return to the  
 20 influencer, to be something that affect the follower's  
 21 behavior. So I am thinking the V as kind of the value  
 22 it can generate by authentic contents, which we have  
 23 seen in a lot of examples of Twitter or search engine  
 24 or other things. So that would have a big impact on  
 25 the followers. We have seen a lot of arguments saying

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1 that, okay, we need advertising revenue because that  
 2 support us to create authentic contents, which  
 3 generate a lot of good value to the followers, which  
 4 sort of encourage the following. So I think it would  
 5 be good to sort of bring the two together and allow  
 6 both to affect the following behavior.  
 7 So overall, I think this is really a novel and  
 8 general paper that applies to both antitrust and  
 9 consumer protection issues. It has a lot of  
 10 interesting insights. I've listed a few of these, but  
 11 we encourage you to the read paper. It is a really  
 12 fun intellectual exercise, and I hope the future  
 13 version would get closer to the real business model  
 14 and FTC practice. I know the Professor in going in  
 15 that direction, so I really look forward to seeing the  
 16 update.  
 17 Thank you.  
 18 (Applause.)  
 19 MR. WILSON: Thanks very much. We have got  
 20 time for just one or two questions before our break,  
 21 if anyone has one or two.  
 22 Oh, sorry, Jonathan.  
 23 MR. ZINMAN: Matthew, I think there's some  
 24 evidence -- I'm thinking of some papers by George  
 25 Loewenstein and coauthors -- that under the type of

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1 disclosure regime you have in mind, that some  
 2 consumers can end up being excessively trusting of  
 3 the -- of the sender of -- of the provider of the  
 4 advice. So I'm wondering if you think that could be  
 5 materially impactful in your setting, for example,  
 6 whether it would move up the optimal time of harvest  
 7 and what implications that might have.  
 8 MR. MITCHELL: You know, I mostly did most of  
 9 my comparative statics on the influencer side. On  
 10 many things, there's a sort of almost equivalence.  
 11 That is, you know, something that -- like you're  
 12 thinking, that makes the total pie shrink or grow in a  
 13 different way. You're thinking it also affects, like,  
 14 the slope of the division between the two, because if  
 15 you're overly trusting, that -- you know, that affects  
 16 the division between the two. So it's probably a lot  
 17 like -- I haven't exactly done that explicitly, but I  
 18 think it's a lot like those things.  
 19 I want to stress, like, in the -- in the -- I  
 20 don't really have a way to behaviorally think about  
 21 exactly the words "too trusting," except that I do  
 22 have a way to think about the possibility that they  
 23 can't sort out one of type signal from the other, and  
 24 that may make them respond excessively. Like the one  
 25 I was thinking about was more that under disclosure

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1 policy, you don't know when to follow advice that may  
 2 be good advice but that has hashtag ad on it, but you  
 3 could just as easily put in the reverse, and any cost  
 4 like that of disclosure policy that's going to lower  
 5 the total pie is going to in some sense -- I think  
 6 going to have some of the same implications as M in  
 7 the model.  
 8 MALE AUDIENCE MEMBER: In your model -- I mean,  
 9 it's a moral hazard model where the agent cannot get  
 10 any reward unless he shirks, right? I mean, that's  
 11 when the agent gets a reward. So eventually the agent  
 12 has to shirk. It's the only way the agent can be  
 13 compensated and get some utility.  
 14 In -- in reality, I think that part of what  
 15 these influencers have is -- I mean, they do have some  
 16 value of being there and, you know, being influencers,  
 17 their egos or the attention, the number of followers.  
 18 There might be other ways in which they're  
 19 compensated, by the fact that they are very  
 20 influential, and not necessarily through ads that they  
 21 need to, you know, steal from people.  
 22 I mean, I guess that -- and in your model would  
 23 imply, you know, having, like, some flow utility that  
 24 the influencer gets, what would be the consequences of  
 25 that, and --

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1 MR. MITCHELL: That one is literally an  
 2 extension in the model, and so in the title slide, I  
 3 said a theory of Kim Kardashian and Charlie sheen.  
 4 The story there is that -- two things. So suppose  
 5 that there was just a fixed benefit of having a  
 6 follower, separate from the ads you could run. So I'm  
 7 imagining -- like, I was thinking about the ego  
 8 effect, maybe that you like having a lot of followers,  
 9 and that's where I think of Charlie sheen.  
 10 So what does that do? Well, that's  
 11 unambiguously good for followers because it makes it  
 12 easier to get incentives because the threat of leaving  
 13 them is even more severe. So that explains why  
 14 attention seekers like Charlie sheen get attention on  
 15 the internet, because they make good advisors in this  
 16 model.  
 17 It is not unambiguously good for the  
 18 influencer, though, because it makes it harder to  
 19 extract through the shirking channel, because it's  
 20 easier to get incentives on than to not shirk. So  
 21 that kind of thing is unambiguously good for  
 22 followers. One way to think about that is that Google  
 23 could use as a sort of defense, that we need to --  
 24 we're good, because we want people coming to Google,  
 25 and that makes us want to give them good advice in the

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1 organic search results. So that would be sort of the  
 2 policy way to think about your comment.  
 3 MR. WILSON: All right. Thank you very much.  
 4 I think we are going to take a break now to try and  
 5 stay on schedule. Let's reconvene in just a little  
 6 over ten minutes at 11:35. Thanks very much.  
 7 (A brief recess was taken.)  
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1 KEYNOTE ADDRESS  
 2 MR. ROSENBAUM: We are going to get started, if  
 3 everyone could please be seated.  
 4 So our first keynote address is going to be  
 5 given my Professor Jonathan Zinman, who's a Professor  
 6 of Economics at Dartmouth College, an academic lead  
 7 for the Global Financial Inclusion Initiative of the  
 8 Innovations for Poverty Action, and a co-founder of  
 9 their U.S. Finance Initiative.  
 10 His research focuses on household finance and  
 11 behavioral economics, and he has papers published on  
 12 economics, finance, law, general interest science, and  
 13 his work has been featured extensively in the popular  
 14 and trade media as well. He applies his research by  
 15 working with policymakers and practitioners around the  
 16 globe, and it's our privilege to have him here to  
 17 serve on the scientific committee and to hear his  
 18 keynote address on "Modeling With Behavioral  
 19 Consumers: New Evidence, New Tools."  
 20 MR. ZINMAN: Thanks. Thank you for having me  
 21 at your conference. I very much -- given my fields  
 22 and my interests, I very much feel like a guest here,  
 23 which is quite exciting. Lots of acknowledgments, but  
 24 I want to especially acknowledge the FTC crew, Ted,  
 25 Nathan, and Daniel Wood, for helping me think through

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1 what might be interesting to you all, to this  
2 audience. I hold them harmless, however. If you find  
3 this talk boring, that's on me, not on them,  
4 definitely.

5 I also, of course, want to thank many coauthors  
6 who have provided many, if not most, of the inputs  
7 that this talk is based on, especially my coauthor  
8 Victor Stango, who is my co-conspirator in much of the  
9 work that I'm going to be talking about today.

10 So, okay, all right, game plan for today. So  
11 I'm going to be talking some about a big new project  
12 with Victor Stango and Joanne Yoong, which has  
13 produced two papers -- two working papers so far, with  
14 many more to come hopefully. I want to tackle two  
15 broad questions that hopefully I can convince you are  
16 interesting and worth considering.

17 One is why it's important to take behavioral  
18 biases in consumer decision-making seriously, all  
19 right, and I will at least briefly deal with a lot of  
20 the concerns and critiques about whether we should --  
21 do behavioral factors actually matter out there in the  
22 wild when we have the types of repeat play and high  
23 stakes that we heard about this morning, for example?  
24 And if we are to take behavioral biases seriously, how  
25 do we do so from a modeling perspective?

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1 So one -- one example of this would be, well,  
2 what should the behavioral, in a behavioral I/O model,  
3 look like? Hopefully that's an interesting question  
4 to contemplate for at least some of you.

5 All right. So to get started with some  
6 motivation -- all right, let's say we want to design  
7 or evaluate a policy, all right? So before we get  
8 into something that's close to my heart, we could also  
9 be thinking about designing or evaluating a consumer  
10 protection policy for one of FTC's markets, the  
11 influencer market or the used car market or eBay, all  
12 things we've heard about this morning.

13 All right, closer to my heart and my work,  
14 let's say we want to evaluate the CFPB's newly issued,  
15 as of four weeks ago, final rule on the very  
16 controversial payday loan market, or better yet, let's  
17 back up and model and conduct welfare analysis to  
18 diagnose whether and how we should be intervening in  
19 the first place.

20 All right, so when we're doing this, we need to  
21 decide whether we should consider behavioral factors,  
22 and that might influence consumer decision-making in  
23 our model, in our model of consumer behavior, in our  
24 model of how suppliers are going to respond given how  
25 consumers decide, in our model of how policy is going

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1 to influence both types of parties.

2 All right, and one important question that I  
3 will largely punt on today in the interests of time  
4 and also statistical power is which behavioral factors  
5 to consider. So I'll -- this will come up again, but  
6 just to start fixing ideas, one of the challenges in  
7 behavioral economics and in applying behavioral  
8 economics is that there is a potpourri or panoply of  
9 biases that are thought to potentially substantially  
10 impact consumer decision-making, everything from  
11 present bias discounting to many varieties of  
12 overoptimism to loss aversion, to exponential growth  
13 bias, to statistical biases, like gambler's fallacies,  
14 and so on and so forth, all right?

15 So one of the things, without directly  
16 answering this question of which biases matter in  
17 which context, I'm going to talk about measurement  
18 tools and methodological approaches that can help us  
19 deal with this flowering, deal with this  
20 proliferation.

21 Okay, but first, let me answer the threshold  
22 question so that I can hopefully hold your -- continue  
23 to hold your attention for the next 20 minutes or so,  
24 which is what -- at a high level, what's the evidence  
25 on whether this stuff actually matters out there in

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1 the wild? All right, and let me -- and so I'm  
2 starting by addressing any skeptics.

3 All right. So, first of all, there is  
4 evidence -- still not enough in my view, I go into  
5 this pretty -- and went into this project I am going  
6 to be telling you about today pretty militantly  
7 agnostic, particularly by the standards of practicing  
8 behavioral economists, but let's just say there is  
9 mounting evidence that behavioral tendencies,  
10 tendencies towards bias in consumer decision-making,  
11 at least, these tendencies are closer to ubiquitous  
12 than anomalous, and we have some new evidence on this,  
13 and we are standing on the backs of, among others, two  
14 recent Nobel Prize winners.

15 All right. There's also evidence -- again, not  
16 enough for my liking, again, one of the reasons why we  
17 undertook the project I am going to be telling you  
18 about today -- there is also evidence that the  
19 influence of behavioral factors on consumer  
20 decision-making do not disappear as stakes rise.  
21 There is actually ample evidence from the field --  
22 from field settings at this point that they do  
23 influence large stakes decisions.

24 All right. Perhaps most shockingly, there is a  
25 fascinating and relatively new theory literature, not

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1 yet, to my knowledge, really brought to the data, but  
 2 there's a fascinating new theory literature exploring  
 3 how and why consumers do not necessarily learn to  
 4 debias themselves. They do not necessarily learn  
 5 about their biases or how to correct them.  
 6 And one of the reasons I was excited about the  
 7 panel this morning is it gets us thinking about  
 8 delegation, all right? The panel this morning  
 9 illustrates that delegation, intermediation,  
 10 intermediaries who are providing information, maybe  
 11 misinformation, persuasion, this is all -- it's all  
 12 nontrivial to understand how this affects market  
 13 outcomes even if we assume classical -- classically  
 14 rational consumers. Imagine allowing for behavioral  
 15 tendencies among consumer decision-making, all right?  
 16 So that's a long way of saying we really don't know --  
 17 and there's actually some empirical evidence  
 18 suggesting that we should be skeptical, but let's be  
 19 more agnostic -- we really don't know whether  
 20 delegation and intermediation serves to functionally  
 21 debias consumers and cure the would-be impacts of  
 22 behavioral biases on decision-making.  
 23 Okay. And the last bit of motivation for true  
 24 believers, even if you are already convinced that  
 25 behavioral biases influence consumer decision-making,

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1 we still need to do behavioral I/O modeling, certainly  
 2 when we want to understand the impacts of potential  
 3 policy interventions, because evidence is mounting,  
 4 both theoretical and empirical, that seemingly  
 5 intuitive treatments, seemingly intuitive  
 6 interventions can actually make things worse,  
 7 particularly when there's limited enforcement.  
 8 Okay. So the broader motivation here is, you  
 9 know, apart from any particular market, whether we're  
 10 focused on payday lending or used cars or whatever,  
 11 the broader motivation here is developing tools and  
 12 evidence to inform how we should use those tools about  
 13 how we can build portable models that reasonably and  
 14 usefully capture behavioral consumers, all right? So  
 15 I'm going to be -- I'm going to be talking today a bit  
 16 about different approaches to specifying -- designing  
 17 and specifying models, and what we're going for here  
 18 is building more workhorse, portable behavioral  
 19 models, okay? So that will be -- this is going to be  
 20 my last four slides in approximately our next three or  
 21 four papers, hopefully, which are going to be  
 22 summarized at a high level in these last four slides.  
 23 But first, I want to introduce this project  
 24 that Victor and Joe Ann and I have been working on for  
 25 years and are -- and that is finally bearing fruit in

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1 the form of some working papers. So what we do in  
 2 this project, the Multiple Behavioral Factors Project,  
 3 is we collect data on over a thousand representative  
 4 U.S. consumers using the RAND's American Life Panel,  
 5 and we're -- in this rich data set, we're collecting  
 6 data on various behavioral decision-making tendencies  
 7 of these consumers.  
 8 So rather than doing what behavioral economists  
 9 typically do in lab-type studies, which is bring  
 10 someone into the lab and hammer away at measuring one  
 11 particular bias for, say, 30 to 60 minutes, with a  
 12 very repetitive set of tasks in a lab, and so rather  
 13 than just try to measure whether people exhibit time  
 14 consistent discounting and, if not, whether they're  
 15 present-biased or future-biased, we're going to do  
 16 streamlined versions of that and measure 16 other  
 17 potentially behavioral influences on decision-making.  
 18 So in addition to measuring discounting and any  
 19 discounting biases, we're also going to try to measure  
 20 loss diversion; we're also going to try to measure  
 21 exponential growth bias; we're also going to try to  
 22 measure statistical biases; we're also going to try to  
 23 measure limited perspective memory; we're also going  
 24 to try to measure three different varieties of  
 25 overconfidence; and so on and so forth.

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1 All right, we do this, as I've already  
 2 intimated, using what behavioral commits refer to as  
 3 direct elicitation. So for the uninitiated, what's  
 4 direct elicitation? It's putting people through  
 5 stylized tasks that are meant to reveal their  
 6 decision-making tendencies. The analogy here -- and  
 7 this is -- and I should emphasize, you know, as with  
 8 any methodology or as with any measurement technology,  
 9 direct elicitation certainly has its pluses and  
 10 minuses. We certainly think of it as a strong  
 11 complement to various other methods of measuring or  
 12 inferring influences of behavioral factors on consumer  
 13 decisions and market outcomes, but just by way of sort  
 14 of motivation and history, there's -- there's an  
 15 analogy here to a much longer history in the social  
 16 sciences of intelligence testing and personality  
 17 testing, all right?  
 18 So one can try to infer someone's intelligence  
 19 or cognitive skills by looking at things they do out  
 20 there in the wild, right? So you could try to infer  
 21 cognitive skills from how people perform on their job,  
 22 for example. Well, it turns out you can also try to  
 23 infer and measure cognitive skills and learn a lot  
 24 about people by putting them through stylized tasks or  
 25 tests, all right? So we're on the stylized tasks and

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1 tests side of things here.  
 2 Okay. And so along with collecting this  
 3 rich -- rich in a broad sense, not rich in a deep  
 4 sense -- but in tandem with collecting data on these  
 5 17 different hypothesized behavioral influences on  
 6 decision-making, we also collect a lot of other  
 7 information on people taking our surveys.  
 8 Specifically, we try to measure what one might think  
 9 of as standard or classical decision inputs or  
 10 factors; cognitive skills, for example. You know, we  
 11 do -- we implement some standard short versions of  
 12 intelligence tests. We also elicit classical measures  
 13 of preferences, right, so patience, classical risk  
 14 attitudes. And, of course, we also have a lot of  
 15 demographic information on these folks, including  
 16 things that would be important in, say, any life cycle  
 17 model of consumption and consumption savings  
 18 decisions, all right?  
 19 The great thing about this survey and the panel  
 20 we're part of in this survey is you also get a lot of  
 21 rich data on decisions people are making in their real  
 22 lives, assuming they're reporting reasonably  
 23 truthfully, and we worry a lot about that. Being  
 24 household finance people, in our modules, we're  
 25 particularly focused on household finance, but there

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1 are and will be in future iterations of our working  
 2 papers many other outcome domains that one could look  
 3 at here, human capital type stuff, health type stuff,  
 4 et cetera, et cetera.  
 5 Okay. And so what's coming out of this project  
 6 and our working papers and future working papers are  
 7 sort of two classes of things. One is new tools for  
 8 measuring behavioral influences on decision-making.  
 9 One of our -- one of our papers that's done is partly  
 10 focused on showing that these streamlined elicitation  
 11 methods that we use to measure 17 things instead of  
 12 one thing that might be behavioral influences on  
 13 decision-making, so part of what we do is demonstrate  
 14 in various ways that these streamlined elicitations  
 15 actually do produce useful data, all right?  
 16 So what we have now is a suite of low-cost,  
 17 direct elicitation tools that are portable to a broad  
 18 variety of data collection settings. You know, part  
 19 of what we end up arguing here is you no longer need  
 20 to bring people into a lab and do extensive,  
 21 expensive, high-touch elicitations to learn useful  
 22 things about how behavioral tendencies might be  
 23 influencing consumers' decisions. You can use our  
 24 streamlined elicitations instead.  
 25 We're very worried about measurement error in

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1 all aspects of our data. I'm definitely on record and  
 2 published about being worried about such things in  
 3 prior publications on -- in terms of survey data. And  
 4 so a lot of what we're doing is working on developing  
 5 new -- or at least new for economics -- types of  
 6 measurement error corrections and also comparing them  
 7 to more standard and well understood measurement error  
 8 correction techniques.  
 9 We construct new summary statistics for -- at  
 10 the consumer level for capturing behavioral  
 11 decision-making tendencies. I'll talk in a couple  
 12 slides about how these end up being useful. And so --  
 13 and along with the new tools, of course, we also have  
 14 some new evidence on what we think are some  
 15 foundational and still largely open empirical  
 16 questions. So you can use our data to look at the  
 17 prevalence and heterogeneity across consumers of these  
 18 17 different behavioral factors.  
 19 It turns out many of these factors are quite  
 20 prevalent. They are also quite heterogenous across  
 21 people. Being behavioral on one dimension,  
 22 particularly in directions that have been the focus of  
 23 prior literature -- so, for example, being  
 24 present-biased instead of future-biased, having a  
 25 preference for certainty instead of a preference for

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1 uncertainty -- underestimating the power of the large  
 2 numbers as opposed to overestimating it.  
 3 It turns out that if you're behavioral on one  
 4 dimension, you're substantially more likely to be  
 5 behavioral on other dimensions. So I'll talk towards  
 6 the end about some possible implications of that  
 7 finding.  
 8 These -- these measures -- these measures of  
 9 behavioral stuff turn out to be statistically as well  
 10 as conceptually distinct from classical factors, both  
 11 in terms of measures of fit and measures of  
 12 conditional correlation with the types of outcomes we  
 13 might care about. And as just alluded to, many of  
 14 these behavioral biases do turn out to be correlated  
 15 with real-world decisions and outcomes, like, for  
 16 example, various measures of household financial  
 17 condition, and that's conditional on our measures of  
 18 classical factors, demographics, everything else we  
 19 observe about these folks.  
 20 Okay. So what do we -- what do we do with  
 21 this? How can we model behavioral consumers? How can  
 22 we capture something useful about behavioral  
 23 tendencies in decision-making, understanding that this  
 24 generates substantial additional complications if  
 25 we're trying to build an equilibrium model that allows

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1 for supplier responses, that allows for treatment  
2 effects of policies, or other interventions. So what  
3 should we do with all this?

4 Well, one approach -- and far and away the  
5 standard and most popular approach historically,  
6 whether in behavioral I/O or behavioral anything, in  
7 economics -- is what has been referred to -- and not  
8 charitably -- as the silo approach, right? So  
9 that's -- you know, there are dozens, maybe even a  
10 hundred at this point, of behavioral biases that have  
11 been hypothesized and in some settings suggestively  
12 shown maybe to influence or at least correlate with  
13 decision-making. The approach so far mostly has been,  
14 well, we're just going to deal with these one bias at  
15 a time.

16 All right. There are a lot of folks who, quite  
17 understandably, are concerned about this, right? It  
18 is not very congruent with building portable workhorse  
19 models of behavioral influences on decision-making.  
20 Drew Fudenberg maybe has the most, I think,  
21 high-profile and incisive critique of the hundred  
22 biases/hundred different models problem.

23 But this is a valid way of doing business if  
24 behavioral biases are separable from each other in  
25 terms of how they influence consumer decisions.

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1 Okay, so going back again to something that's  
2 close to my heart, in some of my other work, say I  
3 have reason to believe that that overoptimism about  
4 repayment -- and, you know, there might be some  
5 behavioral stuff underlying that forecast error, which  
6 we could talk about later -- but let's say in a  
7 reduced form way, overoptimism about repayment is an  
8 important feature of payday loan borrower  
9 decision-making that I'm worried about as a  
10 policymaker.

11 Can I just model that and ignore any influence  
12 of present bias, ignore any biases that might result  
13 from people with present bias discounting getting  
14 tempted by quick cash when they drive by one of the  
15 countless payday loan storefronts or when they  
16 encounter one of the countless ads or links to online  
17 payday lenders? Can I ignore that safely?

18 Well, until now, there's been very little  
19 evidence to guide us on this modeling decision. With  
20 our data, you can begin to tackle this empirical  
21 question, and the evidence we're finding thus far is  
22 quite encouraging, surprisingly so, actually. So  
23 basically if what you do is you start by estimating  
24 richly conditional correlations between, say, some  
25 outcome or condition you're interested in, say an

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1 index of overall household financial condition, which  
2 is basically capturing some sort of -- you know, a  
3 series of correlated signals of wealth or financial  
4 stability, all right?

5 So you start by estimating correlations between  
6 that outcome index and single behavioral biases, okay?  
7 When you do that, we find patterns of correlations  
8 that line up very nicely with standard behavioral silo  
9 theories. You know, present bias guys look like they  
10 have worse financial conditions, conditional on  
11 everything else, right? Guys with limited memory, per  
12 our stylized tasks, have worse financial condition,  
13 conditional on everything else.

14 If you then add a vector capturing everything  
15 else we observe about these folks behaviorally  
16 speaking from our elicitations, these results do not  
17 change at all. All right, I did some fun effects  
18 there, because I think this is a potentially profound  
19 and exciting result, all right? It basically supports  
20 standard operating practice in most of behavioral  
21 economics.

22 It suggests that, at least in the one outcome  
23 domain we've looked at so far, and subject to all the  
24 caveats of -- about correlational reduced form  
25 analysis, it suggests that behavioral biases may,

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1 indeed, be separable in ways that are amenable to  
2 siloed modeling where the silo -- where the silo, of  
3 course, you know, may accommodate two or three biases  
4 that interact, all right, but it's -- you know, the  
5 siloed approach is basically one or few biases at a  
6 time, not a dozen or a hundred at a time.

7 Okay, all right. There's another approach,  
8 which is to say, well, consumers are behavioral; we're  
9 not sure how or why. All right? This is the reduced  
10 form behavioral sufficient statistic approach, all  
11 right? So in these models, there's a wedge between  
12 decision utility, what people think their utility is  
13 going to be when they make a decision, and experience  
14 utility, what actually ends up happening, all right?

15 Reduced form models often get a bad rap in  
16 economics, but as I hope to show you, these models can  
17 be very useful, and in other -- and other fields are  
18 very happy to make and explore distinctions between  
19 emergent versus fundamental models, right? And so  
20 this is an emergent model. This is a model where we  
21 have a core specification of how people go awry due to  
22 behavioral influences on decision-making without  
23 modeling all the fundamentals of exactly how they're  
24 going awry.

25 So how do you do this? Well, fortunately, for



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1 all of us, Raj Chetty and my new coauthors, Hunt  
2 Allcott and Dmitry Taubinski, have some great papers  
3 where they -- where they develop and explain this tool  
4 kit far better than I could in two minutes or less. I  
5 have not yet, by the way, seen this approach deployed  
6 in behavioral I/O, although it's possible I've just  
7 missed some interesting papers.

8 But anyway, using this reduced form approach,  
9 people are behavioral in some way. We're going to  
10 specify that coarsely, in reduced form. Even this  
11 approach relies on some key assumptions. These key  
12 assumptions have also have not been validated or  
13 invalidated empirically. Again, you can take the data  
14 and Victor and Joanne and I have generated and poke at  
15 these assumptions, all right?

16 Again, the findings are encouraging for the  
17 most part, although not -- although not universally in  
18 the case of the reduced-form, sufficient statistic  
19 models. So one key thing you need for these models to  
20 work and for them to make sense is you need to posit  
21 it within consumer correlation amongst different  
22 behavioral biases. As I said, on the last slide we  
23 had that or two slides ago we had that.

24 For -- we -- we take that as a jumping-off  
25 point and then actually construct simple

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1 consumer-level summary statistics, aggregating across  
2 behavioral biases within -- within consumer. In doing  
3 that, you find support for another key assumption  
4 these models have, which is that people actually need  
5 to be biased, right? And to my mind, this is actually  
6 what behavioral economics is all about. It's not  
7 about people making mean zero errors. It's about  
8 people tending to make errors in a particular  
9 direction, exhibiting bias.

10 So we find that, and you can use our summary  
11 statistics to illustrate that. Moreover, these  
12 summary statistics end up being strongly conditionally  
13 correlated with outcomes, with outcomes and decisions  
14 in the field.

15 All right. The one caveat here -- and I think,  
16 to my understanding, what really complicates trying to  
17 use these models for policy applications -- is that  
18 when you have heterogeneity in how behavioral  
19 consumers are, it's actually quite difficult, quite a  
20 heavy lift to identify the average marginal bias  
21 distribution you need to do welfare analysis, all  
22 right? So you really -- to make good use of this  
23 method, you really need to have good data and good  
24 identification that allows you to sort of walk down  
25 the behavioral demand curve, and that can be

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1 challenging, although Hunt and Dmitry do a very clever  
2 and thought-provoking job of this in their AR paper on  
3 the light bulb market.

4 All right. So a third approach, which is very  
5 much still under construction, is grand unification,  
6 all right? So is there something fundamental about  
7 human decision-making that produces these 17 or these  
8 hundred different behavioral biases and their links to  
9 decisions in the real world? It's not crazy to think  
10 this could be the case. I mean, we could draw  
11 inspiration from other fields as far-flung as physics,  
12 but closer to home, this is what -- this is very much  
13 what social scientists in related fields on  
14 decision-making have been discovering over the last  
15 many decades.

16 We started over 100 years ago with the model  
17 where there were basically countless cognitive skills  
18 and ways people could be smart or skilled. That has  
19 been distilled to what's sometimes referred to as the  
20 G factor, smarts, intelligence, general intelligence.  
21 Similarly, in personality psychology, all right?

22 We find some encouraging results, one of which  
23 I have -- I have already mentioned. Taking it a step  
24 further, if you subject our data on multiple  
25 behavioral biases to factor analysis, it does look

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1 like there is a single common factor underlying the  
2 17. So that's very exciting and would seem to bode  
3 well for prospects for a grand unification, but so far  
4 we're finding the glass is half empty in the sense  
5 that that common factor does not seem to help us  
6 understand real-world decision-making or outcomes  
7 conditional on what we already observe about people,  
8 but there's still much more work to be done on that  
9 margin.

10 Okay, so last slide. Summing up what to make  
11 of all this and how some of you might be able to think  
12 about using this evidence and these tools going  
13 forward, so you have a setting, you have a market  
14 you're interested in, where you or the policy folks  
15 you're working with have priors about a behavioral  
16 bias or a set of behavioral biases that affect  
17 consumer decisions and possibly welfare. What can you  
18 do?

19 Well, you can use our tools to cheaply and  
20 directly measure the behavioral biases of interest in  
21 the market you're interested in, to see whether  
22 they're prevalent, to see how much heterogeneity there  
23 might be. You can then use that data, the data on the  
24 empirical distribution of your bias or biases of  
25 interest, and data on statistical relationship between

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1 that bias or those biases and the outcomes you care  
2 about and the market you care about to inform your  
3 modeling decisions about how to model competition  
4 equilibrium policy impacts in this market you care  
5 about, right?

6 You can use this data to inform whether you  
7 should or could build a behavioral silo model, where  
8 you're just focused on one bias or, say, the  
9 interaction between two biases, or if it seems like  
10 there may be many biases in play, which are positively  
11 correlated within people, and so on and so forth, you  
12 might want to go the reduced form behavioral  
13 sufficient statistic route.

14 All right. Eventually, hopefully, we or one of  
15 the other teams working on the grand unification  
16 question will have a third option to offer, but I  
17 think we're some years off from that. And I would say  
18 in terms of the overall approach on this slide, Hunt,  
19 Dmitry, and I are putting our money where my mouth is  
20 today and trying to use just this approach in various  
21 markets at this point, and I hope others will join us  
22 on this journey.

23 Thanks.  
24 (Applause.)

25 MR. ROSENBAUM: We have time for about one or

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1 two questions. Okay.

2 MALE AUDIENCE MEMBER: Regarding welfare, how  
3 do you evaluate -- I mean, what is the welfare  
4 criterion that you would use? I mean, these people --  
5 I think in some ways you might be regarding them as  
6 they have -- they don't know how to make decisions,  
7 and so there is some utility function that they really  
8 have, but yet they're behaving in a way that is  
9 inconsistent with that, or be more agnostic to what  
10 are really the preferences. Maybe they have  
11 preferences over, you know, decisions, actions, and so  
12 how do we even go about thinking about welfare?

13 MR. ZINMAN: So for some behavioral biases,  
14 this is -- the answer to that question is relatively  
15 straightforward. So there is a distinction between  
16 biases and preferences, which raise the thorny issues  
17 that you just mentioned, and biases in beliefs or in  
18 the processing of information, right? So for the  
19 latter, it's relatively straightforward. It's -- you  
20 know, it's usually reasonable to use the unbiased  
21 benchmark for our welfare analysis.

22 When people have behavioral preferences, it  
23 is -- it is far thornier to deal with. The most --  
24 you know, I think the -- in recent years, the greatest  
25 focus in behavioral economics has been on

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1 time-inconsistent discounting, in particular, which is  
2 actually sort of a mishmash of preferences and beliefs  
3 if we really want to get per in this case at this  
4 about it, but anyway, the -- you know, sort of the  
5 standard operating practice, to the extent there is  
6 one, is to -- is to imagine that the behavioral guise  
7 would, in fact, be time consistent and would prefer to  
8 be time consistent.

9 MR. ROSENBAUM: One more.

10 MALE AUDIENCE MEMBER: Hi. Just a question on  
11 the summary, these three approaches, the silos versus  
12 this grand unification. If I'm understanding it  
13 right, it seems like if the -- if the silos work, then  
14 grand unification can't work, because what the silos  
15 are depending on is the fact that the part with, you  
16 know, behavioral bias A that's correlated with  
17 behavioral bias B doesn't explain the outcome variable  
18 of interest, that it's the common component that's  
19 uncorrelated with the outcome, and grand unification  
20 requires that all these, you know, 17 or 100 bases,  
21 there's a component of them that together is  
22 correlated with the outcome. So how can silos work  
23 and still there be hope for grand unification?

24 MR. ZINMAN: So I -- I suspect -- I suspect you  
25 are right, that if one works, the other doesn't. I

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1 would hedge in two -- in at least two ways, though.  
2 One is we haven't proved that. We haven't fully  
3 worked that out, nor has anyone else, and there could  
4 be some subtlety and nuance that makes this worth  
5 seeing whether one could prove it.

6 The second thing is that, you know, all of the  
7 evidence I just presented to you from our stuff, at  
8 least, including the evidence of validating the silo  
9 approach, is new and preliminary and consequently  
10 should be taken with a grain of salt.

11 MR. ROSENBAUM: Thank you very much. Let's  
12 thank Jonathan.

13 (Applause.)

14 MR. ROSENBAUM: Now we are going to break for  
15 lunch. There's food outside, and we'll take 25  
16 minutes for lunch. Let's try to be back at 12:45 for  
17 our next panel.

18 (Whereupon, at 12:22 p.m., a lunch recess was  
19 taken.)  
20  
21  
22  
23  
24  
25

1 AFTERNOON SESSION  
 2 (12:48 p.m.)  
 3 PANEL DISCUSSION  
 4 MR. ROSENBAUM: All right, if everyone could be  
 5 seated. I'm going to turn the microphone over to my  
 6 colleague, Keith Brand, who's going to introduce the  
 7 next panel.  
 8 MR. BRAND: Good afternoon. Welcome, everyone.  
 9 My name is Keith Brand. I'm an economist with the  
 10 Federal Trade Commission, and I will be chairing our  
 11 panel discussion this afternoon on cross market  
 12 provider mergers.  
 13 As many of you are likely aware, several recent  
 14 empirical and theoretical studies examined the price  
 15 effects of cross market mergers between healthcare  
 16 providers. For the most part, these studies consider  
 17 whether mergers between healthcare providers in  
 18 nonproximal geographies lead to higher prices even  
 19 though the providers are not close substitutes for  
 20 patients at the point of service.  
 21 I think it is fair to say that the empirical  
 22 analyses and the literature do provide credible  
 23 evidence that prices have increased following such  
 24 mergers, and while the literature has explored several  
 25 mechanisms that could explain the empirical results,

1 it is perhaps less clear that we have good evidence on  
 2 what mechanisms are likely to be the most relevant.  
 3 We have assembled an outstanding panel this  
 4 afternoon to discuss the literature on cross market  
 5 mergers, what research has been done, what we think  
 6 we've learned so far, and what are the most likely  
 7 important next steps in the literature.  
 8 First, to my far left, we have Marty Gaynor.  
 9 Marty is the E.J. Barone University Professor of  
 10 Economics and Public Policy at Carnegie Mellon  
 11 University and the former Director of the Bureau of  
 12 Economics at the Federal Trade Commission. He's also  
 13 a founder and a former chair of the Governing Board at  
 14 the Healthcare Cost Institute.  
 15 Next to him we have Matthew Schmitt, who is an  
 16 Associate Professor of Strategy at the UCLA Anderson  
 17 School of Management.  
 18 Next we have Greg Vistnes, who's a vice  
 19 president at Charles River Associates. He has also  
 20 served as the Deputy Director for Antitrust in the  
 21 Bureau of Economics at the Federal Trade Commission  
 22 and as the Assistant Chief of the Economic Analysis  
 23 Group at the Department of Justice's Antitrust  
 24 Division.  
 25 Finally, we have Matthew Lewis, who's an

1 Associate Professor of Economics in the Department of  
 2 Economics at Clemson University.  
 3 So we have organized our discussion as follows:  
 4 First, each of the panelists will provide some opening  
 5 remarks on the topic, and then we've grouped together  
 6 four topics for discussion after the opening remarks,  
 7 and we plan to leave about 15 minutes or so for  
 8 questions and answers at the end of the panel.  
 9 So we'll start with Greg Vistnes.  
 10 MR. VISTNES: Okay. Well, thank you very much  
 11 for the opportunity to be here and speak here today.  
 12 I think this is a really important topic. I think,  
 13 given all the interest that's out there, both among  
 14 economists as well as some of the different  
 15 enforcement agencies, it's a very ripe topic to have  
 16 this sort of a discussion.  
 17 I just want to sort of open up with what I  
 18 think are three of, to me, the most important issues  
 19 about some of these cross mergers and the enforcement  
 20 issues. First of all, why are we looking at it? What  
 21 is it that makes this, at least to many of us, such an  
 22 interesting topic?  
 23 Secondly, do we have a theory for any of these  
 24 concerns? And maybe even, why do we really care if  
 25 there's a theory? Is that important or not?

1 And then third and related to it is, what are  
 2 some of the policy implications about pursuing an  
 3 enforcement agenda? They are all sort of wrapped up  
 4 with each other.  
 5 So, really quickly, why are we looking at it?  
 6 Well, to me at least, we're looking at it because  
 7 we've heard complaints -- I've heard complaints -- for  
 8 over a decade from managed care plans saying these  
 9 things are bad; these hospital systems with hospitals  
 10 even in different markets, they just make us all in a  
 11 worse situation. And there's never really been a good  
 12 economic theory to explain that, but then part of  
 13 what's recently come out from both the Matts on either  
 14 side of me and from others as well is now there's some  
 15 empirical evidence to back up those concerns, that  
 16 what people are saying, there seems to actually be  
 17 some truth to it, that some of these hospital prices  
 18 for chains seem to be higher, may be due to this --  
 19 call it a cross market effect, but we still don't have  
 20 a good theory. What the heck is the theory?  
 21 The theory that we're looking at is not the  
 22 traditional vertical theory. It's not foreclosure,  
 23 it's not bundling, it's not tying. It's something  
 24 different. Well, what is it? You know, here some of  
 25 my biases are probably starting to come out, but it's

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1 kind of like the conglomerate effects theories of the  
2 1960s. It's kind of like the portfolio power theories  
3 of the 2000s that Europe pursued for a while. It's  
4 not really clear what the heck this is. So what are  
5 we going to make of it?

6 Well, there seem to be at least two aspects of  
7 the theory, and we're going to talk more about the  
8 details of the theory, but there seem to be sort of  
9 two parts of, if there's a theory to explain cross  
10 market mergers that we've come up with so far, that  
11 somehow the theory has to explain linkages across  
12 these markets, and the linkage is not coming, by  
13 definition, from patient flows like it is in the  
14 traditional, but there has to be a linkage to make  
15 cross market effects work.

16 And then secondly, it has to be a really  
17 special kind of linkage. It has to be -- and, again,  
18 we will get into this in gruesome detail -- it has to  
19 be concavity of a linkage effect, concavity of profits  
20 or superadditivity.

21 But then it turns to the other thing is, you  
22 know, yeah, to heck with it. We have empirical  
23 evidence that the effect is there. We have got  
24 complainants. Why do you need a doggone theory with  
25 these economists concerned about proving what everyone

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1 knows is true? Well, there are a lot of good reasons  
2 for it, and we'll, again, get into hopefully a lot of  
3 it in this discussion, but really important, at least  
4 to me, is we need to be able to offer guidance. What,  
5 in essence, we have now is I'll say we have a  
6 possibility theorem. We have proven that it is  
7 theoretically possible. Is it likely? Where is it  
8 likely? What's the magnitude of the effect?

9 And importantly, from the providers'  
10 perspective, what the heck can they merge with if they  
11 don't know which ones are going to be challenged or  
12 not? Some sort of guidance has to be provided there.  
13 So how can we give them that kind of guidance?

14 And then the last thing that I want to mention  
15 that I think is, again, super important with policy  
16 implications are, what are the limiting principles?  
17 Where do we stop? Is it just cross market with  
18 respect to hospitals in different geographic markets,  
19 or do we especially start looking at product markets,  
20 because the theories will probably extend pretty  
21 easily.

22 Do we start caring about acute care hospitals  
23 and children's hospitals and psychiatric hospitals  
24 getting it together? What about acute care or what  
25 about inpatient versus outpatient? What about

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1 hospital physician mergers? What about multispecialty  
2 clinics?

3 And then, heck, why stop here in healthcare?  
4 We have got the world to explore. We have got cable  
5 TV. We've got all sorts of markets where we can apply  
6 this theory, where is the principal issue payer  
7 complaint? I hope not. So we need to wrap this  
8 through.

9 And then why I think this is such a critically  
10 important issue or topic for discussion is we have got  
11 a bunch of really bright economists here. I don't  
12 think the theory is out there yet. There's a lot of  
13 reason to think there may be a concern, but if anyone  
14 can figure out whether or not to accept or reject a  
15 theory, I think that's a great research opportunity  
16 that's going to have some real value for folks.

17 MR. BRAND: Okay. Thanks, Greg. Let's next  
18 turn to Matthew Lewis.

19 MR. LEWIS: Okay. So I'd like to -- just given  
20 that introduction, I think I'll spend my time just  
21 giving some background on the recent empirical  
22 evidence by going over the results of my two papers,  
23 and then I'll leave it to Matt to discuss a few of the  
24 others.

25 Actually, the -- I have written two papers,

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1 both with Kevin Pflum, on this topic. One was more of  
2 a theoretical -- a structural paper which built off of  
3 the structural model of hospital MCO bargaining that's  
4 commonly used to study within-market mergers, but  
5 thinking about a new twist, which is the extent to  
6 which being a member of a hospital system might impact  
7 the bargaining power of the hospital, where  
8 bargaining -- bargaining power is -- when saying  
9 bargaining power, I'm referring to the Nash bargaining  
10 weight, which we will talk more about, but -- so  
11 that's distinct from any local sort of market position  
12 of the -- of the MCO and the hospital.

13 And what we find there is some evidence that  
14 hospitals in systems do have higher bargaining powers  
15 and that -- and that bargaining power is increasing in  
16 the size of the system, even if the system partners  
17 are outside the local market. So this is starting  
18 to -- that paper does not establish any causal effect  
19 of being in a system and how that impacts bargaining  
20 power, but it's suggestive that maybe there's this  
21 opportunity to link up with hospitals in other markets  
22 and somehow increase my negotiating ability through  
23 this bargaining power parameter and get higher prices.

24 And so that inspired the second paper that we  
25 have, which went on and specifically looked at

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1 observed cross market mergers, so over 100 of these  
2 mergers, examining what happens when a stand-alone  
3 hospital is acquired by an out-of-market system that  
4 has no other partners in the local market, and what  
5 happens to the prices of that stand-alone hospital,  
6 the acquired hospital, what happens to the prices of  
7 their local rivals in that market.

8 And we show that, on average, the prices of  
9 those acquired hospitals do go up by something like 17  
10 percent, on average, and also you see an increase in  
11 the prices of their neighboring hospitals. So there's  
12 some suggestive evidence that -- again, that there's  
13 a -- basically a -- you know, some sort of softening  
14 of competition here in the sense that prices and  
15 profit -- price gross margins are going up here, and  
16 what -- and based on this evidence and some  
17 supplementary analysis, we argue that what it -- the  
18 patterns that we see in these price increases appear  
19 to be most consistent with the possibility that the  
20 bargaining power of these hospitals has changed with  
21 the merger. Basically, that they are somehow  
22 acquiring an increased ability to bargain --  
23 bargaining sophistication, some increased ability to  
24 gather more of the rents available.

25 So I think several other papers have since been

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1 put out -- I guess working papers, too -- that used a  
2 similar difference-in-difference approach to study  
3 cross market mergers. The -- each of these studies --  
4 I think this is interesting. Each of these studies  
5 studies a somewhat different set of hospital -- of  
6 cross market mergers and looks at different firms when  
7 they're evaluating the price effects of those mergers,  
8 and so in that sense I think these studies are really  
9 complementary, and what I think we can do -- you know,  
10 so, for example, we focus on acquisitions of  
11 stand-alone hospitals, and we argue that the evidence  
12 there suggests maybe that those hospitals acquire a  
13 stronger bargaining power in that acquisition, but  
14 other types of mergers -- you know, the evidence from  
15 these other studies suggests that there may be  
16 evidence that some of these other mechanisms that Greg  
17 talked about -- or we will talk about -- that there is  
18 evidence that some of these other mechanisms may be  
19 generating price effect -- cross market price effects  
20 in other settings.

21 So I think there's a lot of opportunity now to  
22 bring the results of all those papers together and  
23 think carefully about when and where we might -- we  
24 think we will -- we will see price increase -- price  
25 increases after these mergers and also what we can

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1 tell about what mechanisms may be responsible in  
2 different settings. I think we can do that based on  
3 the evidence we have.

4 MR. SCHMITT: I'll just continue to give you a  
5 description of some of the empirical evidence we have  
6 for cross market merger effects, evidence in addition  
7 to what you just heard from Matt. So, first,  
8 Leemore Dafny, Kate Ho, and Robin Lee have a paper in  
9 which they examine hospital system acquisitions of  
10 other hospital systems, and their focus is on the  
11 outlying hospitals of those systems, so hospitals that  
12 are more than a 30-minute drive away from the closest  
13 hospital belonging to the other system. The goal  
14 there is exactly to shut down direct patient  
15 substitution between the merging hospitals.

16 They find that prices increase post-merger for  
17 the outlying hospitals but only when the outlying  
18 hospital gains a system member in the same state. So  
19 when a hospital gains a system member from out of  
20 state, they find no evidence of price effects.

21 What might explain that, Dafny, Ho, and Lee  
22 note that, while there may not be any direct patient  
23 substitution between the merging hospitals that they  
24 examined, A, and the hospitals may contract with the  
25 same insurer -- they call that common insurers -- and

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1 B, the hospitals may both be valued by the same  
2 employer, imagine if you employ people in the northern  
3 and southern suburbs of a city and you offer a single  
4 insurance plan to your employees, you may care about  
5 both of those hospitals. They call that common  
6 customers.

7 They demonstrate theoretically that both common  
8 insurers and common customers can generate price  
9 effects in standard bargaining models, and both common  
10 insurers and common customers are more likely to occur  
11 in state than out of state.

12 Second, let me touch on my own work in this  
13 area. As regional and national hospital systems have  
14 expanded, they now overlap with one another in an  
15 increasing number of hospital markets. To give you  
16 just one suggestive statistic, about half of U.S.  
17 hospitals now belong to a system that operates in  
18 multiple hospital referral regions, which is a big  
19 market definition, and about a third belong to systems  
20 that have a presence in multiple states. So, in  
21 short, hospital systems compete with one another in  
22 multiple markets simultaneously.

23 In the literature, that's often referred to as  
24 multimarket contact, and there's a large body of  
25 theoretical work and some empirical work demonstrating

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1 that multimarket contact can soften price competition.  
 2 I have a paper in which I examine whether escalating  
 3 multimarket contact between hospital systems, which  
 4 has largely been generated by acquisitions without  
 5 direct horizontal overlap, has led to higher hospital  
 6 prices.

7 I don't know if it's productive to get into the  
 8 details of the measurement there, but I find evidence  
 9 suggesting that, indeed, more multimarket contact  
 10 leads to higher hospital prices. In line with, I  
 11 think, what Matt raised in his closing, in my view,  
 12 what remains elusive is more direct evidence about  
 13 what the true underlying mechanisms are. I think  
 14 there are a few clear obstacles to really nailing down  
 15 specific obstacles -- specific mechanisms empirically,  
 16 but I'll stop for now because I imagine that's  
 17 something we'll get into.

18 MR. GAYNOR: Great. Well, thanks.

19 So let me talk about some conceptual or policy  
 20 issues at a high level, and then I'm sure we will get  
 21 back to specifics. One thing that I think should be  
 22 emphasized is that the issues that are raised here are  
 23 not specific to healthcare. They are potentially  
 24 quite broad and could apply in a whole bunch of other  
 25 industries, lots of retail outlets, online outlets.

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1 For example, if the manufacturer of Skippy  
 2 Peanut Butter and the manufacturer of Charmin Toilet  
 3 Paper wanted to merge, would that be a merger that  
 4 would potentially be harmful to competition and worthy  
 5 of the agency's attention? Mike Vita is looking at me  
 6 like his head is about to explode.

7 We would -- under -- you know, under sort of  
 8 consumer substitution, it clearly would not meet that  
 9 criteria. If you give your kid a toilet paper  
 10 sandwich for lunch, they'll like it even less than a  
 11 peanut butter sandwich, but perhaps that's not -- that  
 12 may not be the correct lens through which to view  
 13 this.

14 So -- but coming back to healthcare, what we  
 15 have at this juncture is we have fact patterns.  
 16 Market participants say things that are consistent  
 17 with cross market mergers, perhaps enhancing market  
 18 power and harming competition. There are stories one  
 19 hears from payers, in particular -- who, after all,  
 20 are the people paying for this stuff -- and sometimes  
 21 from health systems themselves.

22 Actually, could I get the slide, please, if I  
 23 may?

24 So as folks may know, UNC Healthcare in Chapel  
 25 Hill and Carolinas Healthcare in Charlotte, about 130

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1 miles apart, about a two-hour-plus-ish drive on  
 2 interstates, are talking about merging, and the CEOs  
 3 are in the picture of the two health systems, and in  
 4 an interview at newspaper offices, the executives said  
 5 the partnership would give them leverage to negotiate  
 6 better deals with insurers, at which point their  
 7 lawyers' heads exploded.

8 So when -- what -- what does this mean about  
 9 this merger? I don't know. I'm not opining on this  
 10 merger. Obviously, it could be a beneficial or a  
 11 benign merger or go the other way. The point is that  
 12 at least the CEOs of these two merging entities who,  
 13 arguably, very well may not be in the same geographic  
 14 market -- you can take the slide down if you like --  
 15 seem to think that this is going to enhance their  
 16 negotiating leverage.

17 Now, being CEOs and not Ph.D. economists, they  
 18 didn't specify exactly whether that was due to  
 19 concavity functions or shifts in relative bargaining  
 20 rates. I don't know why. Somebody needs to do a  
 21 better job in MBA strategy classes, I think, but  
 22 anyhow -- and then we have the empirical patterns that  
 23 Matt and Matt have ably described. So we see these  
 24 things very carefully done, very, very competent, good  
 25 research, where there are these fact patterns emerging

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1 from the data.

2 As Greg said, it's not entirely clear what to  
 3 make of these things. Now, in some ways, I think  
 4 that's a blessing, right? How does science advance?  
 5 One way science advances is we turn up stuff and we  
 6 look at it and we don't know what to make of it, and  
 7 so then we have to go back to the drawing board and  
 8 think a bit harder about what's going on.

9 Now, it's certainly possible -- and there are  
 10 stories we can tell, and, again, the folks who have  
 11 been working in this research area do have some pretty  
 12 compelling stories that rationalize the observed  
 13 empirical patterns into some existing models, saying,  
 14 you know, you just have to think about who the buyer  
 15 is, and that makes a lot of sense, but I think that  
 16 we're still not quite there yet. In particular, in  
 17 being able to draw clear inferences about whether  
 18 there's harm to competition and what the appropriate  
 19 enforcement policy is.

20 So I think that we do need some further  
 21 thinking about the underlying theoretical framework,  
 22 and obviously some of that's technical, but really the  
 23 question is what kind of behaviors are there that  
 24 would generate this and then some tests that can  
 25 sharply distinguish those behaviors from other kinds

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1 of plausible behaviors.  
 2 And then I think that a fuller -- a fuller --  
 3 what's needed is a fuller model, both theoretically  
 4 and empirically, and, in particular, one has to  
 5 include insurers in that model. That's been a big  
 6 challenge in healthcare because the data aren't  
 7 generally available.  
 8 Kate Ho and Robin Lee, who were mentioned  
 9 previously, are some of the few people that have done  
 10 that kind of work, and they have gotten the data, but  
 11 they have not just gotten the data, they have thought  
 12 hard about what the economics are and been able to  
 13 specify and estimate very careful econometric models  
 14 to capture that.  
 15 So I think we need more about that as well in  
 16 order to be able to make progress on this front, and  
 17 then I think a couple other just thoughts on that.  
 18 One, it can be hard for academics to get a hold of  
 19 data if the dataholders aren't willing to part with  
 20 it, but folks in enforcement agencies do have subpoena  
 21 power if there is an important issue. And while I'm  
 22 not -- I would certainly never suggest that the FTC or  
 23 any agency use those powers lightly, but when there is  
 24 an important matter and it's important to know these  
 25 things, there can be data available that otherwise

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1 might be hard to come by.  
 2 Then I think, as Greg mentioned, looking at  
 3 product markets is important because the general  
 4 notion is not specific to geographic markets. It's  
 5 about product markets, and there are certainly other  
 6 industries. I was not entirely facetious about the  
 7 peanut butter/toilet paper example. There are other  
 8 industries where if this has validity, it would apply  
 9 potentially with real force as well.  
 10 MR. BRAND: Thank you all very much.  
 11 So I am going to turn to two topics that  
 12 address two of the main mechanisms that the literature  
 13 has explored as plausible explanations for the  
 14 empirical results. The first is, as Greg mentioned,  
 15 the concavity or convexity -- as the case may be -- of  
 16 insurance profits with respect to the providers  
 17 included in its network and what may be driving that  
 18 concavity or convexity. And the second, as Matt  
 19 described it, as potentially the merger induces a  
 20 shift in the Nash bargaining weight.  
 21 So I'm going to turn first to Greg on the  
 22 concavity issue just to -- first to frame the issue,  
 23 what we mean by concavity, how that connects with --  
 24 well, what you may think of it as a standard approach  
 25 to analyzing healthcare mergers. And I know a number

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1 of the panelists have some thoughts on is concavity or  
 2 convexity more likely to obtain in the real world.  
 3 So, Greg, if you could kick us off on that.  
 4 MR. VISTNES: Yes. So I think there's a little  
 5 bit of danger as folks up here at the panel right now  
 6 are talking a little bit inside baseball, and everyone  
 7 out there is saying, what the heck is really the issue  
 8 you're talking about? So I might frame a bit the  
 9 issue.  
 10 Standard merger analysis, you know, your  
 11 typical widget merger, it's all based on the notion  
 12 that there are substitutes, and the places where we  
 13 care most about concerns are where one is a really  
 14 good substitute, but what that really means is a  
 15 consumer, when they're premerger, trying to decide  
 16 between one or the other, they say, well, if I lose  
 17 this one, I'm not that much hurt, because I can switch  
 18 over to this other substitute, but if I lose the other  
 19 one as well, because now I can't have either one, I'm  
 20 a whole lot worse off.  
 21 So there's some concavity, or if you flip your  
 22 graph upside, depending on what's on the other axis,  
 23 convexity, but you have curvature. You have  
 24 superadditivity in the sense, in a sense, that by  
 25 losing the second one, I'm worse off. That's what, in

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1 essence, we are trying to get at and what I think a  
 2 lot of the theories in the hospital mergers is all  
 3 about.  
 4 Now, if we're talking about two different  
 5 hospitals in two completely separate geographic  
 6 markets, where we're assuming by definition consumers  
 7 don't go back and forth because they're separate  
 8 geographic markets, different islands, if you lose one  
 9 hospital, well, that's going to hurt everyone on that  
 10 island, but why are they worse off if they lose the  
 11 hospital on the second island? Why do we get that  
 12 linkage? Why do we get that superadditivity or  
 13 concavity in sort of the profit function? Why is it  
 14 so much worse off? And so that's what a lot of the  
 15 theory is all about.  
 16 I like to think of it a little bit as sort of  
 17 the theory of holes, and from the managed care plan  
 18 perspective, who's doing the purchasing and the  
 19 contracting of all the hospitals, is, well, if they  
 20 get a hole in one geographic market because they lose  
 21 the hospital, is it that much worse if they incur a  
 22 second hole in another geographic market? Are they  
 23 getting increasingly worse off the more holes they  
 24 have? And that sort of potentially opens the door to  
 25 the theory having legs.

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1 Now, a really important part -- and this is  
2 where concavity comes in, and I think it's also a  
3 potential danger when people are listening to managed  
4 care plans. It's really easy to ask a managed care  
5 plan, well, gee whiz, if you lose your hospitals on  
6 Island A, and then you lose your hospital on Island B,  
7 are you worse off? And they say, well, of course, you  
8 moron. How could we not be worse off? And people  
9 say, ah-ha, we've got it, cross market effects.

10 And then the economist really wants to say,  
11 well, gee whiz, what I really meant is, is it concave?  
12 Is there superadditivity? In which case the managed  
13 plan care plan again says, you stupid idiot, what do  
14 you mean?

15 So the notion that we're really trying to get  
16 at here is kind of the question you want to ask the  
17 managed care plan, is let's pretend you're negotiating  
18 with both of these hospitals at the same time. Now,  
19 you know you want both of them, and you know that if  
20 you lose either one, you're going to be kind of hurt,  
21 and now you're negotiating now with the hospital on  
22 Market B or on Island B, and then all of a sudden,  
23 someone comes in to your office, in to the negotiating  
24 room and whispers in your ear, hey, we just lost the  
25 hospital on the other island. Does that make you need

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1 Hospital B even more?

2 If it makes you want to pay -- willing to pay  
3 them even more, if it affects your bargaining position  
4 on that other island because you lost the other one,  
5 then you have the linkage, and if you're willing to  
6 pay even more for it, you'll have concavity.

7 So the question is, how can we come up with a  
8 theory that establishes how this linkage and how the  
9 concavity can occur? And I'm not going to get into  
10 the details here. I can tell you that in playing  
11 around with trying to come up with a theory that is,  
12 I'll call it unbiased, that doesn't assume the answer,  
13 because it's really easy to come up with a theory of  
14 cross market effects where you basically implicitly --  
15 and you kind of hide the fact -- but basically you're  
16 assuming this concavity -- but if you don't assume the  
17 concavity but have a really neutral market, it's  
18 really tough to get these effects. It's tough to get  
19 linkages.

20 And to get concavity? That's even tougher.  
21 And to get a theory that's unambiguously concave, as  
22 opposed to sometimes being convex, good luck with  
23 that. I haven't had any luck with that.

24 That leads us to the issue of, what is our  
25 theory going to tell us? What is it going to be good

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1 for in terms of predictive? It goes back a little  
2 bit -- and I'll pass the buck in just a second -- is I  
3 think we do have the possibility theorem. We can show  
4 that. It's possible. But we don't yet -- I certainly  
5 haven't seen anything that gives much in the way of  
6 guidance about saying when it is or is not likely to  
7 be much of a problem, which, again, puts us back to  
8 the theory is having a hard time explaining what seems  
9 empirically, and from people's mouths, to be there.  
10 We've got lots of smoke, but we're trying to figure  
11 out, where the heck is the fire coming from?

12 MR. BRAND: Okay. Any other panelists want to  
13 weigh in on --

14 MR. GAYNOR: Yeah. So I think I'd perhaps be a  
15 little -- a little more positive, but -- but sort  
16 of -- one thing I could imagine doing is taking one of  
17 the stories that seems sensible on its face, and one  
18 of the stories that to me seems sensible on its face  
19 is you have got large regional or national employers,  
20 and they need to have these hospitals -- not just one,  
21 but both -- and then I don't think that writing down  
22 that model is terribly hard, but then -- then testing  
23 it empirically means that going a next step -- and I'm  
24 not criticizing the existing work, I think the  
25 existing work is great -- but one would need

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1 information about not just patients, where they live  
2 and where they go, but who their employers are.

3 That would, I think, allow us to get some  
4 traction and make some progress to address the issues  
5 Greg has been raising. At present, I don't -- I don't  
6 think that has -- that has been done, but I -- all I'm  
7 saying is -- and while I'm not saying, okay, that is  
8 the research agenda, I think with -- with a bit of  
9 thinking -- I'm not saying this is trivial -- that one  
10 could identify, what would you need to do, what would  
11 you need to be able to do empirically, to be able to  
12 test a story that cross market mergers lead to  
13 competitive harm and distinguish that from one in  
14 which they don't?

15 And just to emphasize, this is really  
16 important. Obviously, we don't want socially, nor do  
17 we want the agencies, to go after mergers that are  
18 benign or beneficial, right? That's bad for  
19 everything. We want mergers that are beneficial to  
20 happen, and mergers that are benign, we certainly  
21 don't want to get in the way of any of that kind of  
22 thing, and the agencies don't either. So I think it  
23 is very important to try and get at that. And  
24 actually Matt's got some evidence that some mergers  
25 that go across markets can generate some real savings.



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1 MR. BRAND: Matt or Matt, do you want to --

2 MR. SCHMITT: I guess just to speak to the  
3 concavity or convexity point, you know, my reading of  
4 the literature is that there's been a lot of focus on,  
5 you know, "must-have hospitals," that there are  
6 certain hospitals you just have to have in your  
7 network, and to the extent that there's a must-have  
8 hospital in Market A, a must-have hospital in Market  
9 B, and you really need both, that's convexity.  
10 That's -- I mean, they're complementary. If you don't  
11 have one, you don't have anything.

12 So I think, you know, actually generating  
13 concavity, I think it's definitely, you know, not  
14 clear that that's actually the structure of the  
15 payout.

16 MR. LEWIS: And it's not only the must-have  
17 hospitals, it's -- why would any two hospitals in far  
18 away markets be substitutes even for an employer with  
19 employees in both? So there's -- the linkage could be  
20 there, but it's not clear the direction of the linkage  
21 to me.

22 MR. BRAND: Let me throw out one further  
23 question. So if the -- so as described in Greg's work  
24 and in Dafny, Ho, and Lee, the basic notion of  
25 concavity here is payers negotiating with a set of

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1 is saying, well, an employer is going to offer maybe  
2 just one or two different plans. If mine is not sort  
3 of the most attractive -- you can think of it  
4 certainly in the extreme -- if an employer is only  
5 going to be offering one plan, then that plan has to  
6 cover all the different islands in which that  
7 employer's employees live, and so if I get a hole on  
8 one of the islands, the employer can't offer it  
9 because it doesn't cover some of the employees.

10 Now, the more health plans the employer is  
11 offering, the more scope there is for me to have a  
12 hole in my network, because for any of the employees  
13 who don't like that health plan, because it has a hole  
14 on their island, they can pick another. So that sort  
15 of gives some wiggle room for the theory. But then  
16 you can also sort of think, is it going to give us  
17 convexity or concavity? Does the second hole hurt  
18 more or less than the first hole?

19 Then you can think of it in the following  
20 context, is let's say that all these health plans are  
21 kind of neck-in-neck, almost identical. In that case,  
22 my very first hole is going to put me at a competitive  
23 disadvantage relative to everyone, that first one  
24 knocks me out of the market. After that, you know,  
25 who cares? I'm already out of the market. The second

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1 hospitals. If it loses -- one hospital's an employer  
2 with, say, employees in many areas, many of these  
3 areas would likely hang with that insurer, but if it  
4 loses two or more, then it's less likely to hang -- to  
5 stay with that insurer, so more likely to substitute  
6 away to another insurer.

7 One thought that's occurred to me is that it's  
8 quite -- it seems quite intuitive to turn that around.  
9 I think this kind of relates to what Matt said. It  
10 seems plausible to me that if you're talking to a  
11 health plan that is marketing its product to an  
12 employer with employees in two different -- two cities  
13 that are quite distant, and if that employer -- you  
14 know, the employer has to be -- has preferences over  
15 hospitals in each city, that the insurer may be  
16 thinking, you know, if I'm going up against three  
17 other insurers with both of these hospitals, if I  
18 don't have either one of these hospitals, I am  
19 extremely unlikely to win that business.

20 MR. VISTNES: And I think that kind of theory  
21 is -- that was really the heart of the theory that we  
22 tried to develop in our paper, and one of the things  
23 we found is that, again, it depends a lot on the  
24 assumptions, and the intuition here is, sort of going  
25 on what Keith is saying, the notion is a health plan

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1 and third hole don't matter. I've got convexity as  
2 opposed to the concavity.

3 The flip side is, what if my health plan is  
4 fantastic? Everybody loves me. I can suffer this  
5 hole and they're still going to want me. I can suffer  
6 the second hole; they'll still want me. It's not  
7 until I get three or four holes that my superiority  
8 comes into question, and it's that fifth hole that  
9 really hurts me. Then I've got concavity.

10 So we've got -- we're back to, I'm going to  
11 keep calling it, the possibility theorem. How's that  
12 going to help me in a merger? How am I -- I guess in  
13 principle, but it's tough. It's tough to figure out  
14 when this is going to be a problem or not or, frankly,  
15 if there is the real theory driving it.

16 I won't say it now, but I think one of the  
17 other things we can talk about is, what are some of  
18 the other possible theories motivating some of this  
19 behavior? Because there are a couple of other sort of  
20 very different sort of potential explanations for what  
21 we're hearing. Maybe we're just on the wrong track.

22 MR. BRAND: Okay. I think we should probably  
23 move on to the bargaining weight. Maybe we will come  
24 back to other notions of convexity in the questions  
25 and answers.

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1 So the next topic we'll turn to is the -- is  
2 whether the merger may cause a shift in the Nash  
3 bargaining weight, so a shift in how the joint surplus  
4 that's generated by an agreement between a provider  
5 and an insurer is divided between them. So my  
6 questions may include:

7 What are the likely interpretations of such a  
8 shift in terms of what determines the Nash bargaining  
9 weight in the first place? And how is the merger  
10 changing that? Is it just bargaining skills?  
11 Potentially something else? What is the likely effect  
12 on economic efficiency if that's what's going on?  
13 And, finally, could these -- if this is what's going  
14 on, could such be viewed as antitrust violations?

15 So I'll ask Matt Lewis to start us off, and  
16 then others can chime in.

17 MR. LEWIS: Yeah, okay. I mean, the important  
18 thing, given the discussion we've been having, the  
19 important thing to stress here is that the theory that  
20 we've sort of suggested in our papers as being  
21 potentially relevant is based on this bargaining --  
22 bargaining weight is completely separate from these  
23 issues of concavity/convexity. It doesn't require any  
24 curvature in the profit function of the insurer. It's  
25 a totally -- you know, it's a totally different

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1 mechanism, and it -- it also raises interesting  
2 questions because the potential conclusions from that  
3 kind of change are very different given that, you  
4 know, in the standard bargaining model, this weight  
5 just describes the split of the available surplus.

6 So do we care about how this surplus in the  
7 contract is being split between the hospitals and  
8 MCOs, if that's a transfer between those two, that  
9 maybe it doesn't have efficiency effects, but that's  
10 only for -- you know, for that particular contract,  
11 that may be true, and in the long run, there might be  
12 a lot of other effects as far as effects in the  
13 insurer market, which is why modeling the insurance  
14 market is important.

15 We may have, you know, a change in competition  
16 in the insurer market and an increase in pass-through  
17 to the premiums as a result of this. So I think these  
18 are all the interesting questions that come up here.

19 There's a separate issue which is kind of more  
20 of an empirical identification issue, which is that if  
21 you try to model these -- this bargaining power,  
22 it basically becomes the residual for anything that's  
23 not modeled in the bargaining position. And so you  
24 can get into a trap of finding a change in bargaining  
25 power when, in reality, you have just sort of left

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1 something out of your -- out of your model of the  
2 bargaining position, and that's exactly why  
3 understanding better what drives the shape of the  
4 profit function of the insurer is so important,  
5 because if we really want to measure bargaining power,  
6 we need to -- we need to also -- we need to perfectly  
7 capture the bargaining position.

8 But having said that, I'll just quickly say  
9 that, I mean, I think without having a perfect measure  
10 for bargaining power, there's some, you know, evidence  
11 within what we have done which suggests that, you  
12 know, some of the existing theories on why you might  
13 see cross market linkages through bargaining position  
14 may not be as applicable to the situations where we do  
15 seem to notice some of these cross market merger  
16 effects, and that's why I still think bargaining power  
17 changes may be important here.

18 I'll let you comment.

19 MR. BRAND: Okay, we will go on to the next  
20 topic.

21 So on this next topic, I will also ask Matt  
22 Lewis to lead us off. So the next issue is that we  
23 may be, you know, bucketing up a wide variety of  
24 mergers into what we're calling cross market mergers,  
25 and it's possible that as we explore these mechanisms

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1 that, you know, the mechanisms that are most important  
2 we will see only in a particular merger depending upon  
3 the specific circumstances of that merger.

4 So, again, I'll ask Matt to lead that  
5 discussion.

6 MR. LEWIS: Yeah. I guess what I would say  
7 here is I have in mind sort of an example where -- and  
8 this is an example of the kind of hospital we studied  
9 in -- or merger we studied in our papers. Think about  
10 a fairly large system, maybe 30 or 40 hospitals,  
11 acquiring a hospital -- a stand-alone hospital in a  
12 small town or small city somewhere. If you think --  
13 you know, what do you think the effects of that merger  
14 might be?

15 If you argue that there's a potential for  
16 there -- for the merger to change the bargaining  
17 power, meaning change the bargaining sophistication of  
18 the hospitals involved, you know, do we think that  
19 that's going to happen to this acquired hospital? It  
20 seems likely that a stand-alone hospital might not  
21 have the same resources and experience in bargaining  
22 that a large system would, and maybe there's -- they  
23 can adopt some of those practices or use that  
24 information to better negotiate.

25 You know, do we think that that effect is also

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1 going to appear for the 30 other hospitals in the  
2 acquiring system? Do they get an increase in  
3 bargaining power? I don't see how that would be a  
4 significant -- a significant effect, and yet -- and  
5 now, if we're thinking about the different empirical  
6 papers, I think this is interesting, the Dafny, Ho,  
7 and Lee paper, they focus explicitly on measuring the  
8 cross market effect of mergers on the prices of these  
9 other hospitals, these 30 hospitals in the acquiring  
10 system.

11 So it's -- it's not surprising that we don't  
12 see cross market effects for those hospitals when we  
13 might see one for the acquiring hospital. I mean, I  
14 think there's a lot of -- that could also be true for  
15 some of these explanations of bargaining -- of  
16 bargaining position linkages, but I know it's  
17 important to compare the different sets of mergers  
18 that we've studied in these different -- in these  
19 different papers and try to understand, well, what  
20 does that reveal about where the sources of these  
21 price effects may be coming from?

22 And so I know I have sort of a strong opinion  
23 that I do think that in cases where small systems or  
24 stand-alone hospitals are acquired, this effect of  
25 potentially influencing bargaining power is -- is --

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1 may be a big deal for those hospitals, but for some of  
2 these other mergers between large systems and other  
3 large systems, I don't -- I don't see why they  
4 would -- you know, they may or may not benefit as  
5 much, and we might be looking to other stories there  
6 to explain some of the findings there.

7 Again, Leemore or -- Leemore -- Leemore's paper  
8 also found that the effects were concentrated in her  
9 measurement on mergers that -- on hospitals that were  
10 located fairly closely but not in more distant  
11 markets, and I think that suggests something else,  
12 which we may or may not want to talk about, which is  
13 that maybe the patient market, as we're thinking about  
14 it, is not described or we're not thinking about it  
15 accurately. It may be broader than we might -- than  
16 we might otherwise think, so...

17 Did you want to comment on that?

18 MR. SCHMITT: I know we're not lawyers, but I'm  
19 curious whether this acquisition of a stand-alone  
20 hospital by a 40-hospital system, now we have better  
21 negotiators in place, is that something like -- you  
22 know, that the competition authorities should care  
23 about?

24 MR. LEWIS: Well, that's an important question,  
25 and it's one that I'd like to ask the competition

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1 authorities, and I don't think I'm going to get an  
2 answer in public here, but -- yeah, I mean, it's a  
3 very important question.

4 Also, it's an important question because,  
5 whether that's true or not, acknowledging that those  
6 effects might be there may affect, you know, how we  
7 judge whether or not there are other types of effects.  
8 They certainly will affect the modeling if you have a  
9 structural model that does or does not allow those  
10 effects, that you may get those effects showing up in  
11 other places, and so I think it's important.

12 I don't -- I don't -- you know, I don't know --  
13 I think we need a better model of insurance markets to  
14 know what this pass-through is going to look like, and  
15 even in that case, is there an efficiency effect that  
16 we care about and is there a reduction of competition?  
17 All the descriptions of the changes in the curvature  
18 of the insurance profit function, those very closely  
19 resemble the types of restrictions of competition that  
20 we look at when we look at in-market mergers, but this  
21 bargaining power thing is totally different and is not  
22 the same as a restriction of competition the way we  
23 normally think about it, so that's a very important --

24 MR. GAYNOR: Yeah. I mean, you can certainly  
25 get prices going up, and you can get harm to

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1 consumers. You can get pass-through through the  
2 insurance market without there necessarily being harm  
3 to competition.

4 MR. LEWIS: It depends on the interpretation of  
5 it.

6 MR. GAYNOR: It depends. It depends. And I  
7 agree with you, I don't think at this juncture we  
8 know, right? We have these big effects -- which,  
9 again, that's valuable, we didn't know that stuff  
10 before -- but I don't think at this point we have a --  
11 we have a good handle on that thing. And so, yeah,  
12 it's important for policy.

13 So if an effect like that occurs and if it's  
14 not through harm to competition, it might be of  
15 importance to policy, but it's not so obvious that  
16 it's an antitrust enforcement issue.

17 MR. BRAND: Final thoughts?

18 (No response.)

19 MR. BRAND: Okay. We're running a little late.  
20 We did want to touch on the point that Marty raised in  
21 his opening on potential broader implications of what  
22 we're learning in the literature. So let me throw  
23 that up, and, Marty, if you want to add to what you  
24 said or if any other panelists want to weigh in.

25 MR. GAYNOR: Just briefly, as I said, I mean,

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1 this is potentially a very broad -- a broad issue, and  
 2 so to the extent that what's -- you know, what's  
 3 happening in healthcare markets provides an  
 4 opportunity to try and really grapple with this and  
 5 nail it down, then that's really useful, because it  
 6 will give us an apparatus to start taking to other  
 7 markets, not in a mindless way, of course, but at  
 8 least to start thinking about that.

9 And, you know, one of the nice things about  
 10 markets that are heavily regulated, like healthcare,  
 11 energy, a few other things, is that there are a lot of  
 12 data, because there are reporting requirements, so  
 13 they can be good places to start trying to test some  
 14 economic issues because of the richness of the data  
 15 that are available, but I think we all agree that more  
 16 thinking needs to be done at this juncture before we  
 17 can figure out exactly or more precisely what's going  
 18 on.

19 I think within healthcare, one -- we've talked  
 20 about a few things that might be done. One avenue  
 21 might be to pursue to look at -- look across product  
 22 markets. Again, we have a lot of data on that. Folks  
 23 are focused on geographic markets, and that's fine,  
 24 but there's some other variation that's just sitting  
 25 there in the data. Again, I think we need to think up

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1 a way of sort of more precisely testing hypotheses  
 2 before we just start crunching data, but I think  
 3 there's some more stuff that can be done.

4 MR. VISTNES: I think I would maybe just add on  
 5 to what Marty's saying. I think one of the real  
 6 important things about the empirical work that's been  
 7 done so far with respect to hospitals, what can be  
 8 done even within healthcare, looking at, you know, the  
 9 hospital physician or any of the other product market  
 10 combinations, is if we're still trying to figure out  
 11 what are the drivers of the theory, if we're still  
 12 trying to figure out why is this effect occurring,  
 13 then if we see the effect occurring, for example,  
 14 across geographies, but we don't see it across  
 15 different types of hospitals, or we see it between  
 16 hospitals and physicians but not across different  
 17 kinds of physicians, that will hopefully give us  
 18 insights.

19 The -- looking at the data to find patterns,  
 20 even if it is, in a sense, blindly looking at the data  
 21 just to figure out what seems to be there, I think  
 22 will help us figure out what is there or,  
 23 alternatively, you know, decide that there isn't  
 24 anything there, but more empirical work has got to be  
 25 good.

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1 MR. BRAND: Okay. With that, I think we should  
 2 probably turn to questions from the audience.

3 MALE AUDIENCE MEMBER: Hi. So the possible  
 4 sources of concavity, you know, the standard story is  
 5 concavity is induced by competition between the  
 6 hospitals, and now people have offered alternative  
 7 sources of concavity, maybe, you know, the insurer  
 8 would tolerate losing one provider, but losing two  
 9 would be more than twice as bad, or maybe an employer  
 10 for a similar reason would tolerate losing one  
 11 provider but losing more -- losing two would be more  
 12 than twice as bad, and those are sort of the  
 13 alternatives to the standard competition story.

14 But another source of concavity that people  
 15 don't talk about as much is just plain old risk  
 16 aversion on the part of the managers of the insurance  
 17 companies, right? So this is not concavity between  
 18 the number of hospitals and profits. It's the  
 19 concavity between profits and utility of the insurers,  
 20 right? If you think that you are -- the profit loss  
 21 if you lose one hospital is you would get a not great  
 22 performance review, but the profit loss from losing  
 23 two is you get fired, then that can be a real source  
 24 of ordinary risk aversion that can introduce  
 25 concavity, and that story seems at least as plausible

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1 as the other ones. It does require that the insurer  
 2 manage -- bargainer have a more concave payoff  
 3 function than the hospital manager does, but that is  
 4 entirely plausible. If you are -- if you are sort of  
 5 the local manager of an insurer and you're facing the  
 6 local -- the local sort of behemoth, it's perfectly  
 7 possible that that's true.

8 So I would -- you know, I would encourage  
 9 adding to the list of potential sources of concavity  
 10 something that people are very comfortable with in  
 11 other contexts, which is people are just plain old  
 12 risk averse.

13 MR. BRAND: Anybody want to weigh in on that?

14 MR. GAYNOR: Well, again, I think -- I think  
 15 getting data from insurance firms and the insurer  
 16 market -- you know, this emphasizes that point of  
 17 while it sounds kind of funny to think of insurance  
 18 companies as risk averse? You know, there are very  
 19 active reinsurance markets in which insurance  
 20 companies buy insurance, so it actually does have some  
 21 degree of plausibility on its face, but I think -- I  
 22 think that could be certainly written down and  
 23 specified, but then you're going to need the data to  
 24 get at that.

25 MR. VISTNES: You know, I -- really quickly, to

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1 sort of get to what are some of the other theories, a  
 2 couple of the other sort of theories that have been  
 3 bounced around is what I think of as kind of the crown  
 4 jewel theory. Think of it in a typical department  
 5 store mall, is you have got to have a couple of  
 6 sometimes called like anchor stores. You have got to  
 7 have a Cheesecake Factory or a William Sonoma or, you  
 8 know, something else. None of those are substitutes,  
 9 but they all sort of say, hey, I'm a quality provider.  
 10 This is a good place.

11 Do I like the story, the theory behind it,  
 12 but -- no, but can you understand how maybe it's going  
 13 on in health plans? You know, I need a couple kind of  
 14 crown jewels, and I can lose one crown jewel but not  
 15 too many of them. Maybe that's a theory. You know,  
 16 the other theory -- and I think, again, this is quite  
 17 realistic -- is that people are not entirely rational.  
 18 Unfortunately, again, we're seeing economists don't  
 19 run the world and the world is suffering for it, but  
 20 you have people who may believe, despite the fact that  
 21 we're telling them you're irrational, your profits are  
 22 linear, how many times do we need to tell you this,  
 23 they say, yeah, but still, I kind of think I'm worse  
 24 off losing two, and I think I'm a lot worse off.

25 If they believe that way, if they act that way,

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1 it will generate all the empirical results we're  
 2 seeing. It leaves us -- the enforcement folks and  
 3 policy folks in the uncomfortable situation of, what  
 4 do we do? It's -- it's kind of why we, in a sense,  
 5 are uncomfortable with behavioral economics, because  
 6 it doesn't make sense. How can we make policy based  
 7 on stuff like that?

8 MALE AUDIENCE MEMBER: Yeah. I was wondering  
 9 if I could hear a little more about alternative  
 10 bargaining theories. I thought there was a little  
 11 reference to why they work or why they don't work, and  
 12 the reason is that Nash bargaining in this context is  
 13 pretty new, it's pretty weird, and we do it mostly  
 14 because it's feasible or it's a good place to start.  
 15 As you say, the Nash bargaining parameter is a kind of  
 16 residual, so you can look at it two ways, that if it  
 17 changes, it means the true bargaining parameter  
 18 changed, or it could mean that we're just sort of  
 19 indicating that that's not the right bargaining model,  
 20 right, that if that parameter doesn't stay fixed over  
 21 time, that's just kind of a diagnosis.

22 And, you know, not thinking super formally, you  
 23 can imagine very easily how people would think that  
 24 coordinating bargaining across hospitals will let you  
 25 do a better job. Now, Nash bargains are already

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1 efficient and so forth, but if you think of, say, the  
 2 multimarket contact collusion literature, where you  
 3 can use a little bit of excess threatening power from  
 4 one market to leverage, you know, a better collusive  
 5 deal in Market B, nothing like that happens I think  
 6 with Nash bargaining, but, you know, I think it's  
 7 particular to the model, that really it's not a  
 8 better -- this little hospital, when it says, oh, now  
 9 I'm bargaining with this big hospital, of course, I'm  
 10 going to get a better deal, right? I'm going to  
 11 somehow get -- I am going to extract more somehow.

12 And, again, in Nash bargaining, the pie has  
 13 already been completely and officially divided over  
 14 there, so I don't -- I don't see how it works, but in  
 15 the real world, I'm so sure things are so efficient  
 16 and that there's not a little bit left someplace that  
 17 can now be brought to bear on behalf of this new  
 18 hospital.

19 MR. SCHMITT: Just to add something to that, to  
 20 the extent insurer profits are meaningfully convex,  
 21 then Nash-in-Nash bargaining can yield really strange  
 22 predictions, which is, you know, just another problem  
 23 on top of what you're raising.

24 MR. LEWIS: Yeah. I mean, I definitely think  
 25 that it's worthwhile to try to figure out what these

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1 other bargaining models would predict. I mean, the  
 2 Nash-in-Nash model can be -- it can be generalized and  
 3 it has been generalized to some extent in recent  
 4 papers but actually still within this kind of general  
 5 Nash framework, which isn't the best, I think, for  
 6 this setting.

7 So on the other -- and also, the fact that you  
 8 have this bargaining power parameter, which the theory  
 9 gives you no insight as to how -- as to, you know,  
 10 what determines this parameter, and we have a little  
 11 bit of guidance from some of the -- some results in  
 12 related bargaining models that may be information that  
 13 plays a part in other things like this, but -- so we  
 14 can use some of that intuition, but we know that this  
 15 is a -- this is kind of an imperfect attempt.

16 You know, my position is just to say, you know,  
 17 we don't know what will determine this thing, but  
 18 it's -- it well could be heterogenous across  
 19 hospitals, and maybe hospitals adopt that heterogenous  
 20 bargaining power from their systems. Why does that  
 21 happen? It could be information. It could be some  
 22 kind of patient risk aversion -- you know, any of  
 23 these results could apply, but I totally agree that a  
 24 more -- a more realistic model of bargaining would be  
 25 helpful here, but it's been a problem for us.

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1 MR. GAYNOR: I'll just agree with everything  
2 that's been said, and, again, it's a possibility that  
3 the data and even what market participants had to say  
4 are telling us something, and we just need to go and  
5 think much harder about what the economic behavior is  
6 and what model that generates.

7 MR. BRAND: Okay. Other questions?

8 FEMALE AUDIENCE MEMBER: Just a quick question.  
9 It seems like what you're saying is, if I understand  
10 that correctly, you could have where one of these  
11 hospitals or both of them already have significant  
12 bargaining leverage or whatever because (off mic), so  
13 the merger is not necessarily going to change  
14 anything; it might or it might not.

15 I also heard what you were saying, Greg, at the  
16 very beginning, which is the theory and the evidence  
17 is in a state such that you can't really reliably  
18 predict when a given acquisition of a small  
19 stand-alone hospital by a large system is reliably  
20 going to result in some sort of anticompetitive  
21 effect.

22 So if we have this kind of uncertainty -- you  
23 know, one line of questioning is how do you go and  
24 work on and what kind of modeling to do in the context  
25 of a transaction, but let me ask to the panelists a

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1 little bit broader question. There's a lot of move  
2 afoot in a number of states to think about regulating  
3 price, terms of access, other kinds of conditions on  
4 small, stand-alone hospitals, as they join systems,  
5 and as I think, Matt, you were saying, a very large  
6 proportion of hospitals are already in systems,  
7 although I think there's about 2000 that are still  
8 small stand-alone.

9 Let me just ask you on kind of that policy  
10 front, does that suggest we should be very, very  
11 careful about thinking of kind of across-the-board  
12 regulation or terms of access or pricing regulation on  
13 small hospital acquisition, because we might have some  
14 that could arguably lead to issues but others not?

15 MR. GAYNOR: Well, yeah, it's an interesting  
16 question, but I think, Meg, the -- it's not just a  
17 question about antitrust, right? It's a policy  
18 question, and there could be rationales for regulation  
19 that have nothing to do with antitrust, right, per se,  
20 but if there's a situation in which circumstances  
21 would change in a way that wasn't an antitrust problem  
22 but would really cause social harm, there can be a  
23 rationale for regulation. Very broadly speaking, of  
24 course, we should always think very carefully about  
25 any policy before undertaking it.

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1 MR. BRAND: Okay. Any other questions?  
2 (No response.)

3 MR. BRAND: Okay. Thank you very much. A very  
4 helpful discussion. Thank you.  
5 (Applause.)

6 MR. ROSENBAUM: We will reconvene in about 15  
7 minutes for the next paper session, so 2:00.  
8 (A brief recess was taken.)

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#### 1 PAPER SESSION

2 MR. ROSENBAUM: If everyone would please be  
3 seated so we can get started. Thanks.

4 Okay, we are going to get started with the next  
5 paper session, which is chaired by Igal Hendel. The  
6 first paper is going to be presented by Paolo  
7 Ramezzana on contracting, exclusivity and the  
8 formation of supply networks with downstream  
9 competition.

10 MR. RAMEZZANA: Hi. So I will see how this  
11 works. So today I am going to talk about a fairly new  
12 way of looking at contracting in bilateral oligopoly  
13 with a particular emphasis on the endogenous formation  
14 of supply networks.

15 So before I start, let me give you the usual  
16 disclaimer, that whatever I say today does not  
17 represent the -- necessarily represent the opinions of  
18 the Federal Trade Commission.

19 Okay. So a lot of markets look approximately  
20 like this. You have some downstream firms -- I've  
21 drawn two here, R1 and R2, where R stands for  
22 retailers. These downstream firms procure  
23 differentiated inputs or products from suppliers, and  
24 the dashed lines you see there are potential supply  
25 contracts. And when these downstream firms has

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1 secured some supply contracts, they compete for  
2 consumers in the downstream market, right? So that's  
3 a typical bilateral oligopoly setting.

4 Now, some markets look like this. There is --  
5 in some markets, all supply links are active or at  
6 least most downstream firms carry most products.  
7 Okay, examples of this are big box stores, like Best  
8 Buy, Target; online retailers, Amazon carries pretty  
9 much everything; and online travel agents that carry  
10 pretty much all flights, all airlines, and all hotels,  
11 right?

12 But other markets look different. So in other  
13 markets, some links are not active. So, in  
14 particular, the downstream firms may decide to carry  
15 different types of products. So a good example of  
16 this is the cell phone industry a few years ago --  
17 it's sort of still the case, but especially a few  
18 years ago -- when the iPhone was launched, it was  
19 launched exclusively by AT&T, and that's -- you know,  
20 for four years, and that's the best known example, but  
21 it's not the only one.

22 Around the same time, the Google phone -- you  
23 may remember the HTC G1 phone -- was launched  
24 exclusively by T-Mobile, and also some LG models were  
25 launched exclusively by Verizon. So pretty much every

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1 wireless carrier was offering exclusively some  
2 different type of handsets. And here you should think  
3 of the handsets, S1 and S2, and the wireless carriers  
4 as the distributor, R1 and R2, okay?

5 There are other examples, sport events in pay  
6 TV. Typically sport events are broadcast exclusively  
7 by a channel or a different channel, MVPD, a different  
8 platform, and lately, health insurance companies have  
9 started offering restricted networks, okay? So all  
10 the examples I gave you there involve some type of  
11 contractual exclusivity.

12 However, there are also examples, like the  
13 automobile distribution in the United States, where  
14 there are no exclusive contracts, because those are  
15 actually prohibited by law in the United States by a  
16 crazy maze of state laws that prohibits that, yet  
17 different car dealers typically specialize in  
18 different brands, okay?

19 So these are interesting patterns. So what are  
20 the research questions? What are the -- is there any  
21 interesting research question from a theoretical point  
22 of view?

23 So the first one is, what types of supply  
24 networks maximize industry profits -- that is, produce  
25 a surplus -- and what type of networks maximize

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1 consumer welfare? The other question, which arguably  
2 is even more interesting, is what type of supply  
3 networks can arise as an equilibrium when firms engage  
4 in decentralized contracting, right?

5 So there is an old literature sort of  
6 addressing the first paper. Some of you may be  
7 familiar with a paper by Bazan and Perry (phonetic) a  
8 long time ago talking about that, but we really don't  
9 have a full-fledged model addressing the second  
10 question, what are the equilibrium networks? So here  
11 I develop, I present a model of bilateral contracting  
12 in which firms can use transfers to induce other firms  
13 to enter into a relationship with them, okay?

14 So this model combines two streams of  
15 literature. One is the literature on the formation of  
16 economic and social networks with transfers, so Bloch  
17 and Jackson is an example, there's a lot of work by  
18 Jackson and others on this; and with the literature on  
19 vertical contracting, and there's a few famous papers  
20 there, okay?

21 So this framework allows me to identify, to  
22 study a few factors that may actually influence the --  
23 affect the structure of supply equilibrium networks.  
24 So the spectrum includes the degree of supplier and  
25 retailer differentiation; the mode of downstream

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1 competition; Cournot/Bertrand, how intense it is; the  
2 availability of exclusive contracts; and the firm's  
3 ability -- or actually, in the context of this  
4 paper -- inability to commit to the terms of the  
5 contracts. Okay? So that's the broad picture of what  
6 I do.

7 Now, one may say, well, but we do have a  
8 framework, which is actually very popular in IO at the  
9 moment, which sort of looks at contracting between  
10 multiple suppliers and multiple retailers, and that's  
11 the Nash-in-Nash bargaining framework, right? And  
12 there you can see some of the papers in this  
13 literature.

14 I particularly want to draw your attention to a  
15 recent theory. There is a paper by Collard-Wexler,  
16 et al., that provides some theoretical foundations for  
17 Nash-in-Nash, and more to the point of this, it  
18 provides a very nice discussion of the assumptions on  
19 which it is based and on the limitations of those  
20 assumptions.

21 Okay. So what are these assumptions or what is  
22 this approach? So the first thing to say is that  
23 Nash-in-Nash focuses more on the division of surplus  
24 between suppliers and retailers rather than focusing  
25 on the structure of vertical contracts or focusing on

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1 the structure of the networks that emerge. So that's  
2 a different type of question it's answering, right?

3 The other assumption is based on the contract  
4 equilibrium approach; that is, when two firms  
5 negotiate a contract, they take all other contracts as  
6 given, including contracts to which they themselves  
7 are a party. So if a retailer has negotiated a  
8 contract with a supplier, that retailer is not allowed  
9 in that approach to maybe modify its contract with the  
10 other supplier, right?

11 Now, it turns out that's not a big deal if all  
12 they want to do is predict the division of surplus,  
13 and, in fact, Collard-Wexler, et al., show that there  
14 is fairly general conditions. Nash-in-Nash bargaining  
15 gives you the same result, is a more general,  
16 multilateral bargaining -- strategic bargaining aid,  
17 okay?

18 It is, however -- it is, however, a problem for  
19 what I want to do here. To see that, look -- follow  
20 the following example. Consider a supply network, a  
21 contract equilibrium supply network, in which  
22 everybody trades with everybody, okay? And now  
23 consider a deviation in which a retailer, R1,  
24 approaches S1 and asks for exclusivity. It asks S1  
25 not to trade with R2, right?

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1 So in the contract equilibrium approach, that's  
2 all he can do. He cannot go to S2 and try to modify  
3 the other contract. He can only modify one contract  
4 at a time, because he has to take it as given that S2  
5 continues to trade with R2 in that approach, right?

6 Assume that this deviation is not profitable.  
7 The parameters are such it's not profitable, right?  
8 Well, there is another deviation if one looks at the  
9 marginal approach, which would be my approach, in  
10 which R2 could approach both suppliers at the same  
11 time and ask both suppliers to be excluded within, you  
12 know, excluding R2. That deviation might well be  
13 profitable even if the one in the middle is not. So  
14 by focusing on Nash-in-Nash -- on contract  
15 equilibrium, using Nash-in-Nash bargaining, you may be  
16 missing something, okay?

17 So another assumption that Nash-in-Nash uses is  
18 that given an exogenously given set of links or  
19 networks, every bilateral negotiation, every link,  
20 it's assumed to yield gains from trade. An  
21 implication of that is that the only equilibrium --  
22 the only possible equilibrium is all links active.

23 There are some recent papers by Ho and Lee that  
24 discuss these issues. I'll talk about them at the  
25 right point in the presentation, not now.

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1 Finally, Nash-in-Nash typically simplifies the  
2 structure of vertical contracting. It either assumes  
3 that payments between suppliers and retailers are only  
4 lump sum, without any margin on input price, or goes  
5 to the opposite extreme, that they are linear, okay?

6 Okay. So the approach I propose today, before  
7 I give you the model, improves on this along the  
8 following dimensions: It allows firms to optimize  
9 across all their bilateral relations at the same time,  
10 to modify all the contracts at the same time. It  
11 allows firms to use nonlinear contracts with a fixed  
12 fee and a marginal input price. It allows firms to  
13 enter into and actually compete for exclusives, okay?  
14 And, especially, it's sort of able to generate -- to  
15 give predictions on the endogenous emergence of supply  
16 networks or a type of supply networks, right?

17 So these are the advantages -- oh, sorry -- but  
18 my approach, to be fair, also has some drawbacks. So  
19 Nash-in-Nash gives point predictions regarding the  
20 division of surplus. It will tell you exactly -- you  
21 know, it will give you a price point. My approach, as  
22 you will see, would only give you ranges for the  
23 transfer. It would only give you the bargaining set  
24 of the transfers. One can get quite a bit of mileage  
25 out of that, as I will show you, but to be clear,

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1 that's a drawback. For applied work, one needs to do  
2 a bit more, okay?

3 Okay. So let me give you a sketch of the  
4 model. There are more than two suppliers, in this by  
5 S, more than two retailers, in this by R, and, of  
6 course, if all of these firms are active, you have S  
7 times R differentiated products.

8 The model evolves in two stages. In the first  
9 stage, all firms engage in simultaneous contracting  
10 without public commitment. So it's secret  
11 contracting. Firms cannot commit to the terms of the  
12 contracts, okay? And once all contracting is done, in  
13 stage two, retailers with at least one contract engage  
14 in downstream competition. It could be Cournot,  
15 Bertrand. I actually address both, okay?

16 Now, stage two is completely standard here,  
17 okay? So let me talk about stage one a bit. So in  
18 stage one, each firm I submits a contract proposal to  
19 each firm J on the other side of the market. This is  
20 basically an extension of Bloch and Jackson, 2007, to  
21 vertical contracting.

22 Each firm I submits a proposal to -- a contract  
23 proposal to each firm J on the other side of the  
24 market, so all firms submit simultaneous proposals to  
25 other firms, and the contract proposals contains three



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1 elements. One is a lump sum or a fixed fee, if you  
 2 will, to be paid by the retailer to the supplier; the  
 3 other is a unit wholesale price; and the third is a  
 4 set of exclusive clauses, if any. There could be  
 5 none, okay?  
 6 Now, if the proposals that two firms, say  
 7 supplier S and retailer R, submit to each other are  
 8 consistent, then these two firms enter into a  
 9 contract, and the supply link is formed, okay? And a  
 10 proposal that is consistent, if both firms name  
 11 exactly the same wholesale price, exactly the same set  
 12 of exclusive clauses, and the retailer offers a lump  
 13 sum which is at least as large as the one that has  
 14 been demanded by the supplier, okay?  
 15 Now, a model like this is replete with  
 16 coordination failure, vertical coordination failure,  
 17 horizontal coordination failure, so I'm not going to  
 18 even go into that. So there's a ton and a half of  
 19 Nash equilibria with different networks. So Nash  
 20 equilibria is really not the right -- I mean, this is  
 21 on purpose. I did the model like that on purpose.  
 22 Nash equilibria is really not the right concept here.  
 23 So instead I rely on coalition-proof Nash  
 24 equilibrium. So the nice thing of coalition-proof  
 25 Nash equilibrium is that it allows players to engage

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1 in prepaid, nonbinding -- and the nonbinding part is  
 2 important -- communication, right? So to be clear, it  
 3 can't be used to enforce collusion, because firms, you  
 4 know, can commit to what they discuss, and so every  
 5 type of agreement that is reached must be  
 6 (indiscernible) compatible. So you still have a lot  
 7 of space for competition and division and all of that,  
 8 okay? It's just a way to eliminate silly coordination  
 9 failures.  
 10 And going a bit more into details, the outcome  
 11 is a coalition-proof Nash equilibrium if there is no  
 12 deviation by any coalition that leaves all the members  
 13 of the coalition better off. And that's not the end  
 14 of the story, though, because this deviation must, in  
 15 turn, be robust to follow the deviations, okay? There  
 16 must be in other deviation from the division, so on  
 17 and so forth.  
 18 It's very similar -- to keep it simple, it's  
 19 very similar to subgame perfection, okay? You can  
 20 find a profitable deviation, but once you get there,  
 21 it -- you know, you may want to do what you set out to  
 22 do, okay? So it's just some consistency.  
 23 Okay. So how can one use this to solve the  
 24 model? The model can be solved in two steps. First,  
 25 for any network  $g$ , you must find a profile of

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1 wholesale prices such that there is no dev -- such  
 2 that in the same network, they cannot re-arrange the  
 3 wholesale prices and make profits, okay?  
 4 Now, without public commitment, with secret  
 5 contracting, there is obviously opportunism. So the  
 6 only wholesale price with that characteristic is  
 7 wholesale prices equal to marginal cost, okay?  
 8 Of course, if firms were able to commit  
 9 publicly, then the wholesale price would be greater  
 10 than marginal cost, and actually I am working on a  
 11 related paper, but -- or if you must give firms  
 12 incentives to engage in an ongoing investment, if  
 13 there is a problem or a hazard, again, the wholesale  
 14 price is above marginal cost, right? But in this  
 15 stylized model, the wholesale price is equal to  
 16 marginal cost.  
 17 Now, this is not new. It's a very standard,  
 18 well-known result from the vertical contracting  
 19 literature. All I do here is to extend these inside  
 20 to a much more complex environment, with multiple  
 21 suppliers and multiple retailers, and to a different  
 22 equilibrium concept, coalition-proof Nash equilibrium,  
 23 which, by the way -- you can read the paper on that --  
 24 but it turns out to be very convenient, because it  
 25 solves existing problems that have been identified by

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1 Rey and Verge in 2004.  
 2 But all I want to say here is that the result  
 3 on wholesale price is a key ingredient to what I do,  
 4 but it's really not a big contribution on the paper.  
 5 It is just an ingredient, okay? So the main  
 6 contribution of the paper is characterized in  
 7 equilibrium networks, right? So in this model, when  
 8 network  $g$  is in equilibrium, if there exists at least  
 9 one profile of transfers,  $tg$ , such that there exists  
 10 no deviation from the network  $g$ , then it's profitable  
 11 for all the firms and it is self-enforcing, okay?  
 12 Now, to be clear, it's enough for there to be  
 13 one transfer for  $g$  to be in equilibrium, but  
 14 typically, there are many possible transfers that  
 15 support an equilibrium  $g$ , and so what I'm doing here,  
 16 I'm just really only characterizing the bargaining  
 17 set, the set of terms, okay?  
 18 Now, let me go back a second. So in the paper  
 19 I discuss some general methods for verifying whether a  
 20 division is profitable and self-enforcing. I don't  
 21 have time to go into details here. Let me just show  
 22 you very quickly just what the intuition is.  
 23 For example, a deviation from a network  $g$  to a  
 24 network  $h$  is profitable for a coalition  $Z$  if the gain  
 25 in gross profits that we generate, the change in the

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1 gross profits produced because of those effects I was  
2 talking about before, are greater than one, are  
3 greater than the change in the transfers received by  
4 suppliers.

5 So if the deviation involves dropping some  
6 retailer from the network, the suppliers were getting  
7 transfers from those retailers, right? And so they  
8 are going to lose that if they drop them. So that  
9 needs to be taken into account, okay?

10 And analogously, you have to take into account  
11 the fact that if the deviation were to drop in some  
12 suppliers, then the retailer no longer pays to those  
13 suppliers, okay? So that's just intuition. You don't  
14 need -- by the way, you don't need to remember any of  
15 this for the rest of the presentation. It will become  
16 very intuitive in 30 seconds, okay?

17 So, but that's one result, and all the  
18 complication in the paper, I'm not going to go through  
19 this now, but it's -- if you find out that there's no  
20 profitable deviation from  $g$ , then you're done.  
21 Answer.  $g$  is an equilibrium; in fact, it's a strong  
22 equilibrium, right?

23 But if you find some profitable deviations,  
24 then you still need to check that those are  
25 self-enforcing, right, from the logic I said before,

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1 and that's complicated, because when you check for  
2 change of deviations with transfers like here, you  
3 have to take into account that a transfer that can  
4 make a deviation profitable depends on what the  
5 transfers were in the previous allocation, and so  
6 there are chains, and that's a very -- one of the very  
7 complicated aspects of solving this, okay? So -- but  
8 this is a general approach. As I said, you don't need  
9 to remember much, just to give you a flavor.

10 Now, let's move to the example that I will use  
11 throughout the rest of the paper. So I look at a  
12 bilateral duopoly with two suppliers and two  
13 retailers, and linear demand, okay? In a bilateral  
14 duopoly, you can have a number of networks. The ones  
15 you see on the screen now are networks that actually  
16 will arise in equilibrium, right?

17 And the networks you see here are all the  
18 networks that want that equilibrium, but they feel  
19 it's impossible. And actually, out-of-play networks  
20 matter here to find equilibrium. So they are on the  
21 network that can arise.

22 Now, demand. I used linear demand, and it's a  
23 convenient thing because it allows me to parameterize  
24 product substitutability, using a prompt  $a$ , and  
25 retailer substitutability, indexed by  $b$ , separately,

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1 okay? And the nice aspect of this is that you can  
2 represent all the results in a unit square, with  $a$  and  
3  $b$  on the two axes, okay?

4 So one can use this model to answer the first  
5 question. What supply networks maximize industry  
6 profits? So this Bertrand competition, let's start  
7 from the top, okay, where  $b$  is close to one and the  
8 four retailers are close substitutes. In that case,  
9 industry profits are maximized by downstream monopoly,  
10 and it's very intuitive, because if  $b$  is close to one,  
11 retailers are very close substitutes, there is a lot  
12 of competition to kill off, right, and it's not very  
13 costly to kick one retailer out because they're very  
14 similar, okay?

15 Where retailers become more differentiated in  
16 the intermediate space, right, it starts being costly  
17 to eliminate the retailer. So you want both retailers  
18 to be active, but competition is still pretty strong,  
19 so you want them to carry different products. And  
20 eventually, when retailers become very  
21 differentiated -- there isn't much competition to kill  
22 in the first place, and it's very costly to keep a  
23 link out, so you want to have all links active, okay?  
24 So that's the network that maximize total industry  
25 profits. That's for Bertrand, Cournot, it's very

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1 similar results, okay?

2 Now, let's move to the real question. What are  
3 the exclusive contracts that emerge -- what are the  
4 networks that emerge in equilibrium when we don't  
5 have -- let's start with a case in which we don't have  
6 exclusive contracts arrangement. So if you don't have  
7 exclusive contracts and you have Cournot competition,  
8 then the only possible equilibrium is with all links  
9 active. Everybody trades with everybody. It's very  
10 intuitive, right?

11 If I'm a firm, I can't prevent my counterparty  
12 from dealing with somebody. If that counterparty  
13 finds it profitable, they will do it. And so  
14 everybody trades with everybody. It's very intuitive,  
15 right? And so this makes things agreeable, and  
16 profits are not maximized.

17 However, it's not general. If the -- you have  
18 Bertrand competition -- that should be grayed out, the  
19 top edge should be gray, it doesn't show up well.  
20 When retailers are close substitutes, pairways  
21 exclusivity is the equilibrium, and the intuition here  
22 is the following. In providing exclusivity, the two  
23 retailers carry two different products.

24 Now, imagine retailer one is thinking of also  
25 getting product two. Now, the good thing is that it

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1 gets variety, but the bad thing is that if he gets  
2 good two, it gets the same good that its rival is  
3 carrying, so it becomes more similar to its rival.  
4 That will instigate a reaction from the rival. That  
5 will instigate the rival to lower prices and start a  
6 price war.

7 So it's completely possible that retailer one  
8 just decides to forbear. He could get the other  
9 product, but he just doesn't get it, okay? And that's  
10 how you can have provider exclusivity even in the  
11 absence of an exclusive contract, okay?

12 Okay. Now, let's see -- I have to go fast,  
13 obviously, given time constraints. Let's go to the  
14 case with exclusive contracts, all right? So you have  
15 to adjust the framework a bit. It's actually very  
16 tricky, but I am not going to bore anybody with that.  
17 So I won't tell you what you need to do to the  
18 framework, but once you make the framework consistent  
19 and ready to go, these are the results.

20 Let's look at Bertrand competition. These are  
21 the three areas in which different networks maximize  
22 total industry profits. There's not equilibrium.  
23 That's what maximize total industry profits, okay? So  
24 downstream monopoly provides exclusivity, and all  
25 links active from top to bottom.

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1 So what happens? Now, first of all, when  
2 downstream monopoly is in equilibrium -- sorry, when  
3 the downstream monopoly maximizes industry profits, it  
4 can always be supported as in equilibrium. Going to  
5 the opposite extreme, when Bertrand comp -- when  
6 retailers are very differentiated in the lower part of  
7 the graph, all links active can be supported as an  
8 equilibrium in most part of the -- no, in the grayed  
9 part of that region, and for intermediate levels of  
10 retailer differentiation, the middle area, it turns  
11 out that provider exclusivity can be supported as an  
12 equilibrium when the suppliers are very  
13 differentiated, when a (indiscernible) differentiated,  
14 which makes a lot of intuitive sense, because the  
15 reason why provider exclusivity increases profits is  
16 that it allows retailers to inherit the  
17 differentiation of suppliers, right? And so you would  
18 expect it's more likely to be in equilibrium when  
19 suppliers are very differentiated, okay?

20 So what I've shown you here are two-strategy  
21 equilibria. The bad news is that in the white area,  
22 it really doesn't exist, the two-strategy equilibria.  
23 There could be mixed-strategy equilibria, and that's  
24 not even sure with this type of equilibria, but I  
25 don't want to -- okay? So that's what happens with

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1 Bertrand. Cournot is very similar. You know, it's  
2 different regions, but it is the same, okay?

3 Now, before I conclude in the next three, four  
4 minutes, let me talk about some implications of these  
5 analyses, okay? So the first one is very  
6 straightforward given this model, and it is that  
7 exclusive contracts in this model always reduce  
8 welfare. That is -- well, let me say it better.

9 When exclusive contracts are actually adopted  
10 in equilibrium, so in that area where they actually  
11 are adopted, and when they actually cause the  
12 equilibrium to switch, which is not everywhere, but  
13 when they have an effect, they always cause the  
14 equilibrium to switch in the direction of less  
15 variety, right, and of less competition, of higher  
16 prices, and that means it's bad for welfare. We all  
17 know there are all the potentially positive effects of  
18 exclusive contracts, but in this model, they're bad,  
19 okay?

20 Now, much less straightforward and much more  
21 interesting, in my view, is the effect of exclusive  
22 contracts on the distribution of profits between  
23 suppliers and retailers. As I told you, here I can  
24 only predict ranges, right? And the upper and lower  
25 bound of those ranges are determined by the credible

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1 deviation, the credible threats available to suppliers  
2 and retailers.

3 In particular, let's just focus on t-upper-bar,  
4 just for the sake of example. t-upper-bar is  
5 determined by the credible deviations available to  
6 retailers, and the idea is because if suppliers want  
7 to raise -- they want to get a transfer which is very  
8 high, if a supplier wants to do that, eventually, a  
9 retailer will just kick him out, right? The retailers  
10 would kick him out if he is too high, right?

11 The ability of the retailer to credibly kick  
12 him out determines how high the t can be, and the term  
13 is t-upper-bar, and (indiscernible) for t-over-bar.

14 Now, it turns out that in this model, the  
15 availability of exclus -- notice this idea of the  
16 availability of exclusive contracts. They don't need  
17 to be adopted in equilibrium. The sheer fact that  
18 they are available changes the credibility of  
19 deviations, and it makes it more credible for  
20 suppliers and retailers to exclude somebody on the  
21 other side of the market. So it affects the outside  
22 options.

23 It turns out that in this model, it affects the  
24 outside options of the retail -- of the suppliers much  
25 more than those of the retailers, and I can discuss

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1 that later during questions, but the availability of  
2 suppliers can kick a retailer out and implement a  
3 downstream monopoly that's very profitable relative to  
4 the alternative, what the -- relative to what -- the  
5 recourse retailers have.

6 And so when -- in this model, when exclusive  
7 contracts become available, they make suppliers  
8 unambiguously better off and retailers unambiguously  
9 worse off. I would like you to note here that this  
10 approach is very similar to -- so this is very similar  
11 to something that Bernheim and Whinston found in a  
12 1998 JPE paper on exclusive dealing. It's different  
13 from the approach taken in Ho and Lee in a recent  
14 paper and in the paper you may have seen by Eli  
15 Liebman. In that case, in those last two papers --  
16 so, first of all, they don't have downstream  
17 competition, so -- well, Liebman has it but doesn't  
18 make much with it, and Ho and Lee assume there is no  
19 downstream competition, so they focused on a different  
20 issue.

21 But basically in those papers, the idea is that  
22 retailers -- that's health insurance companies in  
23 their model -- can commit to exclude, ex post, one or  
24 more suppliers, one or more hospitals, and by  
25 committing ex post -- by creating artificial scarcity,

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1 they will induce hospitals to be more aggressive and  
2 get -- so they will get better terms, but in order to  
3 obtain that, they actually do need to exclude somebody  
4 on the equilibrium path and cause some damage. That's  
5 not what happens in my model.

6 Finally -- and I'm almost done, just basically  
7 one minute -- but I want to talk about two papers, one  
8 by Lee and Fong, Robin Lee and Fong, and the other one  
9 by Rey and Verge, which ask a similar question. They  
10 look at what type of supply networks arise, but their  
11 approach is quite different from mine. They assume  
12 that firms first form all the supply links, the  
13 network, without being able to use any transfers at  
14 the network formation stage, and they can't even use  
15 long-term contracts. So they can just -- you know,  
16 they can just form the networks without compensating  
17 each other.

18 Once the network has been formed, then they  
19 Nash bargain, and Nash bargaining takes place under  
20 conditions of hold up here, right? What does that do  
21 to the equilibrium of the model? Well, hold up makes  
22 it more difficult for two firms that want to create a  
23 link -- and I assume that's jointly profitable -- to  
24 move money around to make sure that happens, because  
25 one of those firms is afraid maybe to be held up and

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1 won't play along.

2 You can always delete a link unilaterally, so  
3 it doesn't do anything to the ability to delete a  
4 link. It only makes it more difficult to create  
5 links, hold up. So it tends to produce networks that  
6 are narrower. It's more difficult to withstand the  
7 network. And so the two figures you have there on the  
8 left is my approach with transfers, and as you see,  
9 the bottom part is all links active; the upper part,  
10 there is some exclusivity. The right side is one that  
11 occurs in Rey and Verge, there's more exclusivity,  
12 right?

13 Nice approach, interesting in some markets. I  
14 don't think, though, that it's very realistic in  
15 markets with large firms, like the deal between AT&T  
16 and the iPhone -- sorry, AT&T and Apple on the iPhone,  
17 there were big payments probably up front, right? And  
18 it's also not very suitable to study in exclusive  
19 contracts, because no firm would commit to exclusivity  
20 if it can't be compensated, right?

21 So, in conclusion, I developed a new way to  
22 look at bilateral contracting in -- bilateral  
23 contracting in bilateral oligopolies. These identify  
24 some potentially important factors to determine the  
25 structure of supply networks, but so far, it has

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1 focused more on the division of surplus than -- more  
2 on the structure of networks and contracts than on the  
3 division of surplus.

4 So possible next steps would be to do more work  
5 on the division of surplus. That's really  
6 complicated, but that could be a step. And the other  
7 one is to find a way to empirically implement this, to  
8 simplify it and empirically implement.

9 And the other thing one could do is study  
10 markets where firms can publicly commit to the  
11 wholesale prices, and I'm doing that in ongoing work.

12 That's it. Thank you.

13 (Applause.)

14 MR. ROSENBAUM: The discussant is Ali  
15 Yurukoglu.

16 MR. YURUKOGLU: Okay, thank you for inviting me  
17 and thank you to the organizer --

18 MALE AUDIENCE MEMBER: If you could get closer  
19 to the microphone.

20 MR. YURUKOGLU: There's a lot of -- it was very  
21 interesting to read this paper, a lot of rich  
22 economics. Let's jump right in. I was going to start  
23 by motivating with some examples. I think Paolo did a  
24 good job of that. Let me mention one or two more that  
25 he didn't mention.

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1 So you see this with -- these exclusive deals  
2 with department stores and clothing brands. For  
3 example, Target will do these collaborations with  
4 high-end designers that are exclusive to Target; also,  
5 soft drinks in restaurant changes. In many cases of  
6 bilateral oligopoly, we see interesting cases of  
7 incomplete supply networks.

8 This paper is really about defining equilibrium  
9 notions that will get you those interesting cases and  
10 trying to generate networks like this in markets where  
11 buyers and sellers have market power, payoffs are  
12 interconnected across negotiations, and contracts are  
13 potentially complex, not just about price. And like  
14 he mentioned, it's really sort of combining two  
15 different theory literatures, one on vertical  
16 contracting and one on coalition-proof Nash  
17 equilibrium.

18 Okay, so I am going to sort of have a  
19 high-level comment about both of those, which I'll go  
20 into the details, but -- so a lot of what makes this  
21 go is the assumption of secret contracts, okay, and  
22 flexible contract spaces. That's what gets you -- it  
23 makes it easy to solve the pricing equilibrium, okay?  
24 So you get wholesale prices which are equal to the  
25 marginal cost of production.

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1 And so my comment about that is going to be,  
2 well, how do you deal with the fact in reality that we  
3 see very often linear prices above wholesale cost, and  
4 if you build that in in a natural way, would that  
5 change the results?

6 And then I have some comments on the --  
7 pointing out some trade-offs between thinking about  
8 using coalition-proof Nash equilibrium or something  
9 like a Nash-in-Nash equilibrium.

10 So I'm going to refer to Nash-in-Nash as Horn  
11 and Wolinsky, they're the same thing, basically comes  
12 out of this Horn -- this paper by Horn and Wolinsky.  
13 There's a common misperception, I'd say, that Horn and  
14 Wolinsky has nothing to say about equilibrium supply  
15 networks. It does. I'll show you a simple example  
16 now, which is basically some supply networks can't be  
17 part of any Horn and Wolinsky equilibrium.

18 So if you just want a very simple example that  
19 generates this, imagine you have two upstream --  
20 identical upstream manufacturers and a single  
21 downstream retailer, okay? The network where only one  
22 manufacturer provides to that retailer can't be part  
23 of any Horn and Wolinsky equilibrium, okay? That's  
24 because you have to think of the uncontracting party.

25 There's a negotiation problem between those two

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1 that's not being solved, okay? So if they have  
2 identical costs -- the manufacturers have identical  
3 costs and you propose an equilibrium with only one  
4 link, okay, if that price in that link is above cost,  
5 there's an incentive to sign a contract with the other  
6 manufacturer. So that can't be in equilibrium, okay?

7 And if that price is at exactly equal to cost,  
8 that pair actually has an incentive to deviate the  
9 price upwards when the other firm is not there, okay?  
10 So Horn and Wolinsky does, in fact, give you  
11 predictions about equilibrium supply networks, okay?  
12 So that's sort of a starting point.

13 Now, Horn and Wolinsky has its own warts, okay?  
14 So I have heard Steve use the adjective "weird," also  
15 I've heard "schizophrenic," or "unnatural," okay, lots  
16 of colorful language. It's true, Horn and Wolinsky  
17 only looks basically at pairwise deviations, and some  
18 of those are you might think extremely unrealistic,  
19 because they're holding your own company's contracts  
20 fixed when you're thinking about what would happen if  
21 we were to sign a different contract with another  
22 party, okay, and that feels a little unnatural, though  
23 I -- I'm not going to get into it here, but there are  
24 some very good theorists who think of that as a  
25 feature, not a bug, and perhaps on that -- perhaps

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1 less unrealistically, it doesn't deal with deviations  
2 that involve multiple firms, okay? So that's what  
3 Paolo is getting at here with the coalition-proof Nash  
4 equilibrium.

5 Okay. So the main difference here is that  
6 instead of Horn and Wolinsky only looks at these  
7 pairwise deviations, the coalition-proof is going to  
8 look at multilateral deviations. Let's just think  
9 about the trade-offs in using that for analyzing real  
10 markets, okay?

11 One thing is that when you only have two sides  
12 of the market and you're thinking about a multilateral  
13 deviation, that's necessarily going to involve two  
14 firms on the same side of the market, okay, which is  
15 going to lead to issues of horizontal coordination,  
16 like do we think that these firms actually can make  
17 those deals?

18 I would like to see an equilibrium notion that,  
19 if it wants to get at multilateral deviations, it sets  
20 it up in a way that, like, the communications only go  
21 through the vertical channel, that it doesn't involve  
22 firms, you know, who compete with each other  
23 coordinating their deals, you know, you take -- you  
24 take that input, I take this input, and we'll agree  
25 not to go on each other's territory, because they

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1 might for legal reasons not want to do that.

2 The other thing is -- so these words like  
3 "schizophrenic" and "unnatural," "weird," I think can  
4 be applied very well to the coalition-proof Nash  
5 equilibrium as well, okay? So it's got a wart, which  
6 is that the deviations you have to check for only have  
7 to be immune to further deviations within that pair,  
8 okay, where you might think, well, if there's a  
9 profitable deviation by a set of three firms, okay, it  
10 might be that once that deviation is made, there is  
11 now a deviation in that world consisting of some sets  
12 of those firms and a third party who wasn't part of  
13 the original deviation, okay? That's not ruled out in  
14 coalition-proof Nash equilibrium, okay? So that seems  
15 a bit schizophrenic to me as well.

16 Okay, and another complaint about Nash-in-Nash  
17 is, well, what's the game, the noncooperative game  
18 that gets you there, okay? Is this sort of a similar  
19 question here?

20 Now, the benefit of Nash-in-Nash, which I've  
21 mentioned, is tractability, and that's, I think, a  
22 clear benefit here, which is for the analysis we  
23 restricted to two-by-two for computational reasons,  
24 right, the number of combinations you have to check  
25 gets large, so I would be sort of curious to know how

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1 well this performs when you have bigger networks, like  
2 realistic networks in terms of size.

3 I think estimation, you could probably -- it  
4 might be one of those cases where, like, it's -- you  
5 can estimate it, but it's much harder to simulate it,  
6 okay, because you could just use the necessary  
7 conditions for estimation, but this is all just to say  
8 this is worth looking at. It's not -- like, this  
9 doesn't in one fell swoop get rid of all the problems  
10 of Nash equilibrium. It's not like a Pareto  
11 improvement, but it's something to add to our toolkit.  
12 It might be more applicable in some industries than  
13 others.

14 Okay, along similar lines, I have seen a bunch  
15 of papers recently that sort of take standard  
16 supply/demand models in IO, that's BLP Demand, Nash  
17 pricing at the downstream level, and they try to  
18 generate interesting supply networks by playing around  
19 with the rules of the contracting game. When I think  
20 there's actually -- like, there's an alternative,  
21 which is you could try and play with the supply and  
22 demand models to generate different incentives that  
23 will lead to different supply networks, okay?

24 So, like, most of these models have linear cost  
25 functions, okay, whereas you think certain types of

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1 nonlinear cost functions will lead to exclusive  
2 dealing, okay, so that if by shipping you -- like  
3 think in the hospital case, if I ship you a lot of  
4 quantity by putting you in a narrow network, then the  
5 hospital knows it's going to get a lot of quantity,  
6 okay, and if the hospital's cost curve is concave,  
7 you're moving the hospital to a flatter part of their  
8 cost curve, lower marginal costs, so you should expect  
9 better prices in that case, okay?

10 You know, costly capacity for the retailer  
11 might be a reason you don't stock every item.  
12 Nonlinear pricing by the downstream firm, in a lot of  
13 those narrow networks, the insurance company actually  
14 has a deal with the hospital that's not in the narrow  
15 network, and they use that hospital in other products,  
16 okay? So they are negotiating. They just don't offer  
17 it to -- in certain products. That seems more about  
18 product design at the downstream level than about, you  
19 know, some weird trick on the contracting game.

20 One-stop shopping by consumers, like why does  
21 Target have those exclusive collaborations with  
22 designers? Okay, you know, there's models out there  
23 that say if it's hard to observe prices, but you can  
24 observe what's being stocked, like they do a promotion  
25 saying we have this collaboration, and you have

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1 one-stop shopping, okay, then that's a way -- that  
2 type of exclusivity is going to be gen -- is going to  
3 be generated without any sort of playing around with  
4 the fine details of contracting.

5 Okay. So I think it would be useful -- if we  
6 want are models of incomplete supply networks, I think  
7 there's a lot of room still to play with demand and  
8 supply conditions rather than details of the  
9 contracting game.

10 Just as a last comment, so I mentioned this at  
11 the beginning about -- so a lot of the analysis is  
12 simplified I think in a very pragmatic way by assuming  
13 that contracts are secret and there's a flexible  
14 contract search, so a two-part tariff is enough, okay?  
15 In those models, in any equilibrium, the price that  
16 the manufacturer charges the retailer is going to be  
17 equal to the manufacturer's cost of production, okay?

18 This is very robust, goes back to Hart and  
19 Tirole. It seems natural because there's nothing  
20 really preventing firms from using flexible contracts.  
21 The problem is, in reality, we see linear pricing  
22 above wholesale costs sort of all the time, okay,  
23 cable TV, music streaming, certain medical procedures,  
24 something like basic inputs for basic industries. So  
25 I think these models are missing something that leads

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1 to more linear contracting, because there's other  
2 stuff going on that is pushing these firms away from  
3 that benchmark of getting linear prices at wholesale  
4 costs. And I'd be curious to see, when you put those  
5 in, sort of how much you can still do and whether it  
6 would change the results or not.

7 Okay. So to wrap up, it's a really interesting  
8 paper wrestling with really important issues in  
9 antitrust and IO. I think, you know, very theorists  
10 look at this is very fruitful right now. It combines  
11 insights from contracting vertical relations with  
12 coalition formation theory. You know, a nice part of  
13 the paper is it predicts a wide array of supply  
14 networks, which I think is great.

15 I'd like to see a little bit more about what  
16 this coalition-proof can do that Nash-in-Nash cannot  
17 and whether it's worth the computational -- you know,  
18 Nash-in-Nash with -- allowing the analyst to play with  
19 the supply and demand model and whether, you know,  
20 those benefits are worth the computational costs or  
21 not.

22 Thank you.

23 MR. ROSENBAUM: We have time for some  
24 questions.

25 MR. RAMEZZANA: First of all, maybe just really

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1 quickly, Ali, really an excellent discussion. The  
2 only thing I wanted to say is that, absolutely,  
3 wholesale prices are different from marginal costs  
4 generally. I'm actually working on a paper now in  
5 which there's public commitment, and so they will be  
6 greater, but, yeah, there are a lot of circumstances  
7 in which you have double moral hazard, and that's the  
8 case, so that's a great comment, and I agree with  
9 that.

10 MALE AUDIENCE MEMBER: I believe this is taking  
11 a slightly different angle, but I've found that one of  
12 the issues with Nash-in-Nash is that when you're  
13 thinking about the disagreement payment, you're not  
14 allowing to have a next round in which you  
15 renegotiate. Even if a contract fails with one party,  
16 then you can renegotiate with another potential party.  
17 So like if a hospital does not agree to something and  
18 maybe you are going to divert and change your price, I  
19 mean, that will change the bargaining with the -- you  
20 know, with other hospitals.

21 I heard there are sort of recursive concepts of  
22 Nash-in-Nash. I mean, are you familiar with that? I  
23 mean, is this --

24 MR. RAMEZZANA: Well, so what he's saying is  
25 that they could recontract the outside options in some

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1 sense. If we did agree, I can go back and re-optimize  
2 my outside option, not only -- no, I should look into  
3 that. Yeah, no, I mean, to be honest, I -- no, I'm  
4 not familiar with the -- with those more in-depth  
5 treatments. I should look at it.

6 There are -- there are a number of other  
7 equilibrium concepts one should explore, and  
8 eventually I may get to that. Also, sort of in the  
9 literature on coalition-proof Nash equilibrium,  
10 coalitional equilibria, there are -- equilibrium is --  
11 there's a book by the by Bloch and Dutta, you know, if  
12 you look forward, because here basically you -- if  
13 coalition deviates to a certain outcome, then it's  
14 completely nearsighted. It's not looking at the fact  
15 that once they get there, they maybe deviate farther.  
16 They just do things one step at a time, and they just  
17 get there and say, okay, this doesn't work, something  
18 else happens.

19 The smart people would usually think, okay, if  
20 we go there, this is going to happen, and they are  
21 going to look at the endpoint of this. So that's not  
22 what I did here, and that's not how CPNE works. So  
23 I'm not sure it addresses your question, but  
24 generally, I think there are -- I agree with you,  
25 given -- this has been a lot of time already, but

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1 given a bit more time, one can try to figure out more  
2 refined equilibrium concept, which maybe make --  
3 either make this consistent with Nash-in-Nash to some  
4 extent or anyway can help. Yeah.

5 MR. ROSENBAUM: Any other questions?

6 (No response.)

7 MR. ROSENBAUM: We will move on to the next  
8 paper. Thanks, Paolo.

9 (Applause.)

10 MR. ROSENBAUM: All right. Next we have  
11 Michael Geruso, presenting Contract Design: Evidence  
12 from the ACA Health Insurance Exchanges.

13 MR. GERUSO: First, thanks very much for having  
14 me. I'm really happy to be here at my first FTC Micro  
15 Conference. This paper is joint with Tim Layton and  
16 Daniel Prinz. Daniel's a graduate student, not on the  
17 market yet.

18 Right, so just to give a bit of background and  
19 orient you to what we're going to do in this paper,  
20 sort of at the heart of this is this fundamental  
21 tension in health insurance markets between offering  
22 consumer choice, trying to enforce  
23 nondiscrimination -- and we can talk about why  
24 nondiscrimination might be a good thing from a social  
25 planner's perspective -- and then, as a result of

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1 that, dealing with selection.

2 So in the exchanges, which is what our paper is  
3 about, that's our market setting, but this is also  
4 true in Medicare, in privatized Medicare and  
5 privatized Medicaid, the rules of the game are that  
6 you need to enroll anyone who wants to join a plan,  
7 you can't charge different people different prices,  
8 and, in particular, you can't -- you know, so  
9 there's -- you can charge people who are different  
10 ages different prices, but you can't link premiums  
11 that people pay in these markets to their health  
12 status. That's something that's very popular among  
13 consumers.

14 So if you think of the recent debate over  
15 repealing and replacing the Affordable Care Act, the  
16 idea of preexisting conditions and coverage for  
17 those has come up over and over again. And so these  
18 regulations enforce a fairly intuitive sense of  
19 fairness in these markets, but they also connect --  
20 you know, you can backstop all of this with very clear  
21 economic theory about insuring consumers against  
22 exposure to long-run risk.

23 The trouble with these kinds of regulations is  
24 that they also open the door for inefficiencies  
25 related to selection, and the reason is is that price

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1 is just one of many potential screens in these  
2 markets. So you can say that you can't charge  
3 different people different prices, but what's much  
4 harder to observe and what this paper's going to be  
5 about is do you -- do you distort other aspects of the  
6 contract to try to keep certain people out of your  
7 plan.

8 Now, it turns out that there is a very widely  
9 implemented and standard solution to this problem,  
10 which is risk adjustment, and since probably only a  
11 minority of the people here are into health insurance,  
12 the basic idea behind risk adjustment is you want to  
13 give the insurer a payment that compensates them for  
14 the expected cost of the enrollee that they're taking  
15 on. So if you are going to take on someone with  
16 diabetes, then the regulator is going to take a  
17 payment away, is going to tax a payment away from plan  
18 that enrolls a healthy 25-year-old, and it's going to  
19 give that money to a plan that enrolls, you know, a  
20 64-year-old diabetic.

21 And when that's working properly, at least  
22 under conventional wisdom, you are just exactly  
23 compensating expected costs, and all enrollees look  
24 equally profitable even though they're differentially  
25 costly. That's the basic idea. That's widely used in

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1 Medicare, Medicaid, exchanges in the U.S., but also in  
2 every regulated, competitive health insurance market  
3 around the world.

4 Okay, so that's all just sort of setting the  
5 stage for where we start in this paper, and where we  
6 start is a couple years ago we started observing these  
7 kinds of reports in the papers that describe the idea  
8 that patients are being discriminated against in terms  
9 of the prices that they're paying for their  
10 prescription drug coverage. So I sort of pasted on a  
11 few of the headlines. "HIV Patients Excuse Health  
12 Plans of Using Drug Costs to Discriminate." "Health  
13 Insurers Discriminate Against Patients who Need  
14 Specialty Drugs." The idea there is that, you know,  
15 or at least in many of these stories or in the  
16 consumer complaints that were coming in through HHS  
17 was that, you know, even though prices couldn't be --  
18 premium prices couldn't be differentiated across  
19 people with different health status, that somehow this  
20 was still working its way through to the benefit  
21 designs.

22 Now, when we saw this as economists, we  
23 thought, okay, one of two things is happening: either  
24 it's the case that insurers are still operating in  
25 this -- because these are markets with risk

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1 adjustment, so either it's the case that insurers are  
2 still set in this mind-set that a costly patient is an  
3 unprofitable one, or they're actually correctly  
4 understanding the incentives, with some level of  
5 sophistication, and what they're finding are the  
6 places where the risk adjustment is sort of, you know,  
7 not properly calibrated in some sense. There is still  
8 some error, some margin -- some margin for profitable  
9 selection.

10 And so that's what we look at in this paper,  
11 and so there are these anecdotes pointing to the idea  
12 of limiting access to entire classes of drugs as a  
13 backdoor for discrimination, and the kind of  
14 complaints and the kind of statements that you would  
15 see HHS making, but also the complaints that are  
16 coming out of consumer groups, were that most or all  
17 of the drugs that treat some specific condition -- so,  
18 you know, the whole set of alternative substitute  
19 therapies -- were placed on the highest cost-sharing  
20 tier. So it's that anecdote that in the paper we're  
21 going to evaluate systematically, and data.

22 So what do we do in this paper? We're going to  
23 study this kind of selection-related formulary design,  
24 so the way that plans are creating their prescription  
25 drug formularies, using data from the 2015 ACA



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1 exchanges, or now they call them marketplaces for as  
2 long as they still exist, and we investigate whether  
3 the drugs treating chronic conditions are, first of  
4 all, just trying to figure out, are they a plausible  
5 screen? Can insurers actually, at least in principle,  
6 make money by selecting -- by selecting consumers with  
7 this kind of screen.

8 And the reason why you might think that  
9 prescription drugs are the right place to look for  
10 this kind of activity is, you know, among all the kind  
11 of healthcare goods that healthcare consumers consume,  
12 you might think of drugs as being -- especially drugs  
13 that treat chronic conditions where I need to take  
14 this drug every month -- as being particularly  
15 transparent in terms of both need and price.

16 So we're going to sort of, you know, in the  
17 next 20 minutes ask and answer two questions. First,  
18 is there scope for selection? So is it the case that  
19 there is some problem with the risk adjustment system  
20 that's leading to the ability to profitably screen  
21 certain kinds of consumers? The answer there, I'll  
22 show you, is yes. The second question is, you know,  
23 saying that that incentive exists is one thing, and  
24 then the question is, are there -- are the insurers  
25 appearing to respond to that? And the answer there is

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1 yes, and with, to my mind, what's a pretty significant  
2 level of sophistication. I'll tell you, as we go,  
3 sort of why we think that's the case.

4 So just to give a little bit of orientation on  
5 the literature, and I won't spend much time here, you  
6 know, the first talk that we heard today was based on  
7 the Akerlof lemons model. In health insurance, the  
8 way that we apply the Akerlof lemons model is we think  
9 about selection impacting the composition of a risk  
10 pool and then ultimately feeding back into prices in a  
11 competitive or imperfectly competitive market, and  
12 there's been a lot of both good theory and good  
13 empirical work on that, Einav, Finkelstein, and  
14 colleagues.

15 One thing that that model really can't say  
16 anything about, because it assumes it away, is the  
17 kind of phenomena which you didn't hear, which is that  
18 the contract itself changes. It's not just that you  
19 change the risk pool, and by changing the risk pool,  
20 you change the break-even price in a competitive  
21 market, but it's that insurers are not sort of passive  
22 participants. They design plans, and they can design  
23 plans with these ideas in mind. Of course, this is  
24 kind of the original idea of Rothschild Stiglitz, but  
25 there's also been other good empirical or theoretical

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1 work thinking about this idea applied to health  
2 insurance markets. Where there's a gap is that  
3 there's almost no empirical work on this.

4 So in this paper there's basically no theory.  
5 We're just taking sort of the envelope of insights and  
6 kind of empirical predictions from the existing  
7 theoretical literature -- so Veiga and Weyl, Azevedo  
8 and Gottlieb, some papers by Tom Maguire, and of  
9 course Rothschild and Stiglitz, and we're going to  
10 take that in and we're going to look for empirical  
11 evidence.

12 Okay, so the first part of the exercise is just  
13 trying to understand, you know, how well is the risk  
14 adjustment working? Is there plausible space to use  
15 formularies as a way to screen out unprofitable  
16 consumers?

17 So I will try not to make you learn more about  
18 healthcare regulation than you absolutely need to to  
19 get through the slides with me, but there's two broad  
20 categories of regulations that are intended to deal  
21 with this problem. The first are things like a  
22 coverage mandate. So in the Affordable Care Act, in  
23 the exchanges, there are things like essential health  
24 benefits. This is where the regulator says to the  
25 insurer, you must cover X.

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1 The other family of regulations are payment  
2 adjustments. So rather than saying you must cover X,  
3 even though X is going to attract unprofitable people  
4 to your plan, instead what we will do is we will  
5 adjust the payments so that those facts, on net, after  
6 the risk adjustment or reinsurance, are no longer  
7 unprofitable.

8 And so I've mentioned a bit about how risk  
9 adjustment works, but what risk adjustment is doing is  
10 it's going to make a payment to an insurer based on  
11 the diagnoses and demographics of the people of the  
12 risk pool that's enrolled in its plan. And  
13 reinsurance is going to make a payment based on the ex  
14 post realized healthcare costs of people enrolled in  
15 the plan.

16 Okay, so to answer the first question, which is  
17 about do these incentives exist net of risk adjustment  
18 and reinsurance, we're going to go to detailed health  
19 claims data. These data are not going to be from the  
20 marketplaces, the exchanges themselves. It's going to  
21 be out of sample, because that's where we can get  
22 claims data. And what we're going to do, in those  
23 claims data, we will see a person's costs, and we'll  
24 ask the question, what would the risk adjustment and  
25 reinsurance payments have been if this person

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1 generated that claims history while enrolled in an  
2 exchange plan?

3 So, you know, we can just take off the shelf  
4 the algorithm from the regulator, HHS, and we can say,  
5 here's what the risk adjustment payment would have  
6 been, here's what the reinsurance payment would have  
7 been, and ultimately here's how unprofitable or  
8 profitable this consumer would have been if enrolled  
9 in your plan and generating these claims in an  
10 exchange plan.

11 So just to give a bit more detail on how we do  
12 this, premiums here are not sort of, you know,  
13 completely stable or completely constant across all  
14 people. We're just going to take the average cost in  
15 the sample and assign it actually a fair premium. All  
16 the variation that we are going to be identified off  
17 of is the implied risk adjustment, and implied  
18 reinsurance risk adjustment, remember, is a function  
19 of diagnoses and demographics, and reinsurance is just  
20 a function of did you -- did you generate claims that  
21 were in excess of some attachment point, at which  
22 point the reinsurance kicks in?

23 This gives us profitability at the individual  
24 level, and then what we want to do now is try to  
25 connect to the anecdotes that said what insurers

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1 appear to be doing is taking all of the drugs that  
2 treat some condition and moving those to a restrictive  
3 tier, and in the complaints, usually the specialty  
4 tier of drugs. So we are going to group consumers  
5 within therapeutic classes of drugs.

6 So some examples -- so we are just going to  
7 take a standard issued definition of these classes.  
8 So anticoagulants or blood thinners or statins or oral  
9 contraceptives, antidiabetic agents, these kinds of  
10 classes within which we think there are substitutes or  
11 alternative drug treatments, and we're just going  
12 to -- we're going to take all the folks that use one  
13 of those drugs, we're going to calculate the average  
14 cost, conditional on a flag for that -- on a drug for  
15 that class, and look at the expected revenue  
16 conditional on that same flag.

17 And what comes out of that -- I'll try to do  
18 most of this in sort of nonparametric plots. What  
19 comes out of that is a scatter plot that looks like  
20 this, and so the -- each circle is a different  
21 therapeutic class of drugs. The position on the  
22 horizontal axis is the average cost of people who use  
23 a drug in that class, and on the vertical axis, the  
24 average revenue of people who use a drug in that  
25 class, and the size of the bubble is proportional to

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1 the number of consumers in our data that use each  
2 class.

3 What you see is a couple things. The first  
4 fact -- empirical fact that comes out of the analysis  
5 is that for most classes, the selection incentives are  
6 pretty well neutralized. So, a 45-degree line tells  
7 us that, you know, even though someone that takes a  
8 vasodilating agent to treat chest pain is going to  
9 have \$4,000 in expected costs, and the insurer knows  
10 that in some sense at the time that the person is  
11 enrolling, if they knew that they wanted that drug,  
12 they're also going to generate about that amount in  
13 revenue, because there's a small premium, but there's  
14 also an \$18,000 risk adjustment payment for someone  
15 who shows up with that diagnosis in your risk pool,  
16 and there's another \$4,000 or so in reinsurance  
17 payments, right?

18 So for most consumers in most drug classes,  
19 these incentives are really well balanced, and I think  
20 that's pretty interesting and not at all a necessary  
21 outcome since the risk adjustment algorithm doesn't  
22 actually take into account what drugs you take. It  
23 takes into account your diagnoses, and that's going to  
24 be correlated to some degree with the drugs that you  
25 take.

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1 But it's not universally true, so there are  
2 these outliers. So, for example, by logical response  
3 modifiers treat multiple sclerosis. A person who's  
4 going to demand a drug in this class is going to  
5 generate an expectation of \$61,000 in costs but much  
6 less in revenue, even after taking into account  
7 \$34,000 in risk adjustment transfers and a sizeable  
8 reinsurance payment of, like, \$9,000 as well.

9 And so when we go on to the second part of the  
10 analysis, we try to see, you know, are plans  
11 responding to this incentive? What we'll look at is  
12 basically vertical deviations from this 45-degree  
13 line, and that vertical deviation is, you know, in  
14 dollar terms, in level terms, how unprofitable is a  
15 person who predictably will demand a drug in this  
16 class?

17 Very briefly, something else that came out of  
18 this which I have to mention because it -- unless I  
19 mention it, I don't think it will come across just by  
20 looking at this last picture, is that there's  
21 absolutely no correlation after risk adjustment and  
22 reinsurance between costs and profitability, and what  
23 that's going to mean is that when we look at insurer  
24 sophistication response to this, the insurer has to be  
25 more sophisticated than merely saying we are going to

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1 try to keep expensive people out of our plan, because  
2 there's no longer any correlation between expensive  
3 people and unprofitable people.

4 Just for time, let me skip this, just a  
5 different look at the people that you want to avoid.  
6 So why are there errors in the payment system? So,  
7 you know, one possibility is that in the time between  
8 the payment system being calibrated and used, there  
9 was some technological change in how -- you know,  
10 what -- how costly it was to treat a particular  
11 condition, but, you know, more generally, there's no  
12 reason to think that these things would be orthogonal  
13 to profitability since they weren't included in the --  
14 in the algorithm that tried to -- that tried to net  
15 profitability to zero for each group.

16 We will skip that for time. All right, so then  
17 the second goal of the paper is trying to ask, you  
18 know, not just do these incentives exist, but do plans  
19 respond to them and with what degree of apparent  
20 sophistication. So for here now we'll actually go --  
21 so all of that so far has been a sort of out-of-sample  
22 prediction, looking at basically employer health  
23 plans, large self-insured employer health plans and  
24 the claims generated there. So now we want to ask, do  
25 drugs that predict unprofitable patients, are they

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1 actually covered ungenerously by exchange plans? And  
2 so for that we will turn to exchange data. So we will  
3 get the universe of formulary data from 2015 from the  
4 exchanges. We'll do that both for -- so we will look  
5 at the exchange data, and we will also use employer  
6 plan formulary data as a sort of comparison point, so  
7 we can do a difference in differences. And the unit  
8 of analysis here is always going to be at the drug  
9 class, so grouping together all the potential drug  
10 therapy substitutes by plan.

11 When -- as we go forward, as I keep talking  
12 about restrictiveness, what I mean by restrictiveness  
13 is if you took a plan's cost-sharing tiers and you  
14 sort of ranked them from most generous to least  
15 generous, there's a very clear breaking point at the  
16 level of specialty drugs, and one of the reasons for  
17 that -- although we could talk more about this if  
18 you're interested -- is that's generally a level at  
19 which you go from a copay regime, so you pay 30 or 60  
20 or 90 dollars, whatever your plan says, to you pay a  
21 coinsurance rate, 20 percent, 25 percent, whatever it  
22 is, and that could be a really important difference,  
23 and we show that in the paper for high-cost drugs.  
24 It's also the level at which there's -- you know,  
25 states have taken regulatory action. So, for

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1 instance, New York State outlawed the use of a  
2 specialty tier in health plans in the state.

3 So when I say restricted drugs, I'm talking  
4 about specialty drugs or drugs that are left off of  
5 the formulary altogether or drugs for which, if you  
6 want to use them, there needs to be some sort of  
7 nonprice hurdles that you need to jump over, like step  
8 therapy or prior authorization.

9 So just very briefly, the -- we're going to be  
10 comparing in some sense employer plans to exchange  
11 plans and how they differentially respond to this  
12 selection incentive. The selection incentive doesn't  
13 exist in employer plans. They're just sort of a  
14 useful control group for us. Because it doesn't exist  
15 in these plans, they're not subject to the risk  
16 adjustment and reinsurance rules, but those plans  
17 are -- exchange plans and employer-provided plans,  
18 they're just differentially generous, so as we go  
19 forward, we will be controlling for that differential  
20 generosity.

21 So here's -- here's kind of the main result in  
22 a picture, although, you know, I'll show something  
23 with a little bit more detail in a minute. So what  
24 we're doing here in the -- on the left-hand side,  
25 we're taking the drug classes in the bottom tenth

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1 percentile -- bottom ten percentile of these selection  
2 incentives. So these are the guys that are actually  
3 relatively profitable, where the risk adjust arrow is  
4 going in the direction of you'd want to -- you'd want  
5 to get these guys into your plan, and the two bars on  
6 the right are the 90th percentiles and up of this  
7 selection incentive. So these are the guys that you  
8 want to avoid. These are guys that demand drugs that  
9 you -- that predict unprofitability.

10 What you see is that there's really -- there's  
11 no gradient here in employer plans, nor should there  
12 be, because employer plans aren't subject to these  
13 incentives, but we want to -- we want to use employer  
14 plans as a control group, because we want to control  
15 for the fact that, you know, some drug class versus  
16 another drug class might be more subject to moral  
17 hazard, where it might make sense to be -- where it  
18 might just be more expensive. There might be sort of  
19 good, efficient reasons to restrict consumer access to  
20 these drugs or make it a little bit harder, but what  
21 you see is that across -- across these percentiles of  
22 how profitable or unprofitable the patients are,  
23 there's basically no reaction in the employer plans  
24 and a relatively large reaction as a share of the  
25 drugs that are restricted access in the exchange

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1 plans.

2 So here's taking that kind of  
3 difference-in-difference idea and just doing it a  
4 little bit more fleshed out and fully. So here what  
5 we're doing is we're taking all of the drug classes  
6 and we're grouping them into ventile bins, so there's  
7 20 points, and within each ventile bin, we're saying,  
8 all the way on the left, these are the drugs that  
9 point here (indicating), these are the ten classes of  
10 drugs that are the most profitable, and we're asking  
11 along the vertical axis, how frequently are drugs in  
12 that class restricted access in exchange plans  
13 relative to employer plans?

14 All the way to the right are the least  
15 attractive drugs or the drugs that predict the least  
16 profitable people. And so, you know, one of the  
17 things you see here is that most of the points are in  
18 the middle, sort of the neutral selection incentive,  
19 but that's -- that makes sense because most of the  
20 points lie along the 45-degree line in the first  
21 picture I showed you, so it's only really in the  
22 points where we -- in these sort of outlier points  
23 where sort of the entrant binds in some sense, where  
24 there's a mistake that then we can see how insurers  
25 respond to that payment system mistake.

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1 You know, I don't think -- in terms of the  
2 coefficient estimates here, I don't think there's  
3 anything more important to glean than what you can see  
4 on the nonparametric plots, but just so you can  
5 understand what we do as we go forward in some  
6 additional specifications, the actual regression that  
7 we run in the parametric specifications are, we have  
8 drug class fixed effects, statins, anticoagulants,  
9 what have you. We have plan fixed effects. Then  
10 we're asking how, within a plan, across drug classes,  
11 does this selection incentive predict how generously  
12 or ungenerously, relative to other drugs in the same  
13 plan, the drug is covered.

14 And so we find that -- we find that these drugs  
15 that predict unprofitable people are both tiered  
16 ungenerously in terms of being on specialty tiers more  
17 often. They're also tiered less generally in terms  
18 of -- generously in terms of requiring some kind of  
19 nonprice hurdle to be met. So whether it's step  
20 therapy, we have to try other drugs first, or a prior  
21 authorization, where you need to call the insurance  
22 company, and there are reasons why we think that might  
23 be important in this context, which we talk about in  
24 the paper, having to do with the cost-sharing subsidy  
25 reductions.

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1 Okay, so with the last four minutes, let me say  
2 a bit about insurer sophistication, because, you know,  
3 while I think it's good to have these kind of  
4 parameter estimates that come out of the paper, to me,  
5 the story of the paper is do insurers respond to these  
6 incentives, yes, and how sophisticated are they in  
7 responding to these. That's where I think we have  
8 some interesting things to say.

9 So what's important is in this setting, the  
10 drugs themselves are a small fraction of cost. So  
11 here we're using the same ventile bins from the most  
12 profitable group all the way to the left to the least  
13 profitable -- most unprofitable group all the way to  
14 the right. Those are the guys you want to avoid. In  
15 all of these cases, drugs are a relatively small share  
16 of the costs. So the drug is a signal for the patient  
17 profitability. It's not actually the thing that's  
18 driving that profitability or unprofitability. And as  
19 I showed before, there is no correlation in overall  
20 cost in patient profitability. So there has to be  
21 some level of savviness on the part of insurers if  
22 they're actually responding to these net of risk  
23 adjustment and reinsurance incentives.

24 So we spent a lot of time thinking about this  
25 in the paper, because this is something we really want

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1 to understand, and one of the things we do is we start  
2 just dividing up this graph into vertical slices,  
3 where we're looking at just patients that are equally  
4 costly but differentially profitable.

5 So just relaxing the parametric assumptions  
6 even further, looking within vertical slices, so folks  
7 that take cardiac glycosides, vasodilating agents, and  
8 gonadotropins, these are all people who are going to  
9 generate the same healthcare costs, roughly, in  
10 expectation, but they're also, in expectation, going  
11 to generate very different profits. And the fact that  
12 insurers are responding to that profit motive  
13 indicates some, in our minds, serious sophistication.

14 So with two minutes left, you know, these are  
15 just the regression specifications that show that kind  
16 of comparison within vertical slices. I don't think  
17 it's useful to go over them, other than to say that we  
18 get the same results when we condition on these  
19 vertical slices, meaning patients with the same  
20 underlying expected cost.

21 Also, just to summarize, in the paper, we do a  
22 lot of work ruling out other alternatives, potential  
23 explanations for this, you know, like is it the case  
24 that this selection incentive is correlated with moral  
25 hazard? You know, some drugs, if -- if there's more

1 price sensitivity within a drug class, then you might  
 2 want to restrict access to it in the same way that --  
 3 well, I'll leave that there.  
 4 Is it just about nudging consumers towards more  
 5 cost-effective options or generics? No. Even when we  
 6 look just at the generics within a class, the generics  
 7 are more likely to be left off of a formulary if they  
 8 predict a patient is going to be unprofitable, if they  
 9 have predicted an unprofitable enrollee. So it's not  
 10 about nudging to cost-effective alternatives. It's  
 11 not about a nudge to go generic. It's also not about  
 12 nudging consumers to products for which the pharmacy  
 13 benefits manager gets a better deal.  
 14 So we can do all of this by looking within  
 15 pharmacy benefits managers and saying, here are --  
 16 here's United Health Plan's employer plans in Texas,  
 17 and they use some PBM. Here's UnitedHealthcare's  
 18 exchange plans in Texas. The same insurer, the same  
 19 PBM, generates very different formulary structures in  
 20 the two markets and in a way that's correlated with  
 21 the selection incentive that we document.  
 22 Okay. So with the last half minute, just to  
 23 conclude, some important take-aways here are, first,  
 24 even though what we're interested in here are the  
 25 deviations where there's a breakdown in the risk

1 to regulate all the dimensions along which insurers  
 2 can design their plan to try to cream-skim enrollees.  
 3 If you say that, you know, you can't put these drugs  
 4 on the specialty tier, then they will put more  
 5 nonprice hurdles in consumers' ways.  
 6 Really, the only way, in our view and from this  
 7 paper, to ensure this kind of access is to get the  
 8 payments right to the insurers to remove the financial  
 9 incentive. I'll leave it there.  
 10 (Applause.)  
 11 MR. ROSENBAUM: Discussing the paper is  
 12 Sebastian Fleitas.  
 13 MR. FLEITAS: Okay. So thank you very much,  
 14 and thank you (off mic). Oh, sorry, yeah. So this --  
 15 okay, there we go.  
 16 Okay, so the idea here is that risk adjustment  
 17 and reinsurance introduced in the exchanges is a way  
 18 to compensate for enrolling costly employees, so this  
 19 is important why? Because we don't want to deny  
 20 access to these -- to these enrollees, and basically  
 21 we wouldn't want to price-discriminate them, because  
 22 then they will be exposed to risk -- reclassification  
 23 risk, so we don't want that. So basically we want  
 24 these schemes to work and to -- and to make equally  
 25 profitable to enroll up a consumer that is very

1 adjustment system, overall, it's important to  
 2 understand that risk adjustment and reinsurance are  
 3 doing a pretty good job of protecting consumers with  
 4 preexisting conditions from having plan designs  
 5 tailored against them. So here we're looking at  
 6 drugs, but, you know, you might think about hospital  
 7 networks being formed in a way, you know, leave out  
 8 the really good cancer hospital if cancer patients are  
 9 unprofitable, and risk adjustment and reinsurance seem  
 10 to be doing a good job in this sense overall.  
 11 Where we see deviations, where you can  
 12 predictably tell who's going to be profitable based on  
 13 the drugs they demand, we see insurers following those  
 14 incentives. And it's not about high cost. It's --  
 15 insurers are sophisticated enough to understand who's  
 16 profitable.  
 17 Then a couple last notes on regulation, I think  
 18 a lot of the ways that policymakers and regulators  
 19 often think about this is what we need is really  
 20 strong essential health benefits controls, where we  
 21 need to say that you must -- you must, you know, cover  
 22 some drug in each class. Those are in place in the  
 23 Affordable Care Act health insurance exchanges.  
 24 The problem is that this product is incredibly  
 25 multidimensional, and there's just -- there's no way

1 costly, okay?  
 2 What this problem is, the problem is that this  
 3 mechanism may not work well, so maybe we can have  
 4 issues with this. And basically on top of this, I  
 5 mean, the firms can try to make actions, try to do  
 6 things in order to screen out consumers, okay? So if  
 7 I understand that these consumers are very  
 8 unprofitable, I try to design my formulary, for  
 9 example, in some sense trying to get this consumer out  
 10 of my plan, okay?  
 11 That's a screening mechanism, and the existence  
 12 of the extent of this screening mechanism is actually  
 13 an empirical question, okay? We want to see in the  
 14 data what's going on, okay?  
 15 So this paper basically is going to do two  
 16 things, as Michael said. So the first thing, it's  
 17 going to show that actually with this (indiscernible),  
 18 that the adjustment and the insurance works pretty  
 19 well for a lot of drugs, for a lot of drug classes, so  
 20 in that sense, it's pretty (indiscernible).  
 21 But also the paper shows that there are some  
 22 payment errors, and these payment errors can be used  
 23 for a screen, and actually, this is trying to show,  
 24 okay, what's the strategy there? The strategy is to  
 25 use a difference-in-difference approach, okay, and

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1 basically it's going to compare the exchanges, so what  
2 happens in the ACA, with the employer-sponsored  
3 insurance.

4 Basically the idea is that this way we can --  
5 so as Michael said, there is no incentives to deviate  
6 with these mechanisms in the employer health  
7 insurance, so basically the idea is that the  
8 difference in differences is going to allow us to  
9 control, by plan and drug class, fixed effects, okay?

10 So we want to control whatever is the same for  
11 all the drug classes and whatever is the same for all  
12 plans, okay, and then we want to use a gradient of the  
13 drugs to identify the model, okay?

14 So basically what we're assuming here is part  
15 of the trends in the class-specific costs and  
16 revenues, okay? So this is the main assumption of the  
17 paper, and we are going to go through these in a sec,  
18 okay?

19 So basically let me tell you that this is a --  
20 as you may see by the presentation by Mike, basically  
21 this is a very nice paper. I think it's important.  
22 It's actually transparent. The paper is very  
23 detailed, so it has a lot of results, so we can track  
24 what's going on here, and it's very clear. So  
25 basically it was a pleasure to read the paper.

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1 I think it's an important paper. So basically,  
2 as I said, two main results. So the main thing,  
3 (indiscernible), these things works relatively well.  
4 The second thing, there are still errors. The firms  
5 are using these errors to screen consumers. It is  
6 important, obviously, for policy reasons.

7 And actually, the second thing is that here the  
8 insurers are relatively sophisticated, okay? So they  
9 can understand that cost is not the same as revenues  
10 minus costs, so they can do that, and this is  
11 important in the way we design the mechanism, okay?  
12 It's very important for the policy, okay?

13 The main contributions, basically this paper  
14 adds to the literature that highlights the important  
15 role of nonprice characteristics in strategic  
16 behavior, and this I think is important for three  
17 things. First, to understand the use of screening  
18 strategies by firm, so generally in -- in how they  
19 work. For regulation, it's extremely important,  
20 because we need to understand how much these remedies  
21 can alleviate the problem. So, for example, essential  
22 health benefits or the risk adjustment system, how to  
23 compute those.

24 And obviously, for modeling in economics, it's  
25 extremely important, because it makes characteristics

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1 not being exogenous, okay? So it is extremely  
2 important for us, because then in the dynamic setting,  
3 for example, we introduce the endogeneity of the  
4 characteristics, and it is extremely problematic, for  
5 example, if we have a setting which is  
6 multidimensional, when we have a lot of state  
7 variables, for example, the (indiscernible), okay? So  
8 this is going to be a problem. Also it's important  
9 because we have the ACA, which is a relatively new and  
10 important market, okay?

11 So let me tell you very briefly three comments  
12 about this paper that I have, maybe some things that  
13 are there, so...

14 The first thing is that I see the paper, we see  
15 a lot of the evidence, so we compute the cost -- the  
16 average cost and the average revenues, okay, but we  
17 don't play that much with the standard deviation,  
18 okay? So since you are having to use a lot of data,  
19 you can compute actually what's the standard deviation  
20 here.

21 This can be important because we would like to  
22 understand if this -- if this standard deviation is  
23 coming from consumer heterogeneity or it's coming from  
24 cost heterogeneity. So it's treating different  
25 conditions, okay?

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1 So maybe one thing to do is just to use the  
2 standard deviation of this cost minus revenue measure  
3 in the regression, you know, interactive with  
4 exchanges, obviously, and trying to see if this  
5 gradient also change with the standard deviation,  
6 okay, if there is some response with this, okay?

7 But a little bit more problematic is that this  
8 opens -- if consumers are heterogenous, this opens  
9 some challenge to identification, and basically the  
10 idea is that the selection mechanism works basically  
11 pricing out of the market some consumers, okay? So  
12 placing restrictions to leave some part of the  
13 consumers out of the market, okay?

14 Therefore, this may lead to different  
15 elasticities of consumers who are in the two markets,  
16 and by the two markets, I mean the exchanges and the  
17 employers, okay? So basically the price elasticity of  
18 these two guys, of these two people are going to be  
19 different, and basically the drug and plan fixed  
20 effects don't account for this, okay, because these  
21 are specific to the plan under the right class, okay?

22 So basically here is -- the scope of selection  
23 here can be problematic with the heterogeneity of  
24 consumers, okay? And basically (indiscernible) is the  
25 main (indiscernible) assumption, okay? This also can

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1 be problematic in the sense that this selection, these  
2 guys that don't -- are not being covered in the  
3 exchanges can go to other places, so maybe they go to  
4 exchange insurance.

5 The employee insurance is also, like, changing  
6 the composition of this group, so maybe the cost for  
7 one part of this group is not the same as the cost of  
8 the other group, okay? So in that sense, obviously,  
9 maybe the small group market is a more close  
10 substitute than the ACA, but in any case, I mean, it  
11 would be nice to see what's the flows of these guys  
12 going from one market to the other, because this can  
13 generate some issue, okay?

14 So I think one thing to -- we can do to try to  
15 understand this a little bit, obviously higher  
16 variance of price elasticity is going to open more  
17 opportunity for reselection, okay, for having  
18 different types of consumers in the two different  
19 markets. So one way to do this is to estimate this  
20 different price elasticity in these (indiscernible),  
21 okay, and use this -- this -- again, the amount of  
22 price heterogeneity of the -- of the elasticity -- of  
23 the heterogeneity and elasticities in order to also  
24 use with exchange, okay?

25 The idea, as I said, is just if you have more

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1 three last ventiles, okay? So this is something that  
2 is happening in the class that are very unprofitable,  
3 okay? It's not having a (indiscernible) distribution,  
4 but it's mostly having the ones that are very  
5 unprofitable, okay?

6 And the same is true when we control a pharmacy  
7 benefit managers, okay? This is Table A-9 in the  
8 appendix, and we can see basically the effect seems to  
9 be very, very concentrated in the ventile number 20,  
10 okay? So this is something that happens with this  
11 class, okay?

12 And then you can see again the same graph that  
13 actually Michael presented in the presentation, okay?  
14 So it is true, as Michael said, that all drugs  
15 represent a small fraction of cost all over the  
16 different classes, okay, but it's also true that if  
17 you see how the share of drugs represented here  
18 increase relatively high in the upper -- up from  
19 ventile number 16, actually, okay? So it's very  
20 correlated, the share that the drugs represent in  
21 terms of cost, okay, with the very unprofitable  
22 condition.

23 I think that the clear reason for that is that  
24 drugs utilization is not using the risk adjustment  
25 mechanism, okay, so in that sense, this induces

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1 heterogeneity in one class than in the other, it opens  
2 more opportunity for having more selection in one or  
3 the other, okay?

4 So the second comment is also -- is a question,  
5 like how -- if there is an also story about higher  
6 costs, okay? Not in the way of sophistication that we  
7 discuss in the presentation, but in a different way,  
8 okay? So basically the idea here is that the firms  
9 are using these formularies in order to send a signal  
10 for consumers, saying if you are unprofitable  
11 consumer, don't come here. This is seen as an  
12 (indiscernible), because you are costly for me, and I  
13 don't want you here, okay?

14 But also it can be -- so it can be that they  
15 respond this way because they have a higher cost with  
16 these particular classes, okay? There is going to be  
17 also a story of costs or a story of pass-through, that  
18 these firms are actually sending a signal saying,  
19 okay, we have a higher cost using these drugs, so we  
20 will send it to you, okay?

21 So the first thing to note is here is that if  
22 we see a table in Appendix A-1, okay, so with the  
23 three measures of profitability, and we see the number  
24 on (indiscernible), we see that most of the results  
25 concentrate in the last ventile, okay, at least in the

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1 correlation, okay?

2 But maybe it's just the firm is saying, okay, I  
3 have these -- I mean, these costs are much higher,  
4 okay, they use drugs, so one way I want to reduce this  
5 or tries to do some pass-through to consumers is to  
6 increase the cost of these drugs, okay?

7 So I think one thing -- one easy thing to do  
8 here is just to control for the -- for the share of  
9 drugs that comes here, okay? So basically using the  
10 same regulation, just use the share. In that sense,  
11 what you want to use as a defined variation is the  
12 changes in other expenditures and nondrug  
13 expenditures, okay?

14 So this is very easy to do, so easy, but it can  
15 be informative of how much of that pass-through is a  
16 story -- a cost story and how much is a screening  
17 story, is that when drugs not are even in my cost,  
18 okay?

19 So the third thing and last thing is about  
20 competition in this market, okay? So basically  
21 obviously with these incentives, the firms are going  
22 to respond in equilibrium. So the first thing we  
23 would like to know is how much heterogeneity we have  
24 by market characteristics. This is also kind of easy  
25 to do.

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1 So just interact the exchanges with some market  
2 characteristics, like the number of competitors or  
3 these kind of things, can give you some idea of how  
4 this -- how they respond. So this also, like, can  
5 give you some -- some clues on why we see all the  
6 effect concentrating on the very unprofitable  
7 consumers and not a lot of fight -- or maybe a lot of  
8 fight, actually -- with the profitable consumers.

9 And maybe they are competing very, very hard  
10 with the profitable consumers, and that's why we don't  
11 see effect there, and they try to get all -- everyone  
12 is trying to get rid of the unprofitable consumers,  
13 okay?

14 Also, the last thing is our dynamics here,  
15 okay? I think there are at least two sources of  
16 dynamics that can be interesting to understand here in  
17 this market. The first one is the learning, okay? So  
18 basically we have a cross-section of data, so we are  
19 going to go through that, but learning here can be  
20 important. I mean, obviously, the firms need to learn  
21 how to play this regulation, how the adjustments are  
22 doing, so basically learning is an important  
23 perspective here.

24 The second one is inertia, okay? So basically  
25 the inertia has also been documented in healthcare

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1 markets, and we have a dynamic competition. There are  
2 some elements of dynamic competition, some markets,  
3 for example, in Medicare Part D, so we see clearly  
4 these investing and harvesting dynamics, when the  
5 firms further reduce prices to capture consumers, and  
6 then increase the prices to exploit them. Something  
7 like that can be happening here, okay? So there are  
8 ways to do this.

9 So basically the easy way that doesn't require  
10 any extra information that you have available is using  
11 the vintage of plans in the market, okay? So  
12 basically you have for the exchanges every plan that  
13 was offered in each of these -- of these markets, so  
14 you can check what's the vintage of this market,  
15 what's the number of years a plan is in the market,  
16 okay, and use this variable to check that, okay? So  
17 you will inspect, like, some effects on the industry.

18 Other ways to do it is just using market shares  
19 of plans by condition, trying to see if the plans --  
20 the newer plans have higher market share -- lower  
21 market share of -- of profitable conditions and higher  
22 market shares of unprofitable conditions, if that  
23 makes any sense, or maybe approximating the market  
24 share by condition using shares of expenditures.  
25 Maybe that's easier way to do it, but it's true that

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1 it's difficult to get information -- individual  
2 information for exchanges.

3 Okay, that's it. Thank you very much.  
4 (Applause.)

5 MR. ROSENBAUM: We have time for one or two  
6 questions.

7 MS. JIN: Thank you.

8 I think the results are really fascinating. I  
9 have two questions. One is, how does this relate to  
10 the market power of pharmaceutical companies? Is it  
11 true that unprofitable drug classes are the ones that  
12 has more market power on the pharma side, and that's  
13 why they charge super high price to the insurers and  
14 sort of force the insurers to either sort of drop the  
15 drug or use other tactics to deal with the high cost?

16 Another question is, what's the consequence of  
17 this? Is this just like every exchange plans refuse  
18 to offer coverage for that kind of drug so that it  
19 completely shut out this market to that type of  
20 patients or it's just more differentiation story in  
21 the sense that there's still at least one plan  
22 offering -- offering this kind of drug coverage? It's  
23 just not as many plans as in other classes, so that  
24 could sort of consolidate all the patients in exchange  
25 market into that particular plan, and that could be a

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1 differentiation story that makes this plan more  
2 differentiated from other plans.

3 MR. GERUSO: Yeah, thank you.

4 So to your first question, the -- you know, I  
5 don't think we -- this paper sheds any light on the  
6 role of market power of the -- of the pharma  
7 manufacturer. In part, that's because the way this --  
8 the whole exercise is structured is that we're going  
9 to difference out anything that's constant within a  
10 drug or within a drug class, because we're comparing  
11 how these drugs are tiered in employer-sponsored  
12 insurance plans versus the exchange plans, and  
13 that's -- you know, that's an intended feature, but  
14 that means that that -- you know, that pharma market  
15 power is going to be constant, at least in some sense,  
16 between those -- between those two insurance delivery  
17 mechanisms.

18 And then the idea about, you know, is this  
19 about differentiation, we tried to -- we tried to dig  
20 into this a little bit. We've got future work planned  
21 where I think we'll be able to get at this a little  
22 bit better and also get at some of the competition  
23 questions that Sebastian was bringing up, but, you  
24 know, our initial cuts of the data where we just  
25 looked at let's just divide this kind of -- you know,



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1 there aren't that many insurers, right, so let's  
2 divide this by big carriers, and let's also look,  
3 like, at small, non-national carriers, and we  
4 just didn't see -- although we're limited in our  
5 statistical power to detect -- we didn't see  
6 differences across carriers. That's not exactly the  
7 same as the question of, you know, is there some  
8 carrier that's left offering this plan, but that's  
9 something we are digging into in the next project.

10 I mean, I will say that one of the facts that  
11 motivated this was that this paper in the New England  
12 Journal of Medicine by Jacobs and Sommers that was  
13 pointing out that in Florida basically it was  
14 impossible to get a plan that covered HIV medications  
15 on less than a specialty tier, sort of regardless of  
16 what the actual underlying cost of those medicines  
17 were.

18 So I think it's possible that we're in a  
19 symmetric equilibrium in which, you know, no plan  
20 wants to be the plan that's left holding the bag with  
21 the unprofitable patient, but, you know, certainly  
22 theory -- there's a lot of theory and very little  
23 evidence in this area so far, and there are -- you  
24 know, some of the theories are symmetric equilibrium,  
25 some about a -- you know, it was more separate in

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1 Rothschild Stiglitz. So it's an open question, but we  
2 hope to work on it.

3 MS. SAEEDI: So I have a question. If the cost  
4 that you're showing is only the drug cost or also the  
5 cost of everything else that is the patient cost and  
6 if they are correlated and if they are trying to sort  
7 of avoid these customers from just getting -- sign up  
8 just -- not directly because of the drug cost but  
9 because they cost higher...

10 MR. GERUSO: Yeah. So, you know, on average,  
11 drug costs are 20 percent of the patient cost or even  
12 less -- they're among -- conditional on having any  
13 drug use, it's something like 20 percent, and even  
14 among the most unprofitable patients only rise to 40  
15 percent, and we're doing -- in doing our profitability  
16 calculations, we're using all costs -- hospital,  
17 inpatient, outpatient, visits with doctors -- using  
18 all of that to figure out profitability, because  
19 that's what matters to the insurer.

20 To connect what you're asking with a comment of  
21 Sebastian, when we -- when we start trying to figure  
22 out what are insurers responding to, I didn't  
23 really -- I skipped over it, but we show that they are  
24 responding to costs, they are responding to  
25 drug-specific costs, but even netting those things

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1 out, so just controlling for them simultaneously,  
2 they're simultaneously reacting to the profit  
3 incentive sort of conditional on the costs.

4 I think that's something I didn't get across  
5 clearly in the original presentation, but, you know,  
6 we can control very nonparametrically, very flexibly  
7 for cost. You know, drug costs, nondrug costs, we can  
8 put that in there. They're responding to that which,  
9 you know, is interesting, but they're also separately  
10 and without sort of diminishment responding to the  
11 profit incentive.

12 MR. ROSENBAUM: Okay. Our next presentation is  
13 Fernando Luco, presenting Multiproduct Firms: When  
14 Eliminating Double Marginalization May Hurt Customers.

15 MR. LUCO: Perfect. Thank you.

16 Well, first, thank you for having me here.  
17 This paper is joint work with Guillermo Marshall from  
18 the University of Illinois. What we do in this paper  
19 is to think about markets that look very much as what  
20 Paolo was discussing -- talking about an hour ago.

21 What we want to do here is to think about  
22 bilateral oligopolies where upstream and downstream  
23 firms interact with each other and with consumers,  
24 and, in particular, we want to think about vertical  
25 integration in these markets, okay?

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1 And often what we do when we think about  
2 vertical integration is to think about the trade-off  
3 between the efficiency gains that are specific to the  
4 transaction, eliminating double marginalization, and  
5 at the same time, market foreclosure (indiscernible),  
6 that may lead to increasing costs -- increasing the  
7 cost of doing business for some of the rivals, so the  
8 vertically integrated firm.

9 Now, this idea -- and, in particular, that we  
10 often assume to some extent that efficiencies are  
11 going to be realized -- has driven some very important  
12 economies to suggest that we should approve vertical  
13 integration unless there are clear incentives for  
14 foreclosure.

15 However, this is coming mostly from a  
16 literature on single-product firms, and what we do in  
17 the paper is just think about what happens when we  
18 talk about multiproduct firms. And, in particular,  
19 what's going to happen here is that to foreclosure and  
20 to efficiency gains, we are going to add a third  
21 effect that has to do with how partial elimination of  
22 double margins may lead to actual price increases that  
23 may hurt consumers even in the absence of market  
24 foreclosure, okay? So we may have just efficiency  
25 gains, and this third effect may actually lead to

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1 price increases.

2 So to fix ideas, let me start with a super  
3 simple version of the industry that I just show. Here  
4 I have two upstream firms, U1 and U2, that will sell  
5 different products, substitute products, to a retailer  
6 at prices, Omega 1 and Omega 2, and the retailer will  
7 resell the product to consumers at prices P1 and P2.  
8 A super simple framework, okay?

9 And in this setting, what we want to think  
10 about is what happens if you, one, integrate with the  
11 retailer. So the way we've framed the question is,  
12 well, what's going to happen here? We're going to  
13 eliminate double margins for product one. That's  
14 going to lead to a decrease in the unit cost of  
15 product one, Omega 1 is going to decrease, and that  
16 will have two effects.

17 The first one is something that we are very  
18 familiar with, is that a decrease in Omega 1 will put  
19 a downward pressure on the price of product one. That  
20 product is cheaper to produce, so it's going to put  
21 downward pressure on the product -- on the price of  
22 that product, and that is the efficiency effect.  
23 That's what we think of when we are thinking about  
24 eliminating double margins in these type of  
25 industries.

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1 The second effect is sort of the new thing  
2 here, is that together with making product one  
3 cheaper, you're actually making product one more  
4 profitable, so that may lead the retailer to increase  
5 the price of product two to divert demand to product  
6 one, okay? So let me repeat that, because this is a  
7 key part of the paper.

8 So we have a decrease in the unit cost of  
9 product one because of the elimination of double  
10 margins. That leads to a decrease in the price of  
11 product one, but because the prices [sic] are  
12 substitutes, the retailer has the incentives to  
13 increase the price of product two to divert demand to  
14 product one.

15 Now, we're not the first to suggest that this  
16 exists, so, in fact, the literature comes all the way  
17 from Edgeworth, and so this is a reprint in 1925, and  
18 the original paper is from the 1890s or something like  
19 that, where he was talking about taxation -- and  
20 product-specific taxation -- and when he suggested  
21 this path for product-specific taxes, someone replied  
22 that this is one of the horrible things that happens  
23 when math takes over economics, okay?

24 And that's sort of -- people didn't look at  
25 that that much. It was called the Edgeworth paradox,

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1 and it was not until Michael Salinger, in 1991,  
2 brought the data into vertical integration. So for  
3 this reason, we actually call these the  
4 Edgeworth-Salinger effect, and I am going to refer to  
5 that for the rest of the paper.

6 So in this context, what we do in the paper is  
7 to ask whether the Edgeworth-Salinger effect is  
8 something that we should take into account when we're  
9 talking about vertical integration. So we're going to  
10 ask, what is the magnitude of the Edgeworth-Salinger  
11 effect? Should we consider these in merger  
12 evaluation?

13 And, in particular, as you saw in the previous  
14 slide, while efficiency gains seem to drive prices  
15 down, the Edgeworth-Salinger effect seems to drive  
16 prices up, so we call it that these two effects play  
17 with each other.

18 That is going to put us, of course, in a very  
19 rich -- in the context of a very rich literature on  
20 vertical integration, both in theory and empirical,  
21 but our work is more related to the literature on the  
22 Edgeworth paradox.

23 To answer the question, we are going to use  
24 data from the carbonated beverage industry in the  
25 United States. So let me spend 30 seconds telling you

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1 about the industry, and then I will tell you why we  
2 care about it.

3 So in this industry, we have upstream firms,  
4 such as Coca-Cola Company and Pepsi and  
5 Dr. Pepper/Snapple Group, that sells syrup to bottlers  
6 that have exclusive territories, and these bottlers  
7 can -- some of them can actually interact with more  
8 than one upstream firm.

9 So what I mean by that is Coca-Cola bottlers  
10 can bottle for Dr. Pepper. Pepsi bottlers can bottle  
11 for Dr. Pepper. Coca-Cola bottlers and Pepsi bottlers  
12 cannot bottle for Coca-Cola and Pepsi, okay?

13 Now, why do we care about this industry, aside  
14 from the fact that it fits the picture I had at the  
15 beginning? Well, because in 2009 and 2010, both Pepsi  
16 and the Coca-Cola company vertically integrated with  
17 some of their bottlers in the U.S., and this is going  
18 to be very useful for a number of reasons.

19 First, they didn't integrate with everybody, so  
20 that generates variation in particular structure  
21 across the country, and in a subset of the areas  
22 served by the bottlers involved in the transactions,  
23 these bottlers actually had licenses to sell  
24 Dr. Pepper products, okay? So we are going to see  
25 areas where nothing happened, there was no vertical

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1 integration. We are going to see areas where there is  
2 vertical integration, but the bottler didn't have the  
3 license to sell Dr. Pepper. And we are going to see  
4 areas where there is vertical integration, and the  
5 bottler has the license to sell Dr. Pepper, so we can  
6 actually identify the Edgeworth- Salinger effect.

7 A benefit of this case, in particular, is that  
8 we have no evidence of market foreclosure, and that is  
9 going to allow us to have cleaner identification of  
10 the Edgeworth-Salinger effect. This is basically --  
11 because at the moment the transactions took place,  
12 when there was a change in the ownership of the  
13 bottlers, there were termination clauses in the  
14 contracts between the bottlers and Dr. Pepper that  
15 were triggered, and both Coca-Cola and Pepsi went and  
16 reacquired the licenses to continue selling  
17 Dr. Pepper.

18 So they decided to continue producing these  
19 products, and at the same time, while the FTC cleared  
20 the transactions, subject to a number of nonbehavioral  
21 remedies related to how information regarding  
22 Dr. Pepper could be used by the vertically integrated  
23 firm, but market foreclosure was never really a major  
24 presence.

25 So what is the data here? We have some really

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1 they were actually also serving Dr. Pepper, producing  
2 Dr. Pepper products. So in the end what we have is,  
3 like, three maps that we are overlapping to pin down  
4 in which of these areas each of the effects takes  
5 place.

6 So let me show you the data. Here I have maps  
7 of two parts of the U.S. The map on your right --  
8 your right -- no, the map on your left is the  
9 northeastern United States, and the map on the right  
10 is the Houston MSA, and as you can see, it's  
11 color-coded.

12 So blue areas are areas where nothing happened.  
13 There was no vertical integration in those areas.  
14 Green areas are areas where there was vertical  
15 integration, but the bottler did not have the right to  
16 sell Dr. Pepper. And orange areas are areas where  
17 there was vertical integration and the bottler did  
18 have the right to sell Dr. Pepper. So that means that  
19 we can use, with the in-store product variation, cost  
20 of vertical integration to identify both the  
21 efficiency gains associated to vertical integration  
22 and the Edgeworth-Salinger effect.

23 The Houston MSA is useful to illustrate two  
24 things. First of all, as you can see, the whole MSA  
25 is treated in the sense that there was vertical

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1 novel data, some data that you know very well, so I am  
2 going to be very brief about it. So the part that you  
3 know very well is the IRI marketing data set, that we  
4 have weekly scanner data for the years 2007 to 2012  
5 across a number of regions in the U.S. Our  
6 observation here is going to be a  
7 store-week-brand-size combination, and we are going to  
8 focus on brands that have at least 0.5 percent of the  
9 market. So that's going to leave us with 105 products  
10 that will -- and that's, for example, a 67-ounce  
11 bottle of diet Coke sold in a particular store in a  
12 particular week.

13 Now, where are things going to get novel? We  
14 have an industry publication called Beverage Digest  
15 that produces maps of the U.S. with the territories of  
16 each of the bottlers for both Coca-Cola and Pepsi,  
17 okay? So think of these as you have a map of the U.S.  
18 with state boundaries, forget about the boundaries,  
19 and you put the territories of the bottlers.

20 From there, we are going to be able to identify  
21 which areas were affected by vertical integration, and  
22 we're going to intersect that, if you want, with FTC  
23 documents that identify, in the areas where these  
24 bottlers -- where the bottlers involved in the  
25 transactions were producing, in which of those areas

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1 integration affecting the whole MSA, but only one of  
2 the counties in the MSA actually experienced the  
3 Edgeworth-Salinger effect. So this is going to sort  
4 of define at what level we are going to be defining  
5 treatment, okay?

6 And later, I am going to actually reduce the  
7 sample and we will do this some sample analysis using  
8 neighboring counties that were differentially affected  
9 by treatment, and as you can see, the Houston MSA is a  
10 good example of that.

11 Okay. So, of course, this means that what I'm  
12 doing here is I'm going to follow a  
13 difference-in-difference research design exploiting  
14 this variation of -- the within-store product price  
15 variation, cost with vertical integration, and  
16 together with that, there are a number of  
17 identification threats that we have to take into  
18 account.

19 Some of them, for instance, are what happens if  
20 the Coca-Cola Company, at the point -- at the time of  
21 the transactions, also changes the way it does  
22 advertising or it changes its (indiscernible) policy  
23 or things like that. So concerns like that we can  
24 address using finite structure of our data.

25 Other concerns that are more directly related

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1 to the research design has to do with differential  
2 preference, for example, and we -- in the paper, we  
3 explore those using both summary statistics, and I am  
4 going to show you later a dynamic difference-in-  
5 difference version of our estimation that basically  
6 shows that we don't have differential preference,  
7 okay?

8 So let me jump directly into the results. So  
9 the most -- I'm sorry, no, I forgot one. Let me show  
10 you the equation first. So we're going to study how  
11 vertical integration affects prices, and we are going  
12 to divide these in two parts. So first we're going to  
13 see how vertical integration affects prices of  
14 Coca-Cola and Pepsi products when these are bottled by  
15 a vertically integrated bottler. That is, we want to  
16 estimate the efficiency effect of vertical  
17 integration.

18 So in this estimation -- in this equation,  
19 that's going to be captured by the coefficient B-own,  
20 that we're referring to owned brands, as the brands  
21 owned by Coca-Cola and Pepsi, when these brands are  
22 bottled by other vertically integrated bottler.

23 We are also going to distinguish the effect of  
24 vertical integration on Dr. Pepper brands that we call  
25 the Edgeworth-Salinger effect, and to do that we're

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1 going to have this B-Dr. Pepper coefficient that's  
2 associated with Dr. Pepper products that are bottled  
3 by other vertically integrated bottler.

4 And then in the third line we have a rich set  
5 of fixed effects that is meant to address the  
6 identification concerns that we have in mind. Some of  
7 them, for instance, firm with fixed effects, for  
8 example, are going to allow us to tackle changes that  
9 may happen at the parent firm level. Then we are  
10 going to have county with fixed effects to address  
11 local shocks. We are going to have store and county  
12 product seasonal fixed effects, that they can take  
13 into account seasonal effects and local conditions.

14 And the other thing, we are going to use that  
15 treatment at the county level to class our standard  
16 errors, but, of course, we have done a lot of  
17 robustness in all estimations, okay, and the results  
18 don't really change.

19 So now, yes, let me go into the results of the  
20 paper. So this is the most important table, so  
21 everything that comes later is digging deeper into  
22 what is going on here. So if you want to keep one  
23 result in mind, keep this one. So I have two  
24 coefficients here. The first coefficient is the  
25 average effect of vertical integration on own brands;

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1 that is, the average effect of vertical integration on  
2 Coca-Cola and Pepsi products when these products are  
3 bottled by a vertically integrated bottler.

4 What we have here is the prices of these  
5 products decreased 1.4 percent, so this is a  
6 manifestation of the impact of efficiency gains on  
7 prices. So this is the effect of eliminating double  
8 margins for Coca-Cola and Pepsi products.

9 At the same time, we have that prices of  
10 Dr. Pepper products went up by 3.9 percent when  
11 bottled by a vertically integrated bottler. This is  
12 the Edgeworth-Salinger effect, okay? So the price  
13 of -- the price of Dr. Pepper products are going up by  
14 almost 4 percent, and this is consistent with what  
15 Edgeworth brought out and what Salinger brought to  
16 vertical integration.

17 Now, I note that Andrew is going to bring out  
18 these later, so there is a back-of-the-envelope  
19 calculation here. If you weight these coefficients by  
20 premerger market shares, we still get that the average  
21 price paid decreased by 0.9 percent, okay? So I'm not  
22 saying that this is -- like, the merger is not  
23 welfare-increasing or anything like that. I'm just  
24 saying the Edgeworth-Salinger effect is relevant.  
25 It's huge. It's the same order of magnitude as the

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1 efficiency gains, and it definitely has an impact on  
2 prices, okay?

3 If you look at what happens with -- what  
4 happened with listed prices, not paid prices, we get  
5 the prices increase on average by 1.8 percent, but  
6 what I -- but the table that I like -- I really like  
7 is this one, where we allow all these coefficients to  
8 vary by parent firm. So we estimate different effects  
9 for Coca-Cola and Pepsi.

10 And what you see here is a number of things.  
11 First, prices of Coca-Cola products and Pepsi products  
12 went down by 1 and 2.1 percent following vertical  
13 integration, and prices of Dr. Pepper brands went up  
14 by 3.1 and 4.2 percent following vertical integration.  
15 So both firms or bottlers of both firms reacted in the  
16 same way. So the effects are going in the same  
17 direction because they are basically reacting to the  
18 same incentives, the same changes in incentives.

19 One could be tempted -- and I was tempted -- to  
20 say that the firm that had the largest Edgeworth-  
21 Salinger effect, Coca-Cola, for 0.2 percent, also had  
22 the smallest efficiency effect that would be a  
23 consequence, for instance, of price complementarities;  
24 however, we cannot reject the equality of the 1  
25 percent and the 2.1 percent. We can reject the

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1 equality of the 4.2 and 3.1 percent, okay?

2 So the take-away from this slide is both firms  
3 are reacting in the same way to the changes in pricing  
4 incentives that are caused by partial elimination of  
5 double margins.

6 When you look at this over time, so this is the  
7 dynamic difference-in-difference estimation, you see  
8 other things. First, why do we need this? For two  
9 reasons. First, we want to address the question of  
10 whether or not there are differential preference. And  
11 as you can see, that's not the case in the preperiod,  
12 but second, you want to see when the effects started  
13 to take place, and what we see here is that the  
14 effects started to take place after the transactions,  
15 and it particularly was -- the effect was  
16 long-lasting. So I have no idea what happened with  
17 the second-to-last point over there, but basically we  
18 have very persistent effects over time.

19 Then -- so Ali suggested to these a couple of  
20 weeks ago, we repeated the analysis at the product  
21 level, okay, so here what we're doing is we're  
22 estimating one coefficient for each of the products in  
23 the sample that at some point, somewhere, were  
24 affected by vertical integration. If the story of the  
25 Edgeworth-Salinger effect is true, then we should see

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1 that Dr. Pepper products have their distribution of  
2 coefficients to the right of zero, because we're  
3 expecting prices of Dr. Pepper brands to increase, and  
4 that is precisely what we see here with two  
5 exceptions.

6 With own brands, things are a bit trickier,  
7 because we say, well, the efficiency effect is going  
8 to drive those prices down, but the Edgeworth-Salinger  
9 effect may actually drive those prices up once you  
10 take into account price complementarities, and what we  
11 see here is that it's like half and half. So some of  
12 the owned brands have price decreases; some of the  
13 owned brands have price increases.

14 We can re-estimate these for quantity  
15 regressions, and when you limit the analysis to  
16 products that in this regression have significant  
17 coefficients on vertical integration, we get  
18 elasticities between -- the minimum elasticities are  
19 between minus one and minus 3, which is in line with  
20 what people have found before in this literature.

21 So let me spend -- sorry, no, I forgot this.  
22 So this is one of my favorites. One of -- okay, so  
23 what we do here is to do a subsample analysis where we  
24 drop all counties that were exposed to the  
25 Edgeworth-Salinger effect. So we repeat the analysis

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1 looking only at counties that either did not  
2 experience vertical integration or experienced  
3 vertical integration but didn't have the  
4 Edgeworth-Salinger effect.

5 So what we want to do is to compare the  
6 efficiency gains of vertical integration to what  
7 happens when you put together the efficiency gains  
8 with the Edgeworth-Salinger effect, and what you see  
9 here in the second column is that when you only have  
10 the efficiency gains -- remember that there's no  
11 foreclosure here -- prices went down by 2.4 percent.

12 And in the first column, I replicated the  
13 original regression, the first regression I show you,  
14 and you have to remember that the weighted effects for  
15 that regression was a decrease in prices of 0.9  
16 percent. So we're talking about a huge effect of the  
17 Edgeworth-Salinger -- a huge Edgeworth-Salinger effect  
18 on prices when you include it in the analysis. You go  
19 from the 2.4 percent reduction to 0.9 percent.

20 Okay, let me talk about the additional things  
21 that we have done in the paper. The first thing we  
22 did was to look at bordering counties. So that's  
23 important because we want to have good controls for  
24 the counties that were exposed to either vertical  
25 integration or vertical integration and the

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1 Edgeworth-Salinger effect. So we limited the analysis  
2 just to bordering counties that were differentially  
3 affected by vertical integration, and we find exactly  
4 the same.

5 Second, this is an industry where sales are  
6 very important. We see sales all the time. So we  
7 have -- we redid the analysis both just on regular  
8 prices and just on sales, and we find larger effects  
9 on regular prices, both for efficiency and the  
10 Edgeworth-Salinger effect, but also significant, very  
11 large effects when you look at sales prices. So we're  
12 basically getting the same results.

13 We can play quite a bit with alternative and  
14 more extreme versions of the fixed effects, basically  
15 triplicating the number of fixed effects or something  
16 like that, things like that, and we still find the  
17 same effects. So if there is something that is really  
18 robust coming out of this story, it is the  
19 Edgeworth-Salinger effect is incredibly robust, it  
20 does exist, and we should consider it when we're  
21 talking about vertical mergers.

22 There are, however, some alternative  
23 explanations for our findings. So the first obvious  
24 one is market foreclosure, and I already spend some  
25 time saying why, in this particular case, we don't

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1 think that foreclosure is a concern.

2 The second one that was suggested by Paolo a  
3 month ago or something like that was, well, what if  
4 the bottlers are capacity-constrained, because you  
5 have a decrease in the input costs of Coca-Cola and  
6 Pepsi products, and if you are capacity-constrained, a  
7 natural reaction to that is to increase the price of  
8 Dr. Pepper to free capacity to produce more owned  
9 brands.

10 There are two things there, but the most  
11 important one is that is probably a very good  
12 explanation for short-run effects. The economic  
13 difference-in-difference results suggest that the  
14 effect is actually quite persistent over time. The  
15 other thing is that it seems like expanding capacity  
16 is not that expensive anyway in the long run.

17 Finally, another thing that could be happening  
18 here is, well, what happens if, instead of the  
19 Edgeworth-Salinger effect, what's going on here is  
20 that Dr. Pepper bottlers, in nonvertically integrated  
21 areas, actually change their frequency of sales. And  
22 in the paper we actually ruled that out, and what we  
23 show is that Dr. Pepper bottlers in vertically  
24 integrated areas actually increase a little bit the  
25 frequency of their sales. So we ruled that out, also.

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1 So let me finish with this. We haven't said  
2 the other vertical integration actually is a trade-off  
3 between efficiency and foreclosure. What we say is if  
4 we have multiproduct firms, we have to take into  
5 account the Edgeworth-Salinger effect, and this is, to  
6 my knowledge, the first paper to actually put a number  
7 on the Edgeworth-Salinger effect.

8 What we show is that it counteracts the impact  
9 of efficiency gains to a large extent, and that's the  
10 reason why we believe it should be part of our  
11 standard toolkit when one thinks about vertical  
12 integration.

13 Thank you.  
14 (Applause.)

15 MR. ROSENBAUM: The paper will be discussed by  
16 Andrew Sweeting.

17 MR. SWEETING: Okay, thank you. This is -- I'm  
18 very glad to be discussing this paper. It's a very  
19 clear paper. I think it's a very important paper from  
20 a policy perspective. Fernando did a great job of  
21 explaining what's in there, but just to kind of  
22 reiterate on the main points, right, so they're  
23 looking at this setup where they're focusing on kind  
24 of three firms, so Coca-Cola, Pepsi, and Dr. Pepper,  
25 and they have this geographic variation, okay?

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1 So they are going to see Coke and Pepsi  
2 vertically integrating with some of the most important  
3 bottlers, and then this is going to have different  
4 effects geographically on Dr. Pepper depending on  
5 whether those bottlers also distribute Dr. Pepper in  
6 those particular counties.

7 Okay. So the results, which obviously Fernando  
8 discussed, is that they see the vertical integration  
9 is associated with a lowering of the prices for Coke  
10 and Pepsi's products. On the other hand, they're  
11 seeing that the retail prices of Dr. Pepper's products  
12 tend to go up, okay, and they're noticing that the  
13 percentage increase in price in the second point is  
14 greater than the percentage reduction in the first  
15 point.

16 Okay. So there's just lots and lots of things  
17 to like in the paper. So the theory presented is very  
18 simple, and I think that kind of makes it very  
19 plausible for a lot of different settings. So the  
20 theory they developed, which Fernando actually didn't  
21 say that much about, is in the kind of extreme  
22 simplest form in the sense of the wholesale prices  
23 coming from the syrup makers held fixed, then they're  
24 just going to focus on the incentives once there's  
25 vertical integration to play with the downstream

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1 prices.

2 One reason why this is a good setting to look  
3 at is the beverages are pretty high-margin products,  
4 so we can think the small percentage changes in the  
5 margins are going to have potentially quite large  
6 effects on prices. The empirical analysis is very  
7 transparent. The magnitudes are pretty consistent  
8 across different specifications, and I think it's  
9 particularly nice that they're consistent across  
10 Coca-Cola and across Pepsi.

11 The authors actually draw a very clear policy  
12 conclusion. So, on average, the prices, at least when  
13 you're looking at the nonquantity-weighted form, go up  
14 after mergers, and, therefore, they say, you know, a  
15 standard thing that antitrust authorities should look  
16 at when they're looking at vertical mergers, even if  
17 there's not a risk of foreclosure, is this kind of  
18 Edgeworth-Salinger effect.

19 Okay, so here are kind of my main comments. So  
20 the paper is kind of very clean, and it's so easy to  
21 read because it's kind of short and to the point and  
22 you get to the results kind of super, super quick. On  
23 the other hand, there's -- I think, you know, the  
24 paper would benefit and the reader would benefit from  
25 having kind of more discussion of the context, okay?

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1 So in this industry, what we know is that  
 2 there's a history of bottlers kind of integrating with  
 3 upstream firms and de-integrating with upstream firms  
 4 and legal battles involving people who are bottling  
 5 for other syrup makers, and before this vertical  
 6 integration took place, one relevant thing is that  
 7 Coke and Pepsi owned substantial proportions of these  
 8 bottlers that they ended up integrating with.

9 Okay. So at least one interpretation of this  
 10 is that the Edgeworth-Salinger effects that are going  
 11 to be identified are probably going to be  
 12 underestimates of the true incentives, because these  
 13 incentives should already have been at play before the  
 14 vertical integration that they look at.

15 A second relevant factor which Fernando  
 16 mentioned, the fact that at the time of the vertical  
 17 integration, Coke and Pepsi signed new bottling  
 18 license agreements with Dr. Pepper for these  
 19 distribution areas. I think there needs to be a  
 20 little bit maybe more discussion about what these kind  
 21 of long-term contracts that Dr. Pepper signed, how  
 22 that affects how we should think about the model,  
 23 right?

24 So the way the model and the work is currently  
 25 presented, you would kind of get the impression that

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1 these price changes are basically inflating a lot of  
 2 harm on Dr. Pepper, whereas obviously Dr. Pepper was  
 3 willing to sign these agreements. And one thing I  
 4 went -- I was having a look at Dr. Pepper's earning  
 5 calls around the time that the agreements were signed,  
 6 and there they -- you know, and maybe  
 7 unsurprisingly -- they were portraying the loss of  
 8 these agreements as being very good for Dr. Pepper.

9 They talked about kind of performance targets  
 10 that were in these contracts for Coke and Pepsi, and,  
 11 in particular, what -- they referred to something --  
 12 which I wasn't quite sure how to interpret -- which  
 13 was the repatriation of Dr. Pepper volume from the  
 14 bottlers to Dr. Pepper.

15 Okay, I'm not quite sure how to interpret that,  
 16 but what it makes me think is these contracts  
 17 obviously are connected with partly what Dr. Pepper  
 18 saw its future strategy for the next 20 years as  
 19 being, and also just the length of the contracts and  
 20 the very large lump sum transfers of hundreds of  
 21 millions of dollars that went on probably makes you  
 22 think that these incentives within these contracts  
 23 wouldn't simply involve, you know, pure linear  
 24 pricing, even if there was some margins on the  
 25 upstream being charged.

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1 Okay. I think it would be good to think more  
 2 specifically about also what we see going on in areas.  
 3 You know, in the control group here are both areas  
 4 where Dr. Pepper is vertically integrated and areas  
 5 where Dr. Pepper is distributing products through  
 6 bottlers who are not owned by Coke and Pepsi, and I  
 7 think it may be interesting to separate out those  
 8 different areas to maybe understand, you know, were  
 9 there some things that Dr. Pepper was implementing at  
 10 the same time that maybe went through its own bottlers  
 11 but not through independent bottlers.

12 You know, a lot of branding and promotion here  
 13 is going to be national, so that even if it isn't --  
 14 even when there's this separation across counties in  
 15 the vertical structure, it may be the case that some  
 16 things that happen in the treated counties are going  
 17 to be playing over to effects we see in the control  
 18 group.

19 Obviously, one thing we observe here is retail  
 20 prices, right? So the model Fernando put up on the  
 21 board was vertical integration between manufacturers  
 22 and retailers. Here we have vertical integration  
 23 really between manufacturers, bottlers, who were then  
 24 selling on to retailers, who then sell on to final  
 25 consumers, and what we observe is retail prices, but

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1 retail is kind of excluded from the picture here.

2 Now, I think probably the justification for  
 3 doing this is that carbonated beverages are kind of a  
 4 classic example of direct-to-store delivered products,  
 5 where the bottlers in this case would maintain a lot  
 6 of control over how stuff's presented in the store,  
 7 you know, what goes on different shelves, and so on.  
 8 But I think at least in terms of considering how we  
 9 want to think about correlations and possible  
 10 residuals across counties, when we have the same  
 11 retailers operating in multiple counties across these  
 12 borders, I think is relevant.

13 Okay. So Fernando already mentioned this, so I  
 14 would like to see kind of more focus on quantities,  
 15 right? So if we're just looking at price changes,  
 16 obviously different products are sold in different  
 17 quantities, and for the same product over time, more  
 18 is going to be sold on sale than when it's not on  
 19 sale. So I do really think we could learn -- you  
 20 know, it's interesting to look at what happens to  
 21 quantities if we want to start thinking about welfare.

22 It's also -- if you look at actually what  
 23 happens in the quantity predictions, if you look at  
 24 kind of the mean residual for Dr. Pepper products  
 25 compared with Coke and Pepsi products, it's actually

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1 the case that the Dr. Pepper products are gaining in  
2 quantity relative to the Coke and Pepsi products, and  
3 that's obviously something that's quite different from  
4 what you would see from the price regressions.

5 As Fernando mentioned, it is also the case that  
6 in these vertically distributed areas, Dr. Pepper  
7 actually goes on sale more often after the vertical  
8 integration than before the vertical integration. And  
9 here you can actually see that, at least in terms of  
10 national volume-related market share, Dr. Pepper's  
11 market share is not going down after these agreements  
12 take place.

13 Okay. So I'd also kind of push maybe on  
14 examining the distribution of prices more rarely. So  
15 when you're using the IRI or the Nielsen data, you  
16 know, it's very easy to get kind of 37 million  
17 observations. I'd just be kind of knocked dead by  
18 that, and, you know, just getting -- kind of computing  
19 the fixed effects regression is going to take you a  
20 lot of time.

21 But on the other hand, I think it's also  
22 important to think about, you know, what are actually  
23 the prices being charged in the store and how they may  
24 differ from the kind of average revenue measure that  
25 you tend to get in these scanner data sets, right?

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1 So here I was partly thinking about this  
2 because -- so the University of Maryland is a  
3 Pepsi-only campus, but they -- you know, this is a  
4 kind of example of state-assisted foreclosure in this  
5 case, but one thing they do sell is Dr. Pepper, okay?  
6 And you might have thought that because of the absence  
7 of Coke, it would actually make the incentives to  
8 engage in Edgeworth-Salinger pricing kind of  
9 particularly strong, but at least everywhere that I've  
10 seen on campus, Coke -- Pepsi and Dr. Pepper are sold  
11 at exactly the same price.

12 Similarly, when I was wandering around grocery  
13 stores this weekend trying to think about how  
14 Dr. Pepper and Pepsi are actually priced, wherever I  
15 went, whether things were on sale or were not on sale,  
16 Pepsi and Dr. Pepper were being charged at exactly the  
17 same price in Montgomery County, which is one of, I  
18 believe, these vertically integrated counties.

19 Okay. So, finally, obviously, you know, this  
20 is a very kind of reduced-form paper in kind of a good  
21 sense, partly because that's buying us a lot of  
22 transparency. I think a structural exercise could add  
23 insights here, and really that comes in two kinds.

24 So you could write another paper which kind of  
25 used a structural model to really start thinking hard

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1 about the welfare effects, but I think also just maybe  
2 taking the theory kind of more seriously in terms of  
3 what a model would imply about which products of Pepsi  
4 and Dr. Pepper are particularly close substitutes. In  
5 terms of what are not close substitutes to products  
6 being sold, for example, by Coke, where Pepsi and  
7 Dr. Pepper are the vertically integrated pair, I think  
8 might shed a light, right?

9 Are we seeing the price increases on the right  
10 kinds of products? Given the particular distribution  
11 of tastes for those products and a particular kind of  
12 vertical integration we're seeing, I think would  
13 provide nice confirmation that the story -- of the  
14 story that's going on.

15 Okay. So, in summary, I think this is a really  
16 good paper. I think it should have implications for  
17 policy. I think the authors have lots of scope to  
18 probe, using this data, kind of deeper into these  
19 issues, which have received very little previous  
20 attention, but are clearly very important.

21 MR. ROSENBAUM: Thanks, Andrew.

22 We have time for one or two questions.

23 MALE AUDIENCE MEMBER: Just a question around,  
24 so you showed the kind of effects if Coke and Pepsi  
25 were the ones who integrated with the bottlers, so we

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1 see an overall back-of-the-envelope price decrease of  
2 1 percent, but I'm thinking that if Dr. Pepper was the  
3 one who was integrating, and do you have some kind of,  
4 like, counterfactuals or some kind of thoughts that  
5 you have put on this?

6 MR. LUCO: So it definitely depends -- so the  
7 outcome will depend on the different market shares,  
8 for sure. We don't have anything on that. So that re  
9 -- that's what Andrew is saying, if you push these in  
10 the structural direction, we can actually go and do  
11 that kind of counterfactual, but we haven't done that.

12 MALE AUDIENCE MEMBER: Thanks. That was great.  
13 I was just wondering, I'm having a hard time  
14 differentiating benefits from vertical integration  
15 from benefits from anything else that might increase  
16 the bottlers' profits, like improving the delivery  
17 system from Coke, Coke's delivery system of whatever  
18 it is they deliver to the bottlers, compared to  
19 Dr. Pepper. Wouldn't that have the same effects, and,  
20 therefore, should we look askance at anything that  
21 reduces costs, not just double marginalization?

22 MR. LUCO: Okay, let me see if I understood the  
23 question right. You would get exactly the same  
24 results if we just talk about a retailer that faces a  
25 decrease in the cost of one of the products itself.



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1 That's absolutely true. In this particular case, it  
2 is caused by vertical integration, so that's why we're  
3 pushing in that direction. I don't know if that  
4 answers your question.

5 MALE AUDIENCE MEMBER: Well, I'm just sort of  
6 wondering -- if we think we should be incorporating  
7 this effect into the analysis of vertical integration,  
8 I'm just wondering whether if some -- if Dr. Pepper  
9 came to the FTC and complained that, hey, Coca-Cola  
10 came up with a better way of distributing stuff, and  
11 because of that, the retailers or the bottlers no  
12 longer want to carry my product anymore, should we  
13 say, well, gee, that consumer welfare has gone down or  
14 those losses may outweigh the gains from the savings  
15 of the costs, and, therefore, we should block these  
16 cost reductions.

17 MR. LUCO: It's a tricky question. Let me put  
18 it in this way. Again, any changes in relative costs  
19 are going to cause these type of results. Whether  
20 these are -- whether technological changes or  
21 antitrust concerns, I would say the answer is no. In  
22 this particular case it's because vertical integration  
23 is causing the change in pricing incentives is what I  
24 would be worried. Yeah, that would be it.

25 (Applause.)

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1 MR. ROSENBAUM: Thanks again to Igal for  
2 putting that session together and thanks to all the  
3 presenters and discussants.

4 We will take a 20-minute break, and then we  
5 will come back for Igal's keynote address.

6 (A brief recess was taken.)  
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#### 1 KEYNOTE ADDRESS

2 MR. WILSON: All right. Thanks, everybody. I  
3 think we're starting to run a tad long, so I'm going  
4 to move towards introducing our final panel or our  
5 final session of the evening. This will be the -- our  
6 second keynote of the conference. So Dr. Igal Hendel  
7 will be talking to us about health insurance market  
8 design. Igal is the Ida C. Cook Professor in the  
9 Department of Economics at Northwestern University.

10 His research interests are in applied micro and  
11 industrial organization. Some of his recent work has  
12 touched on markets with asymmetric information and  
13 involves the estimation of dynamic consumer behavior.  
14 In addition, he has served in an editorial capacity on  
15 the board of editors at the AER and previously was a  
16 co-editor both at the RAND Journal of Economics and an  
17 Associate Editor of the JIE. Thanks very much.

18 (Applause.)

19 MR. HENDEL: Thanks, delighted to be here.  
20 Thank you for having it. It's a great conference. I  
21 really enjoyed all the papers so far.

22 So what I'm going to do is -- I'm going to  
23 promise you that it's going to be helpful, you know, I  
24 agree that this is policy-relevant. It's not really  
25 antitrust-related, but, you know, you are going to

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1 tolerate it.

2 It's going to be mostly going over what I've  
3 been doing in the last couple of years, I'm going to  
4 hopefully be doing in the next couple of years, and it  
5 has to do with the design of insurance marketplaces,  
6 exchanges, right? So they are very -- you know, they  
7 are in the news lately every couple of -- every couple  
8 of weeks, they come back again, and so what do we mean  
9 by exchanges?

10 You probably know, you don't need much  
11 explanation, but they have been designed in many  
12 places, Switzerland, Netherlands, and so on, and what  
13 it means is some kind of rules for opening a market.  
14 Typically they involve annual contracts, free entry,  
15 some pricing restrictions, some minimum coverage, like  
16 we saw two papers back, and a well-defined product,  
17 you know, or products, you know, 60, 70, 80 percent  
18 actuarial value, so the customers know what they are  
19 getting -- subject to some, you know, tricks played by  
20 companies -- and that way they can compare prices that  
21 they find in the marketplace.

22 So what are we going to be -- so what we looked  
23 at in the past was at pricing restrictions, at prices,  
24 how do they affect participation, adverse selection,  
25 and so on. As you know, again, if you -- you know, if

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1 you watch some TV or, you know, you look at the news  
2 online, there is -- all the time there is replacing  
3 and -- you know, with alternative plans, better way --  
4 what is it, the -- empowerment and employment and  
5 accessibility and whatever, by a bunch of Republican  
6 Senators.

7 And what all these proposals have in common is  
8 that they repealed the participation mandate, and so  
9 it's perceived as infringing freedom or -- I don't  
10 know what -- you know, whatever it is perceived, they  
11 want to get rid of the mandate, and some of the  
12 proposals, you know, the -- they propose an  
13 alternative, you know, participation mechanism that  
14 I'm going to try to evaluate in a moment, and some of  
15 the proposals also get away with the preexisting  
16 conditions and the pricing of those conditions.

17 So basically what we are doing in the project I  
18 am going to describe is sort of play with these rules  
19 and simulate the market when it changes rules to try  
20 to see how they impact allocation and the coverage in  
21 the market.

22 So what are the main economics behind the  
23 design of these contracts? Well, it's two types of  
24 risks, you know, that were, you know, discussed  
25 earlier today. One is the type itself, right? So you

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1 may get a condition and you may need insurance for  
2 that -- you know, those conditions. The other one is  
3 that that type is changing over time, so one, let's  
4 call it, a reclassification risk, that over time your  
5 type is changing, and you would like insurance against  
6 that.

7 The other risk is conditional on whatever your  
8 type is. You want insurance for the distribution of  
9 health expenses conditioned on your type. So that  
10 generates two issues.

11 One is reclassification of risk if the rules of  
12 the exchange are such that health conditions can be  
13 priced, right? So if health conditions can be priced,  
14 there is no pooling, everybody gets their own  
15 individualized price. In theory, there is going to be  
16 100 percent participation, 100 percent trade, right?  
17 There is no adverse selection because you have an  
18 individual price for you. But if that happens, it  
19 means as you age, you are going to be facing random  
20 premiums, and that is, you know, welfare-compromising.

21 Now, on the other hand, if you prevent  
22 discrimination, you're going to, you know, reduce or  
23 eliminate reclassification risk. Now, if your  
24 condition cannot be priced, great, you are insured  
25 against that risk, but on the other hand, if I'm

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1 priced by the average and I'm in better health than  
2 the average person, well, I may opt out of the market  
3 and may buy suboptimum insurance, be underinsured. So  
4 that's -- that potentially could generate adverse  
5 selection. So these are kind of the main two forces  
6 affected by the pricing rules in the market. So there  
7 is a tension, right? So the more you lower pricing,  
8 the more reckless we get you on risk and the less  
9 adverse selection in the market.

10 The ACA, Obamacare, went to an extreme of fully  
11 banning the pricing of health conditions, so fully  
12 eliminating reclassification of risk, at the potential  
13 cost of generating adverse selection, and, you know,  
14 we do see some, or at least in the numbers from the  
15 Massachusetts Exchange from before, that the lower  
16 coverage were the most popular insurance plans.

17 So one question that one may want to ask is,  
18 well, to what extent should health conditions be  
19 priced? So we trace them kind of frontier, that if  
20 you fully ban them, you become reclassification risk,  
21 and you may induce adverse selection. If you fully  
22 allow them, you (indiscernible) and you induce adverse  
23 selection.

24 Now, how do we answer or how did we answer that  
25 question? Well, we want to compute welfare, and the

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1 answer is going to depend on generating an equilibrium  
2 from some population -- I am going to describe in a  
3 second what did we use for that population -- on which  
4 we want preference, preference to our risk. We want  
5 to know a distribution of types. So think about this  
6 being the market, I would like for each you to know  
7 your type of health type. And I also would like to  
8 know the distribution of health expenses that you face  
9 given your type and how those expenses change over  
10 time, so that these are basically the main  
11 ingredients.

12 When I have all that, I can compute the amount  
13 for each person in the market. I can, you know,  
14 generate some premium, personally breaking even, see  
15 who joins, see if those who are losing money, making  
16 money, and so on, until we convert to some notion of  
17 equilibrium.

18 Once we have that equilibrium prediction, we  
19 can compute, you know, how much surplus is generated  
20 in the market. And, again, what would be the  
21 exercise? The exercise would be we try different  
22 pricing conditions to see where in that frontier we do  
23 an adverse selection and reclassification of risk  
24 would you maximize welfare. So that's what I'm going  
25 to show you in a second, what we found.

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1 That previous question we answered in the  
2 context of studying contracts, one-period contracts  
3 like -- like in the ACA, but we can try, like in other  
4 places, like Chile or Germany, to see what would be  
5 the welfare consequences of long-term contracts. So  
6 both now that insurance companies are committing o  
7 insure you for one period, suppose that they sell your  
8 contract since you are, you know, 32, until you are  
9 65, when you go into Medicare, and the idea is that  
10 that policy could, in principle, guarantee  
11 reclassification of risk from that period onwards, but  
12 at the same time, if the insurance company could price  
13 your observables, could overcome adverse selection.

14 So the question we want to answer is, can we  
15 get outside that frontier that I told you earlier,  
16 between reclassification risk and adverse selection,  
17 by using long-term contracts as opposed to one-period  
18 contracts. And the answer to evaluating welfare under  
19 long-term contracts is going to depend, again, on  
20 preferences of this population, the distribution of  
21 their health type, and how they transition over time.

22 I'm going to say if we have those  
23 ingredients -- and I am going to tell you in a second  
24 where we get those ingredients -- we can simulate  
25 optimal contracts, and we can compute welfare. So

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1 that's basically what I am going to tell you later on.  
2 And, finally, repeal and replace. So as you  
3 may remember, a couple of months ago, a proposal of,  
4 you know, repealing or replacing -- I don't know what  
5 it was -- at the House of Representatives entailed  
6 removing the mandate and instead relying on  
7 participation by 30 percent penalty of premiums when  
8 somebody didn't have continuous coverage, right?

9 So it's not a penalty for being outside, right?  
10 So there is no infringement on freedom. If you want  
11 to be outside the market, be outside the market, but  
12 if you change your mind, you're going to be penalized  
13 by a 30 percent extra premium for coming back.

14 So the Senate Bill had a different inducement  
15 mechanism. It was, again, full freedom. You don't  
16 want to participate, don't participate, but if you  
17 decide to come back because you have got a condition,  
18 it is going to be six months of waiting period to be  
19 covered. Both alternatives -- so, and that one, if  
20 you remember, it was McCain who voted it down with,  
21 you know, one finger, so it didn't go forward.

22 So both alternatives to enhance participation,  
23 it create dynamics, right, because now we have a state  
24 variable. So your choices today depend on what you  
25 did last period. So it's not that easy. It's not

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1 that easy as solving a simple static equilibrium.

2 So although contracts are going to be yearly,  
3 the choice of the consumer today affects their state  
4 in the future, so we have to solve for a dynamic  
5 problem to predict demand, which together with cost is  
6 going to general that equilibrium in that market.

7 So the policy question here, in the context of  
8 this one-year contract, but with consumer dynamics, is  
9 going to be, well, which penalties are better? So how  
10 do you want to induce participation if you get rid of  
11 the mandate?

12 And to answer the question -- you can guess by  
13 now, because I'm repeating myself all the time -- what  
14 we know is preferences, we need total risk, we need  
15 the transitions across health type, and a distribution  
16 of health types, and that's what I want to tell you in  
17 five minutes or maybe ten minutes, how to, you know,  
18 get those ingredients from data that companies have  
19 been more willing lately to share, and once you have  
20 that, we can simulate other either different pricing  
21 groups in a static exchange or one-period contracts  
22 that generate demand dynamics or fully dynamic  
23 contracts in the exchanges.

24 And, again, I am not going to repeat myself.  
25 You know it by now. I can ask you by the end of the

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1 talk what do you need, what are the ingredients, and I  
2 am sure you are going to know. So these are the  
3 ingredients.

4 So what did we use? So what we had is data  
5 from a large company. Most of you have seen, you  
6 know, prior presentations, so you already know the  
7 data, but let me just highlight what I think is  
8 interesting about that data, and what's interesting  
9 is -- and it's not unique to our data, so, again,  
10 other people have used, like, core Microsoft data.

11 And the key is that the data contains for each  
12 person in that population their diagnostics for at  
13 least a year. Here, it was a little bit more. If an  
14 employee stayed longer, we see the trends of how their  
15 health evolved over time because we know their claims  
16 data. We know their ICD-9 codes. So we know really  
17 what they were treated for.

18 Now, knowing what they were treated for and  
19 using a software, a professional software developed at  
20 Johns Hopkins Medical School, now we can forecast what  
21 this -- their actuarial value for the following year.  
22 So that is the key. So think about this, you know,  
23 for -- this is the market. For each one of you, I  
24 know your prior year diagnostics. I pass your data  
25 through the software, so now I have a number that says

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1 the actuarial cost for insuring Steve is \$1,200, and  
2 for each one of you.

3 So now I have a whole population where I know  
4 as much as an insurer would know about that  
5 population, right? So the insurer would ask you  
6 questions, would look at your records, and would  
7 assess your actuarial type. If we have this data,  
8 that's what we know.

9 Now, knowing your type and knowing the ex post  
10 distribution of health expenses across everybody that  
11 looks exactly like you, now we can estimate a  
12 distribution of health expenses for somebody whose  
13 expected cost is \$1,200, okay? So that way we are  
14 going to know not only your type, but we are going to  
15 know the distribution of expenses for the following  
16 year.

17 How is that going to help us? Well, once we  
18 have that, we can compute an expected utility. So  
19 give me risk preferences, a CARA parameter, give me a  
20 distribution of future expenses given your type, so we  
21 can compute an expected utility given any possible  
22 insurance contract. So once that insurance contract  
23 is no insurance, right, so suppose you're not insured.  
24 We know your utility, we know the distribution of  
25 costs, compute expected utility if you are going to

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1 face a full risk.

2 Now, we can do the same thing if you have,  
3 like, an 80 percent actuarial value policy. That's  
4 going to deliver a different expected utility. Now,  
5 we can also compute the gap, and the gap between, say,  
6 the 60 and the zero actuarial value policies is going  
7 to be your willingness to pay for an insurance policy  
8 of 60 percent actuarial value. So it means that in  
9 this population, that I know your type and I know your  
10 distribution of health expenses and a CARA parameter,  
11 now I know your willingness to pay for different  
12 contracts that we may want to design.

13 If I know your willingness to pay, it means  
14 that I know the demand in this market, so I'm ready  
15 to -- sort of to simulate how people are going to  
16 behave at different premiums. Now, given that I know  
17 your type and I know how you are going to behave, we  
18 can compute the actuarial costs of offering each  
19 possible plan. So we have everything, right? So we  
20 know who's going to buy, how costly they are going to  
21 be for an insurer. We can see if they are going to  
22 break even or not, to compute some kind of predicted  
23 outcome for the market. So that's basically what we  
24 are going to do, and there are different assumptions.

25 So this is just summarizing what I tried to say

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1 without an accent. Okay, data. To prove existence,  
2 there is data. These are -- again, this is  
3 ages/states. We are going to partition the states  
4 from healthiest to sickest, just to have enough  
5 observations in each cell, and as you see, the  
6 population unfortunately is getting sicker as they  
7 age.

8 We are going to have transitions for each age  
9 group. We are going to have how they transition from  
10 being healthy to less healthy and then, you know,  
11 luckily some people will go back. So we are going to  
12 use that when we compute the expected utility from a  
13 long-term contract, right? It's going to depend on  
14 how you transition into the future, right? So  
15 persistence is going to be key to compute welfare.

16 Okay, this one is neater. So here what we have  
17 is a 30-year-old in each of the possible health states  
18 from one, healthiest, to sicker, and their expected --  
19 as we roll forward, this mark of probabilities of  
20 transitioning, what is their expected health  
21 expenditure? So what you see is that early on there's  
22 a lot of information, it sort of evaporates after  
23 five, you know, seven, or ten years, and everybody  
24 looks very similar.

25 Now, we find that encouraging because typically

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1 life insurance underwriting in both information of  
2 stuff that happened in the last seven to ten years, so  
3 it means that the actuaries think that this  
4 information evaporates unless it's really a chronic  
5 condition.

6 Okay, so what else do we need? We need a, you  
7 know, solution concept. We are going to think of  
8 breaking even premiums, Riley equilibrium. For the  
9 contracts, I am going to do some dynamic contracts in  
10 a competitive industry when I show in a sec.

11 So part one, one-period contracts, pricing  
12 rule, what did we do? This is, you know, an old  
13 paper, 2015, and so this is what -- we did play with  
14 different rules allowing for more and more price  
15 discrimination. That eliminates adverse selection but  
16 induces more reclassification risk.

17 What did we find? Well, because of adverse  
18 selection was of the order of \$600, so if you fully  
19 forbid pricing health conditions, it's going to  
20 compromise welfare. Around how much? Well, \$600,  
21 which was around 10 percent of the actuarial cost --  
22 of the average actuarial cost from the sample. So it  
23 is substantial, but it was nothing compared to the  
24 welfare loss when you start allowing for more  
25 discrimination.

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1 When you start allowing for more  
2 discrimination, now people face reclassification risk.  
3 These are bigger stakes, so now if you are in bad  
4 health, if you are in stage seven, your premiums are  
5 going to be \$18,000 as opposed to \$1,000. Those are  
6 losses from welfare were way, way, way larger.

7 So our conclusion, our take-away was the ACA  
8 did well in banning pricing of health conditions  
9 because what they overcome is relatively small. The  
10 distortion for adverse selection is small relative to  
11 what they would -- the welfare loss from  
12 reclassification risk.

13 Long-term contracts, so what are we doing -- so  
14 this is current work, and so now what we want to  
15 consider is instead of one-year contracts, assume a  
16 competitive industry that offers to insure the  
17 patient, you know, for the rest of their life until  
18 they transition into Medicare.

19 Now, this is going to be a problem if there was  
20 two-sided commitment, right? So with two-sided  
21 commitment, we just sit together when I'm 25, 32, we  
22 are going to get the -- sort of the efficient outcome,  
23 and there's nothing to solve, and I wouldn't bore you  
24 with that. So what we think is relevant is not that  
25 two-sided commitment. Probably what we think is

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1 relevant is a one-sided commitment problem where the  
2 company guarantees that they are going to insure you  
3 in the future, but the customer can drop the moment  
4 they want, all right?

5 So here I have the agencies who tell me if  
6 otherwise the contract is going to be legal or not,  
7 but I understand that phone companies, cell phone  
8 companies have trouble imposing fees from terminating  
9 coverage. So they look at me, like, what does this  
10 guy -- anyway, so here this is going to be one-sided  
11 commitment. I don't know if it's -- I think some  
12 California courts found the fees -- the termination  
13 fees illegal, basically because they -- the customer  
14 is imposing no damage on the company, so how do you  
15 justify that you -- you just tie them forever? So I  
16 don't know.

17 Whatever it is, let me justify on practical  
18 reasons, every insurance -- life insurance contract  
19 that we are aware of in the U.S. and Canada is under  
20 unilateral commitment. There are no penalties for  
21 dropping coverage. So that's going to be my  
22 assumption, given that nobody complained? Good,  
23 nobody complained, so I am going to -- that's going to  
24 be my assumption from now on.

25 Now, on the unilateral, one-sided commitment,

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1 the issue is going to be that although the company can  
2 offer you insurance forever, it's customers in good  
3 health that are going to drop coverage, and that is  
4 going to make insurance unravel. So the optimum  
5 contract or -- the competitive equilibrium is not  
6 going to involve full insurance against  
7 reclassification risk.

8 So basically this is -- let me skip notations.  
9 So here the only thing I want to say is we solved it  
10 for 40 periods, from age 25, post college, until  
11 Medicare. From the data, we have these Lambdas, your  
12 type, your health type. From the data, we know what's  
13 the distribution of health costs given your type.

14 We assume symmetric learning. As you age, if  
15 you want coverage, you have to show up to an insurance  
16 company, and they can look at your records. They ask  
17 you to fill out questionnaire. So I'm assuming -- we  
18 are assuming that this is symmetric learning.

19 And what we do is we solve for the competitive  
20 equilibrium. And, again, the key are these  
21 transitions. That's how your health is going to move  
22 over time. Now, if these transitions were kind of  
23 completely persistent, once you're 25, you're either  
24 sick and you are going to remain sick or you're  
25 healthy and going to remain healthy, then the

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1 long-term contract doesn't do anything, right, because  
2 it means information is already revealed. If you're  
3 already sick, right, so there's nothing to insure you  
4 for the future, so it's good that there are  
5 transitions across states over time and that the  
6 information is not fully persistent, as I show in the  
7 previous picture.

8 So what do we find? We find that optimal  
9 contracts offer a minimum consumption guarantee, so if  
10 you want to think of -- you know, around it, they  
11 offer a premium that basically is not going to go up.  
12 So if you -- if you develop a condition, they  
13 guarantee not to price you against that, okay?

14 But instead, if you remain in good health, they  
15 are going to give you a break. So think about, you  
16 know, for those that are chairmen here in your  
17 departments, so that's exactly what happens with --  
18 when people in your faculty publish well, right? So  
19 if they didn't publish, they are stuck and you have to  
20 keep paying them the same amount, but if they publish  
21 well, they have an outside option, an outside offer,  
22 and you have to match that higher outside offer.  
23 That's exactly what's going on here.

24 So here what's going on is if the person is in  
25 bad health, the long-term contract insures them

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1 forever. The premium is never going to go up.  
 2 Instead, if they are in good health, they can approach  
 3 a competitor that's going to give them a better  
 4 premium to reflect that they remain in good health,  
 5 and with that premium, they can go back to the  
 6 original firm and say, look, I have a better premium,  
 7 lower my premiums, and that's exactly what the optimal  
 8 contract does.

9 And, you know, this is the counterpart of  
 10 Harris and Holmstrom in the labor context, sort of in  
 11 the chairman context. Somebody who proves to be more  
 12 productive gets a better deal. Somebody who proves to  
 13 be unproductive does not suffer a wage loss. So  
 14 basically that's the nature of the contracts.

15 The consequence is that this optimal coverage  
 16 cannot fully guarantee against reclassification risk.  
 17 The 25-year-old knows that they can insure against bad  
 18 drugs, but they cannot lock themselves in into the  
 19 policy if they happen to be lucky and healthy. So for  
 20 that reason, they cannot equate marginal utilities  
 21 across all the future periods on states, right,  
 22 because if they are in good shape, they are going to  
 23 have better deal, and they cannot transfer resources  
 24 from that good state to a bad one, okay? So there's  
 25 partial insurance against reclassification risk.

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1 So what do we do? We simulate the equilibrium  
 2 with our CARA parameters, some discount factor, under  
 3 competitive assumption, the seven health states. What  
 4 do we get? Let me be very brief, because I'm sure you  
 5 want to run away from here soon. For a flat income  
 6 profile -- so the optimal contract depends on the  
 7 profile of income.

8 For a flat income profile, so somebody whose  
 9 wages increase at the same pace that the medical costs  
 10 of that -- you know, of that group increases, so  
 11 basically the net income is flat, it means that is a  
 12 population without any saving and borrowing. I want  
 13 to neutralize that so we don't -- so the insurance  
 14 company doesn't become a bank.

15 So what we have there is on the left, is the  
 16 first pass. The first pass would be like 53.67  
 17 thousand dollars, and that will be sort of the  
 18 welfare -- the monetary -- the money metric of the  
 19 welfare of a person that manages to consume their  
 20 first base allocation, right? They get full insurance  
 21 against their medical and against their type risks,  
 22 okay?

23 Now, the second number, 52.47, is the welfare  
 24 that same person would get if there are just  
 25 one-period contracts that are fully priced. That's,

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1 if you want, the (indiscernible) of the spot market.  
 2 So you open the -- this is before Obamacare, there  
 3 were just spot contracts, and there were no -- it's  
 4 not true, but suppose that ban on pricing risk  
 5 systemization is removed, insurance companies can  
 6 price whatever they observe, they are going to get  
 7 full trade everywhere that gets insurance, but their  
 8 premiums are going to be jumping around over time.

9 So that would be the second number, 52, and you  
 10 see there is a loss of \$1,200 associated with the risk  
 11 that that premium reflects, all right? So you have  
 12 full insurance against a medical risk, but your  
 13 premium is jumping around. So the welfare loss of  
 14 \$1,200 comes from that risk, from the reclassification  
 15 of risk, comparing these two numbers.

16 Now, the third number is certainty equivalent  
 17 D, for dynamic, that would be the certainty equivalent  
 18 if companies are able to offer dynamic contracts, and  
 19 what you see is that it goes quite up, almost all the  
 20 way to first pass. So it appears that dynamic  
 21 contracts are great, but I'm tricking you.

22 So the reason I'm cheating is that I'm  
 23 computing that where somebody was flat net income,  
 24 right, so with somebody who has enough income early on  
 25 in life that they're willing to put money in that

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1 contract to subsidize their future selves, and  
 2 obviously we -- nobody, right, is that miserable in  
 3 the market to get the same wage at 60 as when they  
 4 were 25. So in a way I'm using it for a population  
 5 that doesn't reflect many workers.

6 If you see the bottom -- the one at the bottom,  
 7 in a second, that's what we call a manager. It's a  
 8 person in our sample who has a much steeper income  
 9 profit, that's a real income profit, and you see that  
 10 the gain from -- there is a gain from long-term  
 11 contracts, but it's much -- it like goes how long --  
 12 how much, like a third or two-thirds of the way. So  
 13 it's not that effective.

14 Why? Because this person is poor when he's  
 15 young, so he's not willing to put that much money up  
 16 front to pay for the future premiums. So dynamic  
 17 contracts help, but it depends on the income profile  
 18 of the worker.

19 The final number is the ACA. Now, what is the  
 20 ACA? Well, the ACA is open the market with static  
 21 contracts, and the reason that number, 52.87, is under  
 22 the first list is because of adverse selection. So if  
 23 you compare the first column to the last one, that is  
 24 the loss from adverse selection.

25 Now, in this particular example, dynamic

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1 contracts do a little bit better than the ACA for the  
2 manager and do a lot better than the ACA for the flat  
3 income, but remember, the flat net income is a  
4 fictitious worker. So we should look at the second  
5 one, and the second one is a very minimal gain from  
6 dynamic contracts, not that much better than the ACA.

7 Finally, the Republican reform. What do I want  
8 to say about the reform? The reform, we go back --  
9 this is, again, ongoing work, so Mike would be very  
10 upset if he knows I am even mentioning this, because  
11 the numbers I'm going to show you at the end are fake  
12 or are, you know, very preliminary numbers that -- you  
13 know, don't tell him. Anyway, I am going to share the  
14 numbers, but don't tell him.

15 So what we're doing here is going back to  
16 one-period contracts, that because the Republican  
17 proposal involved future consequences for today's  
18 actions, now we have a dynamic problem, and what we do  
19 is we solve that dynamic problem -- and let me skip  
20 notation -- but basically this is sort of a Dixit  
21 model, that you are either out or in. If you are out  
22 and you want to have -- want to go back in, you have  
23 to pay a fixed, you know, penalty, and so on.

24 Solving that for a vector of premiums from age  
25 25 to 64, we get the value functions. Once we get the

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1 value functions, we know the month. Once we know the  
2 month, we can compute costs, and keep iterating until  
3 we find a breaking even vector of premiums, which in  
4 principle is going to be in equilibria.

5 Once we do that, we get these numbers that I  
6 just -- I just want to show they exist, but now I'm  
7 going to hide them. Sorry. Okay, I am going to show  
8 you, but do not forget. The only thing I want to  
9 highlight there is the House proposal with a 30  
10 percent penalty, that's very similar. Again, we saw  
11 our -- anyway, I shouldn't -- I shouldn't show you  
12 this.

13 This is a very first cut that we are not very  
14 proud. It was just kind of the first, you know,  
15 simulation we did just to entertain you. Do you see  
16 the House 30 percent, that's very similar to the 4 --  
17 to sort of the ACA kind of \$400 penalty, roughly, that  
18 if not -- so, but on the other hand, the Senate  
19 proposal that keeps you -- and this is -- so we  
20 couldn't wait half a year, so we waited a whole year,  
21 so I keep, you know, cheating here, but anyway, what  
22 you see there is participation is almost 100 percent  
23 because people are really, because they are risk  
24 averse and they are so in panic of developing a  
25 condition and not having coverage, that most of them

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1 participate.

2 Now, what you see -- I find it interesting --  
3 is that for the, you know, older people, that loses  
4 value, right, because the horizon gets smaller and  
5 smaller. So if you think a 64-year-old has an option  
6 value, so those people, you know, sort of pull out of  
7 the exchange, but for younger, they are paying for the  
8 option value of remaining. So, again, I didn't show  
9 you the numbers, and let's move on.

10 But basically that was kind of the take-away,  
11 that if you believe that mandate is an infringement on  
12 liberty, there are ways to induce a participation, and  
13 it really depends on the details. So, you know, the  
14 policy, I think they are important to create  
15 sufficient participation.

16 So what did I say? I tried to say that there  
17 is plenty to be simulated, treating health insurance  
18 policies as financial instruments. The nonfinancial  
19 instrument could be accommodated, but in our  
20 framework, we don't have data on that. Using data  
21 that is becoming increasingly available, hopefully,  
22 you know, the Government could, you know, help us, you  
23 know, get more data.

24 And, again, this is the magic. This is what we  
25 are most proud of. Again, it's not my -- it's not we

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1 are first to use it. I think Bob Town used it first  
2 and then Ben Hallo (phonetic). This helps you have as  
3 much information as an insurance company would have on  
4 the market.

5 I think food is ready. Thanks.  
6 (Applause.)

7 MR. WILSON: Thanks very much. I do think we  
8 have time for just a question or two before we retire  
9 to drinks and snacks.

10 Anybody?

11 MR. GERUSO: So this idea -- so I really liked  
12 the whole research agenda with the long-term risk,  
13 reclassification, and thinking through those things,  
14 but in terms of long-term contracts versus mandate and  
15 subsidy, I mean, I guess your experiment is imagine we  
16 can't have a mandate because it's politically  
17 unpalatable, how does long-term contracts do?

18 But here it seems like behavioral -- so nothing  
19 in my papers has ever acknowledged behavioral  
20 economics exists, so -- but, I mean, in thinking  
21 about, you know, long-term contracts versus mandate  
22 and subsidy seems like the behavioral factors there  
23 could be pretty important, right? So someone believes  
24 that they're invincible when they're 20, just -- I  
25 mean, you -- like, actually, like, in implementing

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1 either a long-term contract or a stay out of the  
 2 market for a year thing, I mean, we might -- if we  
 3 implemented such a policy, we might very quickly  
 4 decide we don't like it, and a couple years later, we  
 5 would have a new ACA because people are not making  
 6 these forward-looking decisions, and, therefore, while  
 7 they're out of the market for a year, a cancer is  
 8 metastasizing in them. So just -- do you have -- can  
 9 you say anything at all about that?  
 10 MR. HENDEL: Maybe. So I can tell you we have  
 11 bigger problems than that, if that's an answer. So  
 12 currently a market like that would be co-existing with  
 13 the employer provider, which dominates for tax  
 14 reasons. So I think for practical purposes, an  
 15 individual wouldn't like to frontload and then a year  
 16 and a half later to find employment, much  
 17 (indiscernible) they want to.  
 18 So the only excuse I have is that there were  
 19 products like that attempted on the market, where the  
 20 insurance company offers you an option of coming back,  
 21 especially if you can prove the reason you're dropping  
 22 is because you found employment, you don't lose your  
 23 savings, if you will, you don't lose what you  
 24 frontloaded. You will be taken, say, later.  
 25 Now, again, I am 100 percent with you that for

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1 behavioral reasons or whatever reasons, many people  
 2 are declining even free insurance at the moment. So  
 3 honestly, just any rational model is not going to  
 4 capture what's going on, and they don't know what's  
 5 going on. So that's all I can say.  
 6 (Applause.)  
 7 MR. WILSON: Thanks very much for an  
 8 interesting day. There are drinks and snacks back  
 9 where food and coffee was earlier today.  
 10 (Whereupon, at 4:15 p.m., the proceedings were  
 11 adjourned.)  
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**In the Matter of:**

**10th Annual FTC Microeconomics Conference**

*November 3, 2017*  
*Day 2*

**Condensed Transcript with Word Index**



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1 FEDERAL TRADE COMMISSION  
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9 FEDERAL TRADE COMMISSION  
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13 DAY 2  
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17 9:00 a.m.  
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21 Federal Trade Commission  
22 Washington, D.C.  
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3  
1 PAPER SESSION  
2 MR. RAVAL: All right, everybody, we're  
3 starting the first session of the day. So this is the  
4 paper session chaired by Steve Berry. So the first  
5 paper we have is An Empirical Model of R&D Procurement  
6 Contests: An Analysis of the DOD SBIR Program by  
7 Vivek Bhattacharya at Northwestern University.  
8 MR. BHATTACHARYA: All right, well, thanks a  
9 lot for having me here. It's been a really fun  
10 conference so far, and hopefully that doesn't change  
11 with this paper. I'll be talking about an empirical  
12 model of R&D procurement contests, and I'll be using  
13 it to study data from the Department of Defense.  
14 Okay, so, the starting point of this project  
15 is that competition plays a nontrivial role in R&D-  
16 intensive markets. If you increase competition, then  
17 you change these firms' incentives to exert effort to  
18 invest in R&D in this case, and that, in turn, can  
19 influence outcomes. And it can do so possibly  
20 adversely. So, ex ante, it's not clear that more  
21 competition necessarily leads to better price, better  
22 quality, better social surplus, better consumer  
23 surplus, or anything else we might hear about. And,  
24 of course, this nontrivial relationship between  
25 competition and innovation has led to a large

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1 empirical literature, a large theoretical literature.  
2 I'm going to focus in this paper -- I'm  
3 going to contribute to the literature by looking at a  
4 very particular type of R&D-intensive market. I'll be  
5 looking at what I call an R&D contest. Now, I'll be a  
6 bit more clear about what I mean by that, but this is  
7 loosely a setting where a bunch of firms are competing  
8 with each other to develop some sort of innovative  
9 product and then supply it to a procurer.  
10 And they often compete over multiple stages.  
11 In my case, they are. They're going to do that. You  
12 can think of these stages as loosely consisting of  
13 an initial research phase where you get a sense of  
14 what you can build and how much the procurer would  
15 value it. If you're successful there, you can  
16 actually go -- move into develop and try to build what  
17 you said you'd build. And if you're successful at  
18 both those steps, you can compete with the other firms  
19 in the contest to deliver the product to the procurer.  
20 In my case, the procurer is going to be the  
21 Government, the DOD in particular. And one nice thing  
22 about -- one thing about these sort of government  
23 procurement contracts or R&D contracts is that they're  
24 often structured in a way that looks like a contest  
25 and that there's a winnowing down of R&D contracts



5

7

1 over time and there's -- there's -- and these  
 2 contracts lead to some sort of procurement, either  
 3 implicitly or, in my case, explicitly.  
 4 So the broad question I'll ask is how do  
 5 they extend to competition and more generally the  
 6 design of these contests affect the outcomes that we  
 7 see.  
 8 And there -- so in order to do that, I'm  
 9 first going to make a methodological contribution,  
 10 that there's a fairly sizable theoretical literature  
 11 on R&D contests, but relative to the theoretical  
 12 literature and relative to the empirical importance,  
 13 there hasn't been much empirical work trying to  
 14 understand the sort of heterogeneity that governs the  
 15 outcomes we see in these contexts.  
 16 So that's what I'll try to do. I'll write  
 17 down a fairly simple model of R&D procurement  
 18 contests, and I'll be very clear about what features  
 19 of the data identify the primitives of the model. And  
 20 throughout the paper, I'll be looking into the  
 21 particular Government program. I'll be looking into  
 22 the DOD Small Business Innovation Research Program.  
 23 All right, so -- and this is essentially the  
 24 structure of the program. I'll walk through it step  
 25 by step. So every year the DOD lets about a thousand

1 to move on to phase two. And phase two is really  
 2 about develop -- reducing development costs. So this  
 3 is figuring out how to actually manufacture the  
 4 product or deliver the product at the minimum cost  
 5 possible.  
 6 This phase tends to be much more intense,  
 7 and they're -- and these -- they're larger R&D  
 8 contracts, and there's a lot more variation across  
 9 firms and the size of the R&D contracts they get.  
 10 In this phase, I'll think of -- in the  
 11 model, I'll think of this as exerting effort to get a  
 12 draw off your delivery cost, and the feature that I'm  
 13 going to -- and when I write down the model, I'll take  
 14 into account that these guys are receiving R&D  
 15 contracts and that there's a limited number of spots  
 16 in phase two.  
 17 Finally, at the end of phase two, if the DOD  
 18 is satisfied with one of these projects, they can  
 19 actually contract with the firm to do delivery. And,  
 20 so, phase three is essentially a delivery phase. When  
 21 I take this to the model, I'll think of this as some  
 22 version -- as the contract price being set through  
 23 some version of Nash bargaining, which effectively  
 24 means that firms are going to expect to capture some  
 25 portion of the surplus.

6

8

1 solicitations for fairly narrow projects. So these  
 2 are like widgets for airplanes. A couple years ago,  
 3 the Navy was looking for something called a compact  
 4 auxiliary power system for one of their amphibious  
 5 combat vehicles, so this is essentially a battery that  
 6 has to satisfy a set of specifications. Any firm who  
 7 wants to build that battery or first develop that  
 8 battery and then build it can submit a technical  
 9 proposal to the DOD, and the DOD is going to score  
 10 these proposals and let a few of these firms move on  
 11 to phase one.  
 12 And phase one is essentially where the  
 13 contest starts. This is a quick-and-dirty phase where  
 14 firms get some R&D contracts from the DOD, and they do  
 15 some preliminary work to try to figure out how to make  
 16 their project technically feasible. Okay?  
 17 When I take this to the model, I'll think of  
 18 this as a setting where these firms are going to exert  
 19 effort and get a draw of value. They're going to get  
 20 a sense of what -- how many features of the battery  
 21 they can actually satisfy and how much that would be  
 22 value -- how the DOD would value that.  
 23 At the end of phase one, these guys write  
 24 another technical report. They extend it to the DOD,  
 25 and the DOD is going to select a subset of these firms

1 So I'll write down this model formally in a  
 2 couple of slides. I'll show you how to identify the  
 3 primitives and estimate them, and I'll use them to  
 4 quantify the inefficiencies that are embedded in this  
 5 setup. Okay, and you can already get a sense of what  
 6 these inefficiencies are going to be, at least  
 7 qualitatively.  
 8 There's something like a holdup problem in  
 9 that firms are going to capture a portion of the  
 10 surplus, not the full surplus, so that means they have  
 11 less than the socially efficient incentives to exert  
 12 effort, but counteracting that are something like a  
 13 business-stealing effect, where if I displace someone  
 14 from phase two, I capture their full profit, so that  
 15 gives me more than the social incentive reason to  
 16 exert effort. And there's also going to be something  
 17 like a reimbursement effect in that these R&D  
 18 contracts are going to be socially neutral transfers,  
 19 but I'm going to treat them like prices as referred.  
 20 And understanding these inefficiencies are  
 21 going to help us understand some simple design  
 22 counterfactuals that I'll talk about. And in  
 23 particular I'll focus on changing the number of  
 24 competitors. If you add another competitor, then,  
 25 sure, you get another draw for the pot, but now

9

1 everyone else realizes they're facing more competition  
 2 and there's an indirect incentive effect of exerting  
 3 effort.  
 4 And I'm going to try to quantify the defect  
 5 and see whether -- whether adding competition is  
 6 actually beneficial in this setting. And I'll also  
 7 talk about changing the intents in margin of  
 8 competition, if you will, by changing the surplus that  
 9 you commit to give these guys in procurement. I won't  
 10 have time to discuss other design changes today.  
 11 So the data that I have comes from the  
 12 Federal Procurement Data System, so I have all Navy  
 13 SBIR contracts from 2000 to 2012. There are a number  
 14 of reasons to focus on the Navy, but for now, just  
 15 worry about the data reasons, that they were nicer  
 16 with data for the most part. There are -- so I have  
 17 the number and the identity of competitors at each  
 18 stage. I have the R&D contract amount at each stage.  
 19 If there's a phase three procurement contract, I see  
 20 the contract amount as well.  
 21 Now, these projects are somewhat  
 22 heterogeneous, so I'll try to control for that as best  
 23 I can by looking -- by getting program-level  
 24 characteristics -- or project-level characteristics  
 25 from the Navy SBIR program office. And, so, I see the

10

1 contract duration, the fiscal year, the division of  
 2 the Navy that developed the project, the acquisition  
 3 program the project is a part of, and I'll also see  
 4 the full text of the solicitations and the abstracts  
 5 of the winning proposals. So that's about 15 or  
 6 20,000 pages of material. I'm going to run that  
 7 through a fairly off-the-shelf machine-learning  
 8 algorithm and essentially generate topics for each one  
 9 of these, these contests, and try to control for  
 10 heterogeneity at that point.  
 11 And here's some examples of topics. You can  
 12 go much finer than that, and it does a pretty good  
 13 job. I mean, the algorithm is built for stuff like  
 14 this.  
 15 So I'm just going to give you a quick taste  
 16 of the data without going into much -- any sort of  
 17 detail about correlations. These tables show -- oh,  
 18 this table shows you the distribution of the number of  
 19 competitors at each stage in the contest. As you can  
 20 see that these are fairly small contests. They're  
 21 usually about two to four competitors in phase one.  
 22 About 17 percent of contests don't even make it to  
 23 phase two. The DOD says that they're not satisfied  
 24 with the research done in phase one, so they just end  
 25 the contest there.

11

1 About three-fourths of these contests are  
 2 conditional on making -- making it into phase two, and  
 3 about three-fourths of them just have one competitor.  
 4 And the rest tend to have two competitors.  
 5 Phase three, the acquisition phase, it  
 6 actually is fairly unlikely. So only about 10 percent  
 7 of contests make it all the way to a delivery  
 8 contract. Okay.  
 9 So I'll think of this as essentially -- I'll  
 10 model this as research being some -- having some sort  
 11 of stochastic component, and, in fact, failure rates  
 12 are going to be important in identifying the  
 13 primitives for me.  
 14 The other key observable are these contract  
 15 amounts. So I'll think of this as measures of R&D  
 16 expenditures. So if I were to plot a distribution of  
 17 phase one contract amounts, it would be a mass pointed  
 18 at \$80,000. That amount is essentially  
 19 institutionally set, effectively across the Federal  
 20 Government, but there's actually a lot of variation in  
 21 phase two and phase three contract amounts.  
 22 So the first distribution shows you that the  
 23 distribution of phase two R&D contracts can be as low  
 24 as \$250,000, can be high as 1.5 million or so. The  
 25 delivery contract can be as low as a few million

12

1 dollars and can go up to about 50 or 20 million,  
 2 sometimes even a bit higher.  
 3 Okay. And that variation was due to cross-  
 4 project variations, or the Navy cares more about  
 5 certain projects, but it's also due to variation in  
 6 who shows up to a project. So that's what that final  
 7 histogram shows you, that's the percent difference  
 8 between the -- I'm looking at contests where multiple  
 9 people show up to phase two, so I'm perfectly  
 10 controlling for project-level heterogeneity, and I'm  
 11 looking at the percent difference between the highest  
 12 funded guy and the lowest funded guy. And that number  
 13 is often between 25 and 50 percent, sometimes larger  
 14 than that.  
 15 I'll interpret that variation as variation  
 16 in value. That's consistent with a bunch of things  
 17 that I discuss in the paper. It's consistent with  
 18 what the Navy discusses or attributes that variation  
 19 to. They say that they give more funding to projects  
 20 with higher transition potential. It's consistent  
 21 with descriptive correlations of project-level  
 22 success.  
 23 Projects with higher funding tend to succeed  
 24 at higher rates, tend to lead to delivery contracts at  
 25 higher rates, both across projects controlling for a

<p style="text-align: right;">13</p> <p>1 bunch of stuff within project, perfectly controlling  2 for heterogeneity. They lead to higher phase three  3 funding amounts. So there are many reasons to think  4 that this is indicative of value and that that's sort  5 of the stance I'm going to take when I take the data  6 to the -- the model to the data.  7 And this is the model that I'm going to take  8 to the data. It's actually sort of scary having a  9 countdown clock staring you down. This is the first  10 time I'm presented with a countdown clock.  11 So this model is -- it's fairly simple. It  12 fits on this one slide. So I'll just walk through it  13 step by step. In phase one, they're N1 firms. I'll  14 think of them as ex ante symmetric. They each exert  15 some effort, B. That's a probability, that's a  16 normalization at some monetary cost I of P dollars.  17 Okay?  18 Generating an effort, P, means that they  19 generate a success with some probability, P. If  20 they're successful, they get a sense of how much the  21 DOD would value their project. That's draw v from  22 some distribution f. The DOD is going to score these  23 projects. They're going to see the Vs, and it's going  24 to let the top N2-bar firms move on to phase two.  25 And if fewer than N2-bar firms succeed, then</p>	<p style="text-align: right;">15</p> <p>1 I'm modeling the procurement stage here.  2 Okay, so you can solve for the equilibrium  3 here. I'm looking for symmetrical equilibrium. It's  4 characterized by a set of integral equations that are  5 fairly easy to understand, but the important part of  6 this slide is that the -- I'm going to make an  7 empirical assumption that the R&amp;D contract that I see  8 in phase two corresponds to this firm optimal amount.  9 Okay, it corresponds to this equilibrium.  10 And that's a bit of a strong assumption.  11 That's saying that the DOD decides your R&amp;D contract  12 is based on what's optimal for the firm. You can  13 justify this in a number of ways. Maybe if the DOD  14 were to give the firm more than the optimal amount,  15 then the firm -- giving the imperfect monitoring, the  16 firm could try to reallocate some resources, try to  17 pocket the rest of the money in some way. If the DOD  18 were to give them much less than the firm optimal  19 amount, it would be running ex post losses. That  20 might not be great for program participation.  21 But I do understand that it's a bit of a  22 strong assumption. What the important part of that  23 assumption for most of the identification and most of  24 the estimation is that this means that the phase two  25 award amount is increasing in value. So this is my</p>
<p style="text-align: right;">14</p> <p>1 not everyone moves -- just the guys who succeed move  2 on to phase two. Now, in phase there, there are N2  3 firms. They each draw -- they each have a draw of v,  4 and they're going to exert some effort, t, to draw  5 some delivery costs, c, from some distribution, h,  6 that's parameterized by t. Okay, and t is in dollars.  7 That's a normalization.  8 Now, N2 is public. That's consistent with  9 how the DOD announces stuff, but firms are not going  10 to know each other's values. They're going to have  11 beliefs or values. These beliefs may or may not  12 depend on their value, depending on whether or not  13 there's selection in that particular setting.  14 Okay. And at the end of phase two, you have  15 some firms. They each have a v, they each have a c,  16 and the DOD is going to see the surplus that each firm  17 would generate if they were to bring -- deliver the  18 product, and it's going to go to the firm with the  19 highest surplus and pay a cost plus contract. It's  20 going to cover the firm's costs and pay them a  21 fraction of the incremental surplus he generates. And  22 he's going to do that as long as v is larger than c.  23 Okay, so there is some sort of selection condition  24 embedded into the model. And, so, essentially phase  25 three is something like Nash bargaining. That's how</p>	<p style="text-align: right;">16</p> <p>1 interpretation for the DOD saying it's -- it gives  2 higher funding to projects with greater transition  3 potential. If you don't want me to assume this  4 equilibrium, I'll show you I can still identify a lot  5 of stuff about values and costs, purely from  6 monotonicity.  7 And that's what I'll try to go through in a  8 couple of minutes. Identification of this model,  9 identifying distribution of values, distribution of  10 costs, and the bargaining parameter, it's going to  11 leverage three features. It's going to leverage this  12 monotonicity thing. I see the distribution research  13 efforts. I need the distribution values. Now I know  14 there's a one-to-one function between them. I just  15 don't know what that function is yet.  16 I'm also going to use the fact that there's  17 a selection condition here. The DOD's only going to  18 contract with the firm that -- with a firm that has a  19 -- that generated a positive surplus. So if the DOD  20 just didn't contract with the firm, I learned  21 something about what the surplus was.  22 Those two assumptions are going to give me a  23 lot of information about values and costs. In order  24 to identify the bargaining parameter, I'm going to  25 have to leverage the equilibrium of the model. And</p>

17	<p>1 I'm going to have to say that somebody's optimizing 2 something, and here it's going to be the firm 3 optimizing its research efforts.</p> <p>4 And I'm going to walk through the 5 identification proof because I think it's fairly 6 straightforward, and it helps understand where the 7 estimates are coming from. So in phase two, I see the 8 phase two research effort, <math>t</math>, and the joint 9 distribution of that with the phase three contract 10 amount. Okay, I need the value distribution, <math>f</math>, the 11 delivery cost distribution, <math>h</math>, and the bargaining 12 parameter, <math>\beta</math>.</p> <p>13 Why do I care about this? Well, the value 14 distribution is going to tell me how much 15 heterogeneity there is and what happens at the 16 beginning of phase one. The cost distribution is 17 going to tell me how much heterogeneity there is and 18 what happens in phase two, so it's going to help me 19 understand where competition might be useful, which 20 phase of the contest.</p> <p>21 So condition on a particular value of the 22 research effort, that's like conditioning on value. I 23 just don't know what that value is yet. I see the 24 distribution of phase three contracts. Right now 25 that's sort of meaningless because it's a combination</p>	19	<p>1 argument and the selection condition that I'm only 2 going to see a contract if values are larger than 3 costs. I haven't used anything about anyone 4 optimizing anything yet. But I haven't recovered this 5 share of the surplus.</p> <p>6 Here, I can go back to the firm's first- 7 order condition, and note that I know everything in 8 that equation except for the bargaining parameter.</p> <p>9 Okay, so that's one equation and one unknown, some 10 hand-waving and some math behind the scenes shows you 11 that there's one, one solution. And loosely what that 12 means is that, well, where this is coming from is that 13 from values and costs I have a sense of the marginal 14 benefit of research, the marginal cost of doing a 15 dollar of research is a dollar, any wedge between the 16 marginal benefit and the marginal cost has to be due 17 to the fact that the firm realizes they're not 18 capturing the full surplus. Okay, and so that's what 19 I'm interpreting as the firm's bargaining parameter.</p> <p>20 So this is identifying a bargaining 21 parameter off some sort of ex ante investment, which 22 is a bit different from how at least in a conceptual 23 sense and from how other papers that identify 24 bargaining parameters operate, like Ali's paper or 25 Matt's paper, but this ex ante investment is sort of a</p>
18	<p>1 of values which I don't know and costs which I don't 2 know and a bargaining parameter that I don't know.</p> <p>3 Okay, but what I do know is that the 4 contract that the DOD was just barely willing to 5 accept is one where the delivery cost equals the 6 value. So if I were to see a lot of these contests, 7 the maximum value would be -- the maximum contract 8 value would be the one where the contract amount is 9 the value, okay, where basically they were just barely 10 willing to trade.</p> <p>11 So I've identified values off the support of 12 the phase three contract distribution. This looks 13 very stark. You can make it less stark by adding some 14 unobserved heterogeneity. I talk about that in the 15 paper, but this is the rough intuition, and in a stark 16 model, this is the formal proof.</p> <p>17 So identify values off the support, and so 18 the value distribution is identified off the support 19 as well. And once I have values, the residual is due 20 to cost, so any residual variation in the contract 21 amount, conditional on the bargaining parameter, is 22 due to a variation that happens in phase two. That's 23 costs.</p> <p>24 Okay, so that helps me identify values and 25 costs. All I've used so far is this monotonicity</p>	20	<p>1 hallmark of R&amp;D, and I hope that that's -- this is one 2 of the observations that could be used in other 3 settings.</p> <p>4 Okay, so identification hopefully was 5 transparent. It's more robust than you think. There 6 are a bunch of extensions in the paper, many of them - 7 - one of which is actually relevant for estimation. 8 And it leads to a fairly tractable estimation 9 procedure.</p> <p>10 Let me run through this really quickly. The 11 loose idea is that given monotonicity I can 12 essentially -- conditional on a bargaining parameter, 13 I can essentially estimate the model without ever 14 having to solve it at all. And the benefit is that 15 that's tractable. It's not hard to solve the model, 16 but it's not easy either, so it helps to be able to 17 not do that during estimation, but it's also 18 conceptually robust. So, once again, if you don't 19 like this monotonicity, if you don't like this 20 equilibrium assumption, you can -- you can estimate 21 everything without actually having to impose it.</p> <p>22 Okay. When I take -- when I actually take 23 this to data, I'm going to have to add in some 24 unobserved heterogeneity -- or observed and unobserved 25 heterogeneity. Those are the covariates that I</p>

21

1 identified a couple of slides ago, the share of -- the  
 2 division of the Navy and the stuff from the machine-  
 3 learning algorithm. I'm also going to add in a degree  
 4 of unobserved heterogeneity. That enters into a  
 5 somewhat -- enters into a setting in a somewhat  
 6 restrictive way.  
 7 I'll let the -- the identification proof  
 8 didn't leverage any sort of cross end restriction.  
 9 Different -- you might be worried the different  
 10 contests -- that the Navy selects different numbers of  
 11 competitors for different types of contests. I'll try  
 12 to allow for that by parameterizing some of the  
 13 primitives by the number of competitors in phase one,  
 14 and I'm going to avoid using the \$80,000 in phase one  
 15 in estimation just because that's sort of an  
 16 institutional number that isn't really representative  
 17 of much. I'll use that as ex post check of how sane  
 18 my estimates are.  
 19 And estimation essentially first proceeds by  
 20 backing out the distribution of the unobserved  
 21 heterogeneity in a way that's similar to Elena's  
 22 paper, and then I'll do the MLE procedure that I  
 23 scanned through in the previous slide, and then after  
 24 I've estimated values and costs, I'm going to actually  
 25 solve the model at that point and then estimate the

22

1 bargaining parameter by imposing the structure of the  
 2 model at the very last stage.  
 3 And, so, here's what we learn from this  
 4 procedure. I'm showing you the distribution of values  
 5 as a function of N1. The Navy value seems to value  
 6 these things at around \$11 to 50 million, but what's  
 7 more interesting is that if you take a guy from two-  
 8 point-fifth percentile and you move him to the 96-7-  
 9 point-fifth percentile in values, you only increase  
 10 his value by about \$1 or 2 million. That's around 10  
 11 to 15 percent of the mean.  
 12 So I'm estimating a fairly narrow  
 13 distribution of values in phase one. Values are  
 14 essentially -- and this is sort of consistent with the  
 15 idea that the Navy has spelled out these projects  
 16 pretty well already. Where is this coming from? The  
 17 idea -- this is essentially a soft upper bound of the  
 18 phase three contract distribution as a function of  
 19 phase two research efforts. There are a number of  
 20 contracts that had low phase two research efforts that  
 21 ended up having fairly high phase three research -- or  
 22 phase three procurement contracts. So that must have  
 23 meant that these had high values when you -- through  
 24 the lens of the model.  
 25 Costs tend to be about \$7 million

23

1 conditional on it being a reasonable cost, but there's  
 2 a lot more variation in the distribution of costs  
 3 here. So there -- a lot of the uncertainty and  
 4 research happens in the second stage. This comes from  
 5 the residual variation in phase three contracts  
 6 conditioning on the phase one value distribution -- or  
 7 research effort distribution.  
 8 And the DOD seems to be providing these guys  
 9 with fairly high-powered research incentives. Firms  
 10 are acting as if they capture a good share of the  
 11 surplus. All right, and if you're interested, the  
 12 implied phase one research cost is about \$30,000,  
 13 which is not \$70,000, but it's in the right ballpark,  
 14 and some unobserved heterogeneity might make \$70,000  
 15 somewhat reasonable as well.  
 16 Okay, so those are the estimates. With  
 17 these estimates in mind, we can sort of figure out  
 18 whether R&D efforts are less or more than socially  
 19 optimal. In phase one, there are multiple effects at  
 20 play that I discussed at the beginning of the  
 21 presentation. It turns out that phase one R&D is  
 22 excessive in the setting in equilibrium. The social  
 23 planner would want these guys to reduce their efforts.  
 24 It's a fairly small effect when there's no  
 25 business stealing. If there's only one guy, there's

24

1 no one to steal the business from. The gain from  
 2 moving to the efficient level of effort is only about  
 3 4 percent. When there's a lot of business stealing,  
 4 though, this can be fairly large.  
 5 Phase two R&D in this model turns out to be  
 6 unambiguously less than socially efficient because  
 7 firms are only going to get compensated by a fraction  
 8 of their marginal contribution to society. So you can  
 9 show that that means that they're always going to be  
 10 less than -- they're always going to exert less effort  
 11 than we'd want them to. In fact, 40 to 50 percent  
 12 less effort than we'd want them to, and the surplus  
 13 can be improved by about 5 to 10 percent here by sort  
 14 of alleviating this holdup problem.  
 15 Okay, so what does that mean for  
 16 counterfactuals? So this table shows you how -- so  
 17 I'm looking at a set of parameters. If you just have  
 18 one guy in the contest, then social surplus is about  
 19 \$140,000 in expectation. And the table shows you the  
 20 change in the social surplus from change in the number  
 21 of competitors in phase one and the number you let  
 22 into phase two.  
 23 So if you increase the number of competitors  
 24 in phase one and you still let only one of them move  
 25 on to phase two, then you have a number of effects.

25

1 You get more draws from the pot, but we already  
2 estimated that those draws were fairly useless because  
3 the distribution of values is very narrow. Now, you  
4 guys -- you also have more -- more duplicate research  
5 efforts. That's socially costly, but these firms are  
6 also adjusting their research efforts downwards. And  
7 that happens to be socially rather beneficial because  
8 we estimated that they're large inefficiencies in  
9 phase one in terms of excessive research effort.

10 Okay. On net, that means the social surplus  
11 tends to be about the same or decrease by a bit. If  
12 you increase competition in both the phase one and  
13 phase two, then you're leveraging the fact that you  
14 see a lot of variation outcomes in phase two. So ex  
15 ante, that means that there's low substitutability  
16 across products in phase two. So if you want one guy,  
17 you want another guy loosely, so the social surplus  
18 increases pretty strongly when you add competitors in  
19 phase one and phase two.

20 The takeaway is that the planner prefers to  
21 invite contestants to in both stages of the contest.  
22 And the main benefits are from the direct effect of  
23 more draws in phase two and the incentive effect of  
24 these guys adjusting their research efforts in phase  
25 one.

26

1 Okay, how does social surplus -- what does  
2 social surplus look like? As a function of the share  
3 of the surplus you give the firms. So where is --  
4 this is varying how much you give the firms with the  
5 point to the right being giving everything to the  
6 firms, and the dotted line that you may or may not be  
7 able to see is where we are. It turns out holdup  
8 costs are fairly low here. We estimated that a couple  
9 of slides ago. So there's a beneficial to -- and  
10 there's a benefit to sort of reducing the share of the  
11 surplus you give the firms and then just economizing  
12 on the other inefficiencies here.

13 Okay, the net benefit turns out to be fairly  
14 small. And as an aside, you might -- ex ante, you  
15 might have been worried that the DOD is giving these  
16 firms too low a share of the surplus by essentially  
17 not giving enough incentives to exert any effort.  
18 That doesn't turn out to be the case here.

19 Okay, so just really quickly, why don't we  
20 actually see this in practice? It turns out that many  
21 of these socially beneficial design changes are  
22 actually privately harmful for the DOD because the DOD  
23 doesn't capture a large share of the surplus. They  
24 end up paying out their R&D contracts. So they're  
25 seeing -- at least at the estimated parameters, there

27

1 seems to be a tension between what's optimal for the  
2 DOD and what's optimal for the social planner. So we  
3 might be somewhere in the middle. With more time, we  
4 could have had more of a discussion on other things  
5 that these estimates might have implied about the  
6 objectives.

7 But let me just end there. I did what I  
8 said I did, and I think that the takeaway is that --  
9 that I'd like to apply to other papers is the  
10 observation that these R&D contracts are -- R&D  
11 efforts are indicative of what happened in the past  
12 and also indicative of what these firms expect in the  
13 future, so that gives you a good deal of information  
14 about the parameters of the model. And that's what  
15 I'm leveraging in this paper.

16 Thanks a lot.  
17 (Applause.)

18 MR. RAVAL: All right, we have Elena  
19 Krasnokutskaya from Johns Hopkins to discuss this  
20 paper.

21 MS. KRASNOKUTSKAYA: So first of all, you  
22 know, I would like to say that this is a very  
23 interesting paper. I enjoyed reading it and at the  
24 end of the day think I've learned new stuff from this  
25 paper. Okay, so what is the paper about? So the

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1 paper uses the data from this SBIR, I guess, program,  
2 that runs R&D contests on the topics of interest to  
3 DOD, and, in fact, on topic of interest to the Federal  
4 Government.

5 So this program is specifically designed to  
6 fund the research by small businesses. And the  
7 funding is allocated on a competitive basis, so at  
8 every stage of the contest, the participation is  
9 competitive -- selection into participation is  
10 competitive. And the goal here is to have a -- to  
11 have products which could be sold -- eventually sold  
12 to the military in the military market or in the  
13 private sector, right? So that's kind of the program  
14 that we have here.

15 So the way the author thinks about this  
16 environment or the way -- the way he studies this  
17 market, he basically writes down a model which links  
18 eventual profitability of this invention to the  
19 competitive pressure in the contest and also to the  
20 funding which is available -- which is made available  
21 to the participants through this SBIR program.

22 And the contest itself is formalized as the  
23 setting where, you know, the R&D is going to  
24 eventually produce an invention associated with some  
25 surplus, and the surplus is separated into the value

29

1 and the cost of delivery of this invention, of this  
2 product. And, so, these two things are unknown ex  
3 ante and then they are sequentially revealed through  
4 the R&D process. So they are sequentially uncovered  
5 during the process.

6 So the model is going to assume that the  
7 success of the invention and the cost of the delivery,  
8 they are stochastic and monotone in the investment.  
9 And that the kind of the contest will result in  
10 winning if the invention -- the -- you know, the  
11 eventual invention is associated with positive  
12 surplus, meaning that the value is greater than the  
13 cost.

14 Methodologically, to actually link the data  
15 to the model and to uncover components of the model,  
16 the paper is going to assume -- the author is going  
17 to assume that the investment, which, of course, is  
18 not -- is not given in the data explicitly, so he will  
19 have to assume the investment is given to SBIR  
20 payment. And, also, he assumes that investment is  
21 monotone in value, and for some components of the  
22 model, he will have to assume that investment is  
23 actually -- investment equal to payment is actually  
24 optimal for the -- you know, given the surplus and  
25 given the environment.

30

1 So there are many good things that I can say  
2 about this paper. So, first of all, of course, it's a  
3 very timely effort thinking about this -- the optimal  
4 structure, the optimal features of R&D contests. You  
5 know, of course, these contests have been around for a  
6 long time. We know that [indiscernible] construction  
7 always involves a contest -- always involves a contest  
8 stage where people compete, where their, you know,  
9 multiple designs compete and then whoever proposes the  
10 best design gets to supervise the construction.

11 So these contests is seen then before, but  
12 we see more and more of them recently where the  
13 Government or private firms run contests to choose the  
14 best design or to kind of to generate more innovation  
15 in a particular area so one kind of very prominent  
16 example that I'm sure a lot of people heard about is  
17 this hyperloop pod competition which was run by Musk  
18 and Tesla company.

19 So, yeah, so this -- there seem to be a lot  
20 of interest in these contests recently, especially in  
21 the private market. So, again, timely effort.

22 So what else? So first of all, I have to  
23 commend the author for making, like, I am sure a  
24 pretty substantial effort of collecting the data that  
25 would be informative about this environment. So he

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1 clearly had to go to multiple sources, put it  
2 together, to make it, you know, informative and  
3 coherent.

4 Second, you know, despite his best efforts,  
5 the data was limited. You know, there are multiple  
6 shortcomings in this data. And, so, he made a pretty  
7 substantial effort to design a model that is going to  
8 take a maximum advantage of the data that are  
9 available to him. So it's also, you know, a  
10 nontrivial -- nontrivial contribution here.

11 Also, you know, given the model, he proposes  
12 a new identification strategy, which very nicely takes  
13 advantage, leverages the features of the bargaining  
14 features and also the selection into the -- into the  
15 third stage that he has in his model. It's a very  
16 nice identification strategy. People probably will  
17 want to use it in the future.

18 Again, the paper provides a number of  
19 insights into how these contests should be optimally  
20 designed. I perhaps should not spend too much time  
21 going into it because I do want to mention a few -- a  
22 few kind of concerns that I had when reading the  
23 paper. So my main -- you know, a number of concerns  
24 that I have are related to the measurements of things  
25 in the paper. So first of all, this whole concept of

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1 value surplus/profitability of the invention.

2 So to the best of my ability, the way he  
3 measures -- you know, to the best of my ability to  
4 understand what was written in the paper, the way he  
5 measures it, he basically links a particular R&D  
6 contest to the subsequent acquisitions by the  
7 Department of Defense. And, so, basically, the  
8 surplus is measured by the observed purchases by DOD  
9 of the invention which came out of this contest.

10 Right, so, first just a purely technical  
11 comment. It wasn't immediately clear to me whether  
12 the way he thinks about profitability was a per-unit  
13 profitability or kind of sort of lifelong, overall  
14 profitability. On one hand, the model seemed to be  
15 talking about per-unit profitability because we talk  
16 about the model looks at this cost of delivery, a unit  
17 of the product, right? So it's kind of a per-unit  
18 profitability.

19 On the other hand, what we measure in the  
20 data seemed to be more for multiple unit, right, in  
21 these profitability, and you would think that this  
22 lifelong profitability would be the right thing to  
23 take into account when thinking about investment,  
24 right, because that's what they anticipate to be the  
25 return to the -- to the R&D process.

33

1 And here I anticipate at least one concern.  
 2 So even restricting kind of return to the investment  
 3 to purely DOD acquisitions, you know, the firm has to  
 4 forecast the future demand for the invention. So it's  
 5 one thing to be able to assess how much they can  
 6 extract -- you know, what would be the value of a  
 7 given unit of the product. And it's an entirely  
 8 different forecast and the procedure thinking about  
 9 how many of those units they will be able to sell to  
 10 DOD. So that's one thing.

11 The second thing is you may not be able to  
 12 see the full realization of the demand in your data  
 13 because, you know, so maybe they bought right now a  
 14 few units, but maybe more purchases are coming in the  
 15 future. You don't know, so not the full demand is  
 16 perhaps realized in the data.

17 Second, when I was looking through the  
 18 documents on the SBIR website, they keep emphasizing  
 19 this, that all these kind of inventions, they have  
 20 their profitability but then -- but then show it is  
 21 not necessarily restricted to military uses. They  
 22 keep encouraging the participants to seek kind of  
 23 private sector sort of applicability of their  
 24 inventions. And they keep emphasizing that the  
 25 invention may be useful also as a stepping stone for

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1 the future products that will be developed, right? So  
 2 they're all like a broader sort of surplus coming out  
 3 of this invention.

4 And, so, perhaps some of it you cannot --  
 5 you know, cannot measure just like obviously there are  
 6 limitations to what is feasible, but I would be, first  
 7 of all, a little bit concerned about the private  
 8 sector potential, right? And one way to deal with it,  
 9 which is perhaps not ideal but maybe better than what  
 10 is done right now, is that maybe limit your attention  
 11 to purely military so that pure -- to the project that  
 12 are aimed at very clearly military uses.

13 So for example, these game-related projects,  
 14 right, the virtual-reality-related project, for sure  
 15 they will be placed on the private market as well, and  
 16 so this is something that you cannot see in the data,  
 17 and it perhaps is a shortcoming of the -- you know,  
 18 like it's a pretty serious distortion in your  
 19 measurement of the value. Okay?

20 So why should we worry about this? So, one  
 21 -- one thing is VM is measured in surplus. VM is  
 22 measured in the social surplus, and that is what you  
 23 aim to maximize by your design of the contest. And,  
 24 so, obviously this is -- this is already not ideal,  
 25 but all -- you know, if you mismeasure social surplus,

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1 if you define it incorrectly, then you probably are  
 2 not going to be able to correctly predict the optimal  
 3 investment that the firm would want to make, you know,  
 4 when doing this R&D process, right? So that also is  
 5 going to induce the distortion in your analysis of the  
 6 investment.

7 So in general, you know, I understand, the  
 8 data are limited. You do the best you can, but I  
 9 would think a little bit more if there is anything you  
 10 can do, like, additional about the investment because,  
 11 you know, even -- even on this SBIR website, they do  
 12 say that they provide seed money, right, so which  
 13 already kind of says that it's probably not equal to  
 14 the investment, or at least maybe again selection of  
 15 projects which it's more likely to be exactly equal to  
 16 investment. It's a little bit -- you know, at least  
 17 acknowledge it in the paper so that people are aware  
 18 that the results are subject to this, you know,  
 19 possible shortcoming.

20 Okay, so, another concern that sort of a  
 21 little bit nagged at me when I was reading the paper  
 22 is whether you measure competitors correctly, right?  
 23 So it seems that the way you think about competitors,  
 24 you always think about people who are participating in  
 25 the same SBIR contest, right? But the SBIR only

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1 finances R&D by small businesses, right? And, so,  
 2 potentially, there are other businesses out there that  
 3 are doing similar research and, you know, the SBIR  
 4 companies may not be aware of those competitors and  
 5 are taking them into account when making their  
 6 investment decisions.

7 So, again, why does it matter? Well, it  
 8 matters, first of all, for your bargaining stage  
 9 because that is going to influence the Government's  
 10 threat point, and as I said, it may matter for the  
 11 optimal investment.

12 So, again, what can be done? I understand.  
 13 So one way to do -- to deal with this, again, if you  
 14 reduce -- reduce the set of projects to those that  
 15 look specifically at the military uses, perhaps you  
 16 can go to this -- go back to this DOD database that  
 17 you used and look at the SBIR topics, related  
 18 acquisitions, which involve non-SBIR firms, right? So  
 19 that could help you to define the set of other  
 20 potential competitors, so other firms that worked on  
 21 similar topics and kind of eventually got a scoop,  
 22 like kind of beat the SBIR companies. So at least --  
 23 at least one way to address it.

24 So another concern which perhaps is not --  
 25 is of a smaller magnitude but nevertheless may be



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1 worth acknowledging in the paper, so this concern is  
2 about whether we are able to recover the correct  
3 distribution of values in this analysis. So one  
4 concern that I had is I already know that we only see  
5 the small companies in the data, but another thing is  
6 that the SBIR participation does involve some  
7 restrictions -- or does impose some restrictions.

8 For example, the products that come out of  
9 the research, which is based on SBIR financing, they  
10 cannot be exported. They cannot be sold abroad.  
11 Also, any patent that comes out of SB-funding research  
12 has -- so the Government has the right of free  
13 licensing of this -- of this patent for any future  
14 production.

15 So clearly firms are going to take this into  
16 account when deciding whether to apply -- to even  
17 apply for SB funding, right? So you would anticipate  
18 that there will be some selection and therefore we are  
19 not going to see the full distribution of values  
20 perhaps, you know, on the basis of the data that we --  
21 that we use -- that we see in the -- you know, coming  
22 out of SBIR program.

23 So, again, even less a concern that  
24 something nevertheless that is worth acknowledging is  
25 that the social surplus generated by the participants

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1 in this SBIR program, it is larger than just the  
2 explicit profitability, the explicit profit that they  
3 collect by selling, you know, the product that was  
4 eventually developed in this contest. So  
5 specifically, some of the losing ideas, they still  
6 result in the published knowledge. They result in  
7 patents. And they serve as a kind of fodder for the  
8 future research, and then in this way they contribute  
9 to social surplus.

10 But, also, the guys who lost, you know, the  
11 SB contest, they nevertheless may sell their invention  
12 in the private market, yeah, okay, so they will sell  
13 the invention in the private market so that, again,  
14 there is some surplus generated here which is perhaps  
15 not taken into account.

16 Just one thing to say, again, the data, very  
17 limited, we are doing the best we can given the data.  
18 But if in the future we have more data, like one  
19 concern that I had is that perhaps we do not get to  
20 learn the value before we learn the cost. Perhaps  
21 this process happens kind of concurrently, and in the  
22 first stage you only get a signal that is then  
23 [indiscernible] clarified in the subsequent stages,  
24 and so then identification will have to be adjusted  
25 accordingly to have such a rich environment.

39

1 And then the final comment, even of smaller  
2 sort of importance is that the heterogeneity of the  
3 projects clearly is important here. And right now,  
4 what is done in the paper is that the author allows  
5 for the distribution of value, distribution of cost,  
6 and, you know, the payments by SBIR to be sort of  
7 scaled in the same way, right, by exactly the same  
8 sort of factor. You may think it's too strong, right,  
9 it's a strong assumption.

10 Perhaps it's the best we can do right now,  
11 like, given the data, but, again, perhaps it's worth  
12 thinking that maybe the scale for values, the scale  
13 for costs could be different, in which case we may  
14 need another variable, we need another measurement.  
15 One thing that I thought, you do get in these  
16 proposals there is an estimate of the cost that they  
17 provide in the second stage. So perhaps that's what  
18 you can use again as a variable to help you to kind of  
19 to better capture the scale of these -- of these  
20 inventions -- of the distribution of cost for these  
21 inventions.

22 So this is all I have. Thank you very much  
23 for your patience. And great paper. I hope to see  
24 more research in this area.

25 MR. RAVAL: All right, we have time for one

40

1 question.

2 MS. JIN: A very interesting paper. I'm  
3 wondering to what extent you observed repeated  
4 interactions between the small firms and DOD. If a  
5 firm got rewarded in phase three, DOD potentially  
6 would have much more information about a firm when  
7 they deliver phase three, and would that information  
8 sort of help them in the future project selection?

9 MR. BHATTACHARYA: Yeah, so these firms, the  
10 conditional winning of phase two contract, I think  
11 there the data said, like, four or five times on  
12 average. So there are repeat purchases. There's some  
13 DOD history. I haven't looked at winning a phase  
14 three contract and whether you win more phase two  
15 contracts, but there's probably an effect.

16 Winning one phase two contract in the past  
17 tends to increase your probability of winning phase  
18 two contracts, but after that, it's pretty flat. So I  
19 think there's some learning between the DOD and the  
20 firm, but -- but maybe not for an excessively long  
21 period of time.

22 Okay, is that it?

23 (Applause.)

24 MR. RAVAL: All right, next we have Allan  
25 Collard-Wexler from Duke, and he's going to present

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1 Market Power and Product (Mis)Allocation in OPEC: A  
2 Study of the World Oil Market.

3 MR. COLLARD-WEXLER: Okay, so we came at  
4 this project by thinking about misallocation of  
5 production, so inputs going to the wrong firms. And  
6 we wanted to understand what was the effect of market  
7 power in generating some of this misallocation of  
8 production. And the setting that we've decided to  
9 look at is the world oil market. And this is a  
10 market, I think, that's very interesting to study for  
11 productive misallocation.

12 First of all, there's a large cartel that's  
13 been active for a very long time, OPEC. It's a  
14 homogenous product market where we're going to be able  
15 to kind of understand production costs at different  
16 parts of the world in a kind of very comparable way.  
17 And I think we're interested kind of in the effects of  
18 market power, but we haven't spent a lot of time on  
19 kind of cost effects of market power and I think this  
20 is where we're getting at.

21 And, finally, I think it's also to bring  
22 questions of market power to the kind of misallocation  
23 literature. And that's why we started this.

24 So this is going to be the main graph to  
25 explain to you the distortion and what we're trying to

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1 measure. So imagine that -- I don't know if there's a  
2 laser pointer? No. So imagine that you have a cartel  
3 with marginal cost 1, so they're the low-cost guys,  
4 and the socially efficient thing would be for marginal  
5 cost 1 to produce everything. But this low-cost  
6 producer happens to be a cartel, and they're  
7 restricting production to  $q_1$ . And because they  
8 restrict production to  $q_1$ , you've got other producers  
9 in the world, and those are represented by this  
10 marginal cost,  $f$ , that's increasing the jump-in. And  
11 there are going to be some competitive fringe. They  
12 produce all the way until marginal cost equals to  
13 price.

14 Now, the typical thing that we do when we  
15 looking at this is look at the quantity distortions,  
16 look at the Harberger triangle that we're -- we're not  
17 producing the socially efficient amount; we're  
18 producing less; and that's causing a welfare loss.

19 And what I want to draw your attention to is  
20 there's also another loss in this setting, and that's  
21 that production's being allocated to the wrong people.  
22 So even if you wanted to produce  $q$  rather than the  
23 social quantity, you wouldn't produce  $q$  that way  
24 efficiently. And, so, this trapezoid that we shaded  
25 in is just representing the increase in total cost of

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1 production, which is a welfare loss, because the  
2 cartel's leading to inefficient allocation or  
3 production between inside the cartel and outside the  
4 cartel.

5 We call that -- that shaded trapezoid  
6 productive distortion, so it's a distortion that  
7 affects the -- that affects the cost of production.  
8 And the goal of this paper is to try to measure how  
9 big that distortion could be in the context of OPEC.

10 Now, as soon as you start this, there's a  
11 problem with oil which is it's a renewable -- it's a  
12 non-renewable resource. So, you know, there's this  
13 question of, well, if I don't use this field today, I  
14 can -- I can just use it tomorrow. And, so, what  
15 we're going to do is to take this kind of depletable  
16 resource setting seriously and that welfare gains are  
17 going to come from we should be producing at low cost  
18 -- we should be kind of moving low-cost fields kind of  
19 early in the production order rather than later  
20 because -- just because of discounting, it's going to  
21 be more efficient to use cheap resources before you  
22 use expensive resources.

23 So it will just be a dynamic version of that  
24 productive misallocation graph that I just showed you.  
25 So really it will be all about the timing of

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1 extraction to take that depletable resource context  
2 seriously.

3 There's been some literature that's tried to  
4 get this productive distortion measure, and the one I  
5 want to point out is in the electricity market,  
6 Borenstein, Bushnell, and Wolak have something similar  
7 because electricity, there's inelastic demand curve,  
8 so there's no quantity distortion, so all you're left  
9 with is productive distortions. And there's a large  
10 literature on misallocation and on cartels and we're  
11 really trying to join the two together. And there's  
12 less literature on OPEC than you think, so we're also  
13 trying to add in on that.

14 So what we'll find is that over the period  
15 1970 to 2015, cost of world oil production are 10  
16 percent higher than they ought to be because of the  
17 OPEC cartel. And this productive distortion has --  
18 over this time period has a welfare of \$163 billion.  
19 So it's saying that these productive distortions could  
20 lead to welfare losses due to market power that are as  
21 large as anything that's been documented. And that's  
22 why we should think about them when thinking about the  
23 welfare impacts of market power.

24 Okay, so some background on oil is there's  
25 large cost differences between oil producers. I think

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1 the 90/10 -- the 90th versus the 10th percentile have  
2 like a nine-to-one difference in cost. For  
3 manufacturing, that's like three to one. And it's  
4 pretty easy to understand why there's such dispersion  
5 of costs of oil extraction. You know, this is in West  
6 Texas. These are just stripper wells, so this  
7 technology is -- you know, you could have done this 70  
8 years ago. It's reasonably easy to do.

9 And then here's another oilfield. This is  
10 off the North Sea off Norway, and this is like  
11 building a skyscraper in the middle of the ocean. So  
12 there's kind of natural reasons why different oil  
13 deposits are going to have very different costs. And,  
14 you know, and that's why which oilfield gets extracted  
15 when is going to have kind of meaningful effects on  
16 total costs of oil production.

17 OPEC is these countries. I would say when  
18 you read about OPEC, it's an imperfect cartel. So  
19 they use quota arrangements rather than, say, telling  
20 Saudi Arabia you produce everything and send a check  
21 back to Gabon. So there's no transfers in this  
22 cartel. There's instances of cheating on quotas. A  
23 lot of people would think that a -- the market power  
24 of OPEC is just unilateral market power by, say, Saudi  
25 Arabia and Kuwait, so it might not even be a cartel

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1 the way we model it but just a set of leading  
2 countries that -- that exercise unilateral market  
3 power.

4 Why is this important? It's -- you  
5 shouldn't even expect OPEC to basically minimize costs  
6 within the OPEC cartel given their -- they're an  
7 imperfect cartel mechanism.

8 And, you know, OPEC is about 40 percent of  
9 world oil production, and outside of the OPEC is the  
10 rest, and some countries like Saudi Arabia and the  
11 United States are 10 to 15 percent of global oil  
12 production.

13 And this is just another way to say it, the  
14 dotted line here is the OPEC market share, and I've  
15 overlaid the price of oil over time, and there's these  
16 big instances in '73, '81, and then recently where the  
17 price of oil has these large spikes. So there's a lot  
18 of movement in the price of oil generated according to  
19 observers by OPEC's decisions to cut production. And  
20 that's why production starts to spike -- costs --  
21 prices start to spike.

22 So to understand misallocation of  
23 production, we needed data on many oilfields and their  
24 costs and their production. And we got this from a  
25 Norwegian energy firm called Rystad Energy. There's

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1 about three different firms that do micro models of  
2 the world oil market, and they assign, you know, costs  
3 and reserves and production to basically all the --  
4 all the oilfields on the planet. And we're leveraging  
5 this data on 13,000 fields.

6 The data is going to be at the field level.  
7 So, like, Ghawar Uthmaniyah is one of the world's  
8 largest oilfields in Saudi Arabia, and that has, say,  
9 like 800 rigs on it or more. So some of these fields  
10 are -- it's not a single well. It's a field with,  
11 say, up to thousands of wells on them. So that's the  
12 level of the data. And this is just to say that we  
13 have detailed rich data on these individual fields,  
14 such as reserves or when they were discovered or how  
15 much they produced from '70 onwards.

16 The first thing you might think is, well,  
17 maybe -- maybe the reason that OPEC produces, say, 40  
18 percent -- 30 or 40 percent of the world's oil is  
19 because it's limited on reserves, so there's only so  
20 much oil in the ground that it has and that's what's  
21 constraining it. And just as a first pass, you know,  
22 OPEC might be 40 percent of production, but it's about  
23 50 percent of reserves in the world. And if you do  
24 something simple, which is to say, like, what's the  
25 ratio of reserves to annual production, so non-OPEC

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1 with current reserves, they can produce for the next  
2 ten years. In OPEC, the same answer is 19 years at  
3 current production.

4 So it's not just -- when I say that OPEC is  
5 producing too little, you can see that because they're  
6 exploiting the reserves less intensely than non-OPEC  
7 members. And that's something we noticed.

8 So I want to give you an idea of what the  
9 variants in costs looks like across the world, both  
10 OPEC and non-OPEC members. And what we've done here  
11 is we've plotted what I call, like, annual costs, like  
12 costs in a year divided by production in a year, and  
13 the black bars are the 5th to the 95th percentile  
14 across all the oilfields in that particular country.

15 And just for -- just to benchmark things,  
16 I've also put what the price of oil is on top of that,  
17 so that gives you an idea of, you know, how these  
18 costs compare to prices. So this is Saudi Arabia.  
19 You know, we estimate today they have a cost of, say,  
20 \$10 a barrel. So they have the cheapest oil reserves  
21 in the world. If you look at countries like Nigeria,  
22 which is an OPEC but isn't one of the countries that  
23 exerts unilateral market power or punishes cheating,  
24 they have costs that are quite a bit higher, say a  
25 median of on the order of \$30 a barrel recently.

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1 A country like Russia has costs of about \$20  
2 a barrel. They're not in OPEC, and you might wonder,  
3 you know, why aren't they producing more, given they  
4 have low costs. And here I'll just note, and this is  
5 outside of the discussion for now, they have a 50  
6 percent pipeline tax. So basically half their revenue  
7 is a direct royalty to the government. So you might  
8 expect there's other reasons why marginal cost and  
9 prices might diverge in terms of production choices.

10 And then if you go to the United States, the  
11 90th percentile well in 2014 had costs of well over  
12 \$90 a barrel. These are mostly fracking, by the way.  
13 And this is exactly the kind of productive distortion  
14 that I want to get at, which is there's tons of oil in  
15 Saudi Arabia in these \$10-a-barrel fields. And the  
16 price kind of skyrocketed to \$90 a barrel in 2014.  
17 And then there's a question of why didn't Saudi Arabia  
18 produce more, and, well, that's because, you know,  
19 that's how it exerts market power by holding down  
20 production. But then when the price is \$90 a barrel,  
21 things like people fracking in North Dakota at \$90 or  
22 \$80 a barrel, like really expensive oil production  
23 starts to enter the market. And that's the kind of  
24 productive misallocation I'm talking about.

25 And you see the same pattern in Canada

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1 where, you know, some of the most expensive oil  
2 production that you can see in the world, which is  
3 exploiting tar sand, starts turning on in the 2000s.  
4 And, again, given that there is available oil that's  
5 at \$10 a barrel, squeezing oil out of -- out of the  
6 sand at \$100 a barrel seems like a very inefficient  
7 thing to do.

8 Okay, so, this is kind of the evidence for  
9 just how big the cost differences are across  
10 countries. But I wanted to get at this measuring the  
11 productive distortion, so I wanted to estimate that  
12 shaded trapezoid. And, so, this is what we're going  
13 to do. We're going to propose a measure -- a  
14 definition of productive distortion, and that's the  
15 difference between -- remember, this is dynamic, so  
16 it's going to be the net present value of the realized  
17 cost of production, given what we see, which we'll  
18 assume is due to the activities of the OPEC cartel,  
19 versus the net present value if firms took prices as  
20 exogenous so that -- that means they're acting as if  
21 they were in a competitive world, but there's an  
22 important caveat, which is they took prices that are  
23 exogenous, but the total production of oil in the  
24 world will be the same as what was realized in the  
25 data.

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1 Why am I putting that caveat that total  
2 production is the same as what was realized in the  
3 data? It's just that I want to keep total production  
4 in this counterfactual at  $q$ , what actually happened as  
5 a net production distortion figure. So we're not  
6 going to be kind of playing around with increases in  
7 total aggregate quantity, just holding quantities  
8 fixed in the competitive counterfactual versus the  
9 data and just looking at how the allocation of  
10 production differs in those two worlds.

11 Okay, we need to put a few assumptions.  
12 We're going to have a very long run view on costs, so  
13 like cost of developing an oilfield from nothing until  
14 depleting the field, and that's going to mix startup  
15 costs, fixed costs, marginal costs and so on, and I  
16 just want you to think that over a long time period  
17 you can kind of combine these together into a single  
18 kind of unit cost.

19 In the paper, we do some derivations with  
20 production functions to get something that looks like  
21 CFT, which is just a constant marginal cost. And  
22 there's going to be some work here. This  $\mu$ -st factor  
23 is just going to try to pick up that. It turns out,  
24 like, the costs of renting a rig move a lot from year  
25 to year, like when the price of oil is \$80, it costs

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1 three times more to rent a rig than when it's \$30 a  
2 barrel. And so this  $\mu$ -st thing is just trying to  
3 capture a variance in input prices of drilling, and  
4 that's why we need to have it in there.

5 And we're going to assume that this -- you  
6 can just think -- for the purposes of this talk, you  
7 can just think of those costs as just being constant  
8 over the whole time period. There's just a CF cost of  
9 a particular field.

10 Now, with this kind of linear marginal cost  
11 structure that's constant, you get a very nice  
12 characterization of the competitive equilibrium. So  
13 just as the competitive equilibrium firms are  
14 maximizing the NPV of profits, subject to a reserve  
15 constraint, in the paper, we have a way of  
16 characterizing this equilibrium, which is through what  
17 we call a sorting theorem, which is just the lowest  
18 cost guy starts producing all the way up until you've  
19 satisfied the total quantity, that restriction for  
20 that year, and then you move on to the next year, and  
21 then -- so you just keep depleting the cheap fields up  
22 until the quantity constraint and then you move on.

23 So really it's just saying the cheap guys go  
24 first. That's what the equilibrium will look like.  
25 And so this allows us to kind of very simply solve for

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1 a competitive equilibrium or 35 years with 13,000  
2 wells without having to do too much to it.  
3 So I want to show you results from comparing  
4 what happened to this competitive counterfactual. And  
5 I'll first start by telling you what happens if you  
6 just look at this competitive counterfactual applied  
7 to a single year. And then I'll do what I call a  
8 dynamic version, which is I'll look at the competitive  
9 counterfactual but from -- starting in 1970 to 2014.  
10 And those differ because oil is depletable, right? So  
11 if you extract something in 1970, you can't use it in  
12 '75. So that's why the dynamics are different. The  
13 reserves are kind of the state variable here.  
14 Okay. And there's a number of modeling  
15 assumptions like discount rates, how quickly you can  
16 extract oil from the ground, given the size of  
17 reserve. What do you assume about the discovery  
18 process of new fields. So we have to make assumptions  
19 on that. It makes sense to kind of run this  
20 competitive simulation all the way until every single  
21 drop of oil in the world has been depleted. So really  
22 the only difference between competition and market  
23 power is going to be just the timing of oil  
24 extraction, not is every reserve going to be  
25 extracted. That will happen, so we're just going to

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1 have to assume things like after 2015 the entire world  
2 reverts to competition, just to fill out kind of the  
3 later years of the model.  
4 Okay, and then there's some work on  
5 estimating costs, which I won't get into, but is done  
6 in the paper. So I just want to show you in 2014 what  
7 happens to output shares. In actuality, that's the  
8 left side. So like the Persian Gulf OPEC members  
9 produced 26 percent of the world oil in 2014. In the  
10 competitive counterfactual, they would have produced  
11 75 percent. That's not surprising. Most of the  
12 world's cheap oil is in the Persian Gulf, and so in a  
13 competitive world, you just see production kind of  
14 ramp out from there.  
15 Interestingly enough, the members of OPEC  
16 that are not in the Persian Gulf would actually see  
17 their shares drop a lot. And if you wondered, well,  
18 you know, is Venezuela really doing anything for OPEC?  
19 You know, our answer would be it doesn't look like it.  
20 It looks like it's producing more in OPEC than it  
21 would in a competitive world.  
22 And then, of course, if it's going to the  
23 Persian Gulf, it's coming out from somewhere, and it's  
24 coming out mainly from non-OPEC members, so the U.S.  
25 produces 13 percent of the world's oil and it produced

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1 1 percent in the competitive counterfactual. So,  
2 again, this is just showing you how market shares  
3 would change under our kind of competitive system  
4 versus what we have.  
5 We then wanted to say, well, what is the  
6 actual welfare cost of this different allocation of  
7 production. And, again, this is for just one single  
8 year, and, you know, the competitive cost of  
9 production, which I'm going to call optimal for second  
10 welfare theorem reasons, is \$121 billion, whereas what  
11 we see given the actual allocation of production in  
12 2014 is a cost of \$240 billion. So there's basically  
13 the cost of oil is about twice as high as it would be  
14 in our competitive counterfactual.  
15 Now, in subsets, that doubling of costs is  
16 really strong, and I'll explain to you why. If you  
17 look at, say, if I just fixed production levels within  
18 each country, but then I made things competitive in  
19 each country, so I allowed all the fields in the  
20 country to produce in a competitive way, then costs  
21 would be 203 billion. So it would be a \$40 billion  
22 savings. So that's like saying there's inefficiency  
23 within the country that we're picking up.  
24 And, now, attributing that kind of  
25 inefficiency to market power seems like it's a very

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1 odd thing to do. It could be measurement problems.  
2 It could be errors by the producers. It could be  
3 expectations that weren't realized. So it could be a  
4 lot of other stuff.  
5 So we're going to try to do something  
6 conservative and say -- and this is in the optimal  
7 OPEC quantity -- which is if you just fixed in this  
8 competitive counterfactual, the total -- that 40  
9 percent of the world's oil comes from OPEC and 60  
10 percent of the world's oil comes from outside of OPEC,  
11 how much more expensive is the total cost of  
12 production than the fully competitive counterfactual.  
13 And that's what this \$154 billion number is. It's  
14 saying just the allocation between OPEC and non-OPEC  
15 countries is causing the cost of oil to be \$33 billion  
16 higher than it would be without that, that restriction  
17 on where all oil comes from.  
18 And, so, we're going to use that kind of  
19 number to kind of -- we're going to call that the  
20 effective market power here. And, you know, we have  
21 these distortions plotted over time. They get bigger  
22 as you get -- in the periods when there is spiking  
23 price of oil, which shouldn't be surprising. You  
24 know, it's not when the price of oil is \$30 a barrel  
25 that you expect big misallocation. It's when the

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1 price of oil is \$90 a barrel that you expect very  
2 expensive oil to kind of hit the market. And that's a  
3 productive inefficiency.

4 Same exercise now. Instead of just doing it  
5 for one year, we're basically simulating out kind of  
6 what would happen over time. That's our dynamic  
7 counterfactual. And you get these results that, like,  
8 in the 1970s, OPEC should have produced in a  
9 competitive world 90 percent of the world's oil. It's  
10 even stronger than that.

11 There's, like, three fields in the world --  
12 Ghawar, Greater Burgan, and -- sorry, there's two  
13 subfields of Ghawar in there that would have basically  
14 produced everything. So they're the cheapest  
15 oilfields in the world. They're like at \$5 a barrel.  
16 In the competitive counterfactual, you should just  
17 deplete them immediately. And then once you've  
18 depleted them by, you know, 1990 or so, you let other  
19 producers kind of kick in. But really it's just  
20 saying the ordering of those fields is very strange.  
21 They should have been depleted immediately.

22 And then we do kind of the same kind of  
23 costs but for this entire path from '70 all the way on  
24 to 2014 or all the way until 2100, which just  
25 represents until all the world's oil gets depleted.

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1 And you get things like the actual cost of oil was 2.1  
2 trillion. The competitive counterfactual would have  
3 been \$1.2 trillion. So, again, the same order of  
4 magnitudes.

5 And then if you look at, you know, how much  
6 of that is because of -- of that increase is because  
7 of that \$900 billion number is because OPEC and non-  
8 OPEC market shares are -- the market share of OPEC's  
9 being fixed at what it actually was, the answer is 148  
10 billion. If you look at what's coming from across  
11 OPEC member distortions, that's 85 billion. So this  
12 is just accounting for where these -- where this  
13 misallocation is coming from.

14 So the headline numbers we're going to bring  
15 up here are if you just count the fact that just  
16 constraining OPEC's market share to be what it was in  
17 the data, you get a number like 148 billion. If you  
18 count not only constraining OPEC's market share but  
19 also that within OPEC members production is being  
20 misallocated and there's good reasons to believe that,  
21 like, Venezuela is producing too much and Saudi Arabia  
22 too little within OPEC because of how the cartel is  
23 organized. They don't have transfers, so they use  
24 kind of market share to move things around. Then you  
25 get a number of 233 billion, you know, incorporating

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1 those within OPEC distortions.

2 Let me add one more twist to all of this,  
3 which is, you know, we're kind of worried that there's  
4 -- we're looking at actuality versus a competitive  
5 model where there aren't any other distortions. And  
6 you might think, well, what we should really be  
7 comparing this is like to a second-best theorem where,  
8 you know, it's competitive but there's also other  
9 distortions like distortionary taxes. So we know that  
10 there's a lot of distortionary royalties here.

11 So even if you move competition but you keep  
12 those distortionary royalties, you know, you're not --  
13 you're not going to get cost-minimizing production.  
14 Or maybe there's all sorts of other wedges that might  
15 be distorting production that don't have to do with  
16 market power but would still affect the competitive  
17 counterfactual.

18 And in the paper, what we show is that even  
19 if you kind of condition on what's the effect of  
20 market power with those distortionary taxes or with  
21 any other distortionary wedge that causes, you know,  
22 the low-cost fields, say within a country, not to  
23 produce first, we get -- the OPEC numbers that we've  
24 been measuring turn out to be very stable. So it's  
25 adding these other distortions. So we feel reasonably

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1 confident that even in the presence of some other  
2 distortions these effects of OPEC seem to persist.

3 So I'll just conclude. There's countries  
4 with clear market power. They're in the Gulf. They  
5 have very low cost of oil production. If you push  
6 production towards those countries, like you would in  
7 a competitive world, cost of oil production would drop  
8 substantially, and this leads to enormous welfare  
9 effects due to market power, and again, not the  
10 traditional channel, but the quantities are too low,  
11 but instead that the allocation of production seems to  
12 be distorted by the cartel.

13 Okay, that's it.  
14 (Applause.)

15 MR. RAVAL: So we have Hugo Hopenhayn from  
16 UCLA to discuss the paper.

17 MR. HOPENHAYN: My discussion will not take  
18 all the time. This is a great paper. I mean, there's  
19 a large growing literature on misallocation, sort of  
20 more in the macrodevelopment side. Allan and the  
21 coauthors here have identified perhaps the -- if you  
22 look at that literature, one of the big failures of  
23 the literature is that while measured misallocation  
24 tends to be very large, identifying the causes of that  
25 misallocation has been, you know, really poor.

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1 And policies that we usually think about,  
 2 you know, generating distortions in allocation,  
 3 distorted taxes, subsidies to firms of one type or the  
 4 other, explain, you know, a very small fraction of  
 5 misallocation. For example, in Hsieh and Klenow's  
 6 study of misallocation in China, all the observables  
 7 that you have at first had explained about 10 percent  
 8 of the misallocation. So finding from that  
 9 perspective sort of there's a holy grail of finding,  
 10 okay, well, what is behind this misallocation. And  
 11 as, you know, previous paper by Allan and coauthor --  
 12 the same coauthors have argued, I mean, a lot of this  
 13 misallocation could be -- basically be it's backed  
 14 out, you know, from structural specifications,  
 15 misspecification of production functions, for example.  
 16 So this one is, I think, very valuable in  
 17 that context because it brings in real data and a very  
 18 clear reason for having misallocation. I'm not going  
 19 to comment too much on the results themselves, I mean,  
 20 in terms of data. It's not my strong point, those of  
 21 you that know me. And the other thing is that I  
 22 think, you know, the paper is very carefully done.  
 23 There's a lot of issues that, you know, they had to  
 24 make assumptions about how much you can extract, at  
 25 what rate, you know, it's a maximum, this 10 percent

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1 rate that you can extract in establishing their  
 2 counterfactuals.  
 3 One thing that I would note only in terms of  
 4 quantitative analysis is that when they look at  
 5 misallocation within countries, in particular within  
 6 countries outside of OPEC, there's very large  
 7 misallocation. And in some ways, it's hard to think,  
 8 I mean, that it's imperfect competition that is  
 9 generating that in that, you know, it's -- the rest of  
 10 the world is a fairly competitive market. It's not  
 11 very concentrated production, and so it's very  
 12 dispersed. And if you take price as given, you know,  
 13 if you have a bunch of competitive firms, they would  
 14 minimize cost subject to that price.  
 15 And, so, what is creating that, you know,  
 16 big distortion that they find there, and then whether  
 17 that could be used in some ways to get a sense of the  
 18 extent of measurement error that there might be, and,  
 19 you know, that, you know, taken to the other  
 20 calculations, you know, sort of to as in Hsieh and  
 21 Klenow they do and sort of to -- you know, make the  
 22 values more, you know, relative to that normal  
 23 measurement error, let's say, so I think that's, you  
 24 know, the only caveat that I would want to point out.  
 25 I mean, I still think, you know, the paper has a big

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1 contribution, and these numbers come out very strongly  
 2 and high.  
 3 So my question is more as to, okay, so we're  
 4 at the FTC. And, so, you're concerned maybe about  
 5 collusion and the cost of collusion. And, so, what is  
 6 it -- from that perspective, what is the right  
 7 benchmark? So -- and Allan very clearly pointed, the  
 8 paper is about misallocation. And, so, the reference  
 9 point in a paper of misallocation would be the optimal  
 10 allocation, or what he called the competitive, which  
 11 would be the optimal allocation a social planner would  
 12 choose, which is the cost-minimizing or sort of  
 13 present value cost-minimizing allocation.  
 14 But if we think about collusion and we're  
 15 thinking about damages, and by the way, I think the  
 16 paper is pointing to something that I don't know how  
 17 aware people are, you know, how important it is in  
 18 measurements, which is that we're used to these  
 19 Harberger triangles, which are about, you know, a  
 20 welfare loss is from cutting output. That's the  
 21 triangle, but we're not used to this calculation that,  
 22 you know, when the rate is -- potentially when there  
 23 is, you know, this missed -- imperfect competition or  
 24 collusion in this case, that generates another  
 25 triangle, rectangle, or I guess the average would be a

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1 trapezoid, no, of the two?  
 2 So I think their paper points out to  
 3 something that is very important and that we should be  
 4 more aware of. And I even thought about, you know,  
 5 having more a macro perspective that what not to  
 6 recalculate, you know, the old, you know, Harberger  
 7 welfare triangles and add to those, you know, the  
 8 rectangles that come from, let's say, a imperfect  
 9 competition that as we know, those of you that, you  
 10 know, have worked with Cournot models, that there is,  
 11 you know, inefficiency in allocation as firms with  
 12 different marginal costs produce.  
 13 Okay, so that -- this is what I'm going to  
 14 say is that I want to put a little bit of this in  
 15 perspective and, you know, ask, you know, what -- and  
 16 sort of what is the right benchmark. And if we're  
 17 thinking about the FTC's thinking about collusion,  
 18 then banning collusion or eliminating collusion is not  
 19 going to eliminate misallocation. It's going to give  
 20 us the misallocation that is generated by imperfect  
 21 competition.  
 22 And as Allan pointed out, I mean, the --  
 23 it's important that collusion here in the cartel is  
 24 imperfect because we know that perfect collusion, I  
 25 mean, with transfers actually could improve

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1 misallocation by actually having the output assigned  
2 efficiently and then doing the appropriate transfers.  
3 So it's not obvious that collusion, per se, hurts  
4 misallocation. Here, the source is going to be that  
5 collusion by raising the price will allow, you know,  
6 certain producers to come into the market that are  
7 inefficient and that would be not even producing in  
8 the absence of collusion.

9 So that's a question, what's the benchmark,  
10 and so I think that's kind of an important question  
11 that we should ask, and the question is -- I mean  
12 depends on what we're after. If we're after, you  
13 know, damages of collusion, there's one thing. If  
14 we're after misallocation and understanding  
15 differences in TFP, I mean, this is the competitive or  
16 optimal one is the natural one.

17 The other question that I'm going to ask is  
18 -- and I guess I played with this a little bit, I  
19 mean, there's really not a lot of -- I mean, there's  
20 really, except for that graphic you saw, there's no  
21 more theory in the present value allocation, there's  
22 no more theory in the paper. So I started playing a  
23 little bit and saying, okay, maybe theory will take me  
24 somewhere, and I'm just going to tell you where I got.  
25 I mean, that's -- and you'll see the theory is, you

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1 know, first year undergraduate micro theory. So, I  
2 mean, it's not very fancy.

3 And, so, I'm going to address the  
4 suppression of this high-cost fringe, make it worse  
5 or -- and we saw an expansion throughout time -- this  
6 high-cost fringe. Did that make things worse or  
7 better? I mean, in some ways, they -- you'd say  
8 that's good, I mean, they created output that would  
9 not produce instead, but, you know, they also  
10 contributed to this misallocation. Is that good or  
11 bad? That's what I'm...

12 So this is the -- I thought I was going to  
13 get some -- oh, how do I go back?

14 You've seen already these numbers. I mean,  
15 he didn't have them -- oh, yeah, he had the same  
16 table. I'm not going to comment any more. The lower  
17 numbers are the ones that correspond more to the  
18 exercise when the benchmark is -- or partly the  
19 exercise when the benchmark is, you know, eliminating  
20 the misallocation that -- the lower one between OPEC  
21 and not-OPEC countries. Of course, this is much  
22 smaller than, you know, the upper numbers, but this is  
23 the number that I think you know realistically you  
24 want to point out when the bench -- I mean, if you're  
25 thinking of this benchmark.

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1 The other thing is that you are not going to  
2 be eliminating the whole misallocation within OPEC,  
3 and not even across OPEC because there is going to be  
4 in imperfect competition some misallocation --  
5 residual misallocation. So these numbers would be  
6 possibly considerably smaller when you consider as a  
7 benchmark in let's say a Cournot equilibrium as  
8 opposed to considering as a benchmark perfect  
9 competition.

10 I don't know how easy it is to think about  
11 even doing that kind of exercise but, you know, I  
12 think it would be nice to have some idea of orders of  
13 magnitude, perhaps comparing for episodes where there  
14 was break in the collusion and sort of thinking of  
15 that perhaps as the allocations that you would see in  
16 the absence of collusion. I really don't know, I  
17 mean, what would be a good...

18 So this is what we know in terms of -- I  
19 mean, Cournot model, the markup rule, the markup of  
20 firms are proportionate to the market shares. From  
21 this, you can back out that there is residual -- I  
22 mean, that there will be a coexistence of firms with  
23 different marginal costs within some range.

24 I did some -- just to give you a benchmark  
25 for this, I played around with the linear demand model

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1 and constant marginal cost. It turns out that the  
2 maximum misallocation that you can get there is if  
3 there is a single other firm with high -- you know,  
4 higher marginal cost producing. And the max is about  
5 the size of the trapezoid compared to, let's say, the  
6 welfare triangle is half that size. So the trapezoid  
7 is half the size of the welfare triangle, but it's  
8 already an important -- it already says that, you  
9 know, we are in that -- in that model. I mean, it's a  
10 bound. We would be missing 50 percent of  
11 misallocation just by looking at welfare triangles and  
12 not looking at misallocation.

13 Yeah, so, to talk about the counterfactuals,  
14 so here is a picture -- I mean a more stylized  
15 picture, a triangle instead of a trapezoid, but the  
16 same thing as what Allan presented. You know, we  
17 started the marginal cost, C. That's a quantity under  
18 collusion. The q, the small q, corresponds to the  
19 cartel's quantity, here assuming that the cartel has  
20 the same marginal costs as in his picture. This is  
21 just for expositional purposes. And the total  
22 quantity with collusion is adding the supply function  
23 that is depicted here, which would be the fringe  
24 firms, all of which have a marginal cost above the  
25 collusive -- or the marginal costs of the colluding



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1 firm.

2 And that would be, you know, this  
3 misallocation if you want a productive inefficiency,  
4 the CL, the -- compared to a deadweight loss. Now, if  
5 we, let's say, eliminated the cartel and as a  
6 consequence now we produce let's say a Cournot  
7 quantity, I mean, I don't know where the Cournot  
8 quantity is, you know, but if it proves a Cournot  
9 quantity, now you can see, I mean, that still there's  
10 going to be room for some fringe.

11 And, so, yes, there is a reduction in this  
12 triangle, but it doesn't disappear. And then, I mean,  
13 my picture, I mean, maybe suggests that that reduction  
14 might not be so large, unless it were a really large  
15 increase in the output, and the marginal costs of  
16 these firms -- like the supply function were  
17 concentrated in the upper levels, closer to price.

18 Second question here, so this says two  
19 things at the same time. I mean, obviously we're  
20 better off that there was this fringe, expensive  
21 fringe, because even though they introduced a  
22 misallocation cost, I mean, they're producing at a  
23 cost that is less than marginal cost -- sorry,  
24 marginal cost that is less than price. So they are  
25 contributing to welfare. And, so, yes, I mean, it's

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1 good that we have these firms; however, you know, it's  
2 not -- you know, we need to take into account that  
3 triangle, so -- in terms of the implications of  
4 cutting output by OPEC.

5 So the fringe expanded considerably during  
6 this period. And, in fact, you can ask the question,  
7 did that fringe expansion hurt welfare. And,  
8 actually, it can, and this is sort of -- maybe it's a  
9 little bit nerdy, but, you know, I just want to show  
10 you because I think it's a very nice calculation that  
11 you can make in this respect. And this is sort of a  
12 very -- again, going -- you know, a micro-level one.

13 So think about just to explain this picture,  
14 c here is the marginal cost of the cartel. Let's say  
15 here I'm taking C-zero to be the marginal cost. I'm  
16 thinking in cost to make it simple of a fringe.  
17 Initially, the capacity of the fringe is  $Q_0$ . And I'm  
18 going to consider an expansion of the capacity of the  
19 fringe. And let's say that given that that's a  
20 capacity of  $Q_0$  of the fringe, now we think of the  
21 cartel, it's going to be best responding as a cartel  
22 to this capacity of the fringe, and its best response  
23 that say that total output would be Output-Q. Okay,  
24 so this is sort of the initial equilibrium with a  
25 given capacity at  $Q_0$  of the fringe.

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1 Now suppose that, you know, you start doing  
2 fracking in North Dakota and all these things that  
3 expands the capacity of this fringe, okay? So -- and  
4 by the way, obviously if we go back, we have the two  
5 sources -- the two -- here's the rectangle -- yeah,  
6 sorry. Here's a rectangle. The size of the  
7 rectangle, CL, versus the deadweight loss. I mean,  
8 that gives you sort of what are these two components  
9 of welfare losses.

10 And, so, now, let's say you got the  
11 expansion of the capacity of the fringe, okay, so  
12 we're going to get a little extra -- two little extra  
13 effects. One is positive, the right one, that is.  
14 We're going to decrease deadweight loss, and that's  
15 kind of that sort of trapezoid but let's say  
16 approximately a rectangle up there.

17 And we have this other rectangle, which is  
18 the increasing in this misallocation cost. Okay? So  
19 which is bigger? And this will tell us whether that  
20 expansion in the fringe is something that hurt or  
21 actually improved welfare, okay? And, so, it's easy  
22 to see here that the -- this isn't a Cournot or linear  
23 sort of -- I'm assuming linear demand. So what do we  
24 know about linear demand, that when one -- you know,  
25 when output is expanded, the response of the cartel

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1 would be -- here's like two firms, is to cut by half  
2 of that expansion its own output, not by the full  
3 size, you know. So there's an accommodating part and  
4 so total output is really -- the total output  
5 expansion is only half of the expansion of the fringe.

6 And, so, these are essentially rectangles  
7 that differ in the base, okay? And potentially also  
8 differ in the height. One goes all the way to the  
9 demand function; the other one goes all the way to the  
10 cost, okay? So a calculation is quite simple. The  
11 change in CL is proportional to the difference between  
12 marginal cost of the fringe and marginal cost of the  
13 cartel. The change in Q is -- sorry, in deadweight  
14 loss is proportional to the difference between price  
15 and the marginal cost of the cartel, but divided by  
16 two because of the compensating effect of the response  
17 of the cartel.

18 So the total change is of the order of, you  
19 know, PC, divided by two, minus C -- 0 minus C. So  
20 here if the cost of the fringe is above half point  
21 between the marginal cost of the cartel in price, then  
22 this expansion of the fringe is actually bad for  
23 welfare. And I think this is kind of probably the  
24 case. You know, I mean, this fringe was -- you know,  
25 their costs were, you know, way above -- much closer

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1 to price than they were to marginal cost. So the  
2 answer there would be expansion of the fringe was  
3 costly, and it actually hurt the welfare of the world,  
4 even though the existence initially of the fringe is  
5 something that, you know, obviously possibly  
6 contributed to value.

7 So, I guess, you know, I don't have much  
8 more to say. I think it's a great paper. I think,  
9 you know, it's a very careful empirical analysis and  
10 dynamic modeling, in taking sort of the right way of  
11 approaching this problem. There are a lot of corners  
12 to cut, you know, that's inevitable, and I think they  
13 did a good job in that sense.

14 My main point is what is the correct  
15 benchmark if we're going to think about misallocation  
16 or versus we're going to think about collusion and  
17 trying to measure -- assess the damages of collusion.  
18 And, well, I think those are sort of the main points  
19 that I wanted to make.

20 MR. RAVAL: All right. Again, we have time  
21 for one question.

22 MR. RAMEZZANA: So I was wondering how  
23 general your optimal extraction path is, that is did  
24 you first start with the low cost field? Now, in a  
25 very stationary environment like that, I can see that,

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1 but in a more complex environment, in which one could  
2 have, you know, big future shocks, unexpected shocks  
3 to the need for oil or the marginal utility of income  
4 on ability of a country to pay for oil, I can see why  
5 maybe you don't want to use all the cheap oil soon.

6 Now, if you can commit perfectly to an  
7 extraction path, yes, then you do that. We use the  
8 cheap ones soon and some better stuff happens, we'll  
9 take it. But there's no commitment in this world, so  
10 maybe like the United States or somebody else, you  
11 don't want to find yourself in 20 years really needing  
12 oil during a period of crisis and having high costs.  
13 So that was just my question, you know, relative to  
14 the welfare criteria.

15 MR. COLLARD-WEXLER: So the way I see this  
16 is like is Saudi Arabia not extracting everything now  
17 because it can't just put the money in a bank and  
18 then, you know, it's using the oil in the ground as  
19 some kind of commitment to savings? And, so, I'm sure  
20 that that kind of institutionally can these countries  
21 save that way, I'm sure that's an issue here. How big  
22 it is, I don't -- I don't know, but I think that's the  
23 -- but that's the gist of the question.

24 So thanks, Hugo, for the discussion.  
25 (Applause.)

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1 MR. RAVAL: All right, we have Jihye Jeon  
2 from Boston University that's going to talk about  
3 Learning and Investment under Demand Uncertainty.

4 MS. JEON: All right, so thank you so much  
5 for this opportunity to talk to you about my research.  
6 So I'm going to start off by saying that in many  
7 capital-intensive industries, firms experience large  
8 waves of investment. And firms in these industries  
9 also invest in long-lived capital while facing demand  
10 that's highly volatile. So their expectations about  
11 how demand will evolve in the future will likely play  
12 an important role.

13 So the container shipping industry provides  
14 an example of these boom and bust cycles of  
15 investment. So in the figure that you're looking at,  
16 the blue bars are quarterly investment in new ships,  
17 and the red line is the price of investment. And, so,  
18 you'll see that investment is highly volatile, first  
19 of all. Also, it is highly concentrated in times of  
20 high price of the investment.

21 So in this industry, firms are exposed to  
22 sharp swings in international trade demand, but at the  
23 same time, supply is hard to adjust in the short run  
24 because there's time to build and also because firms  
25 tend to stick to their preannounced schedules. What

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1 happened recently is interesting. So there was a huge  
2 investment boom when trade demand was booming in the  
3 mid 2000s, and when demand collapsed after the  
4 financial crisis, this led to a huge amount of  
5 oversupply in the industry.

6 And, so, in this paper, I want to understand  
7 what drives these boom and bust cycles of investment  
8 and how firms invest under demand certainty, and I'm  
9 going to focus on the role of information. And I'm  
10 going to think about these things in a setting where  
11 there's market power and strategic considerations.

12 And, so, what I mean by focusing on the role  
13 of information is the following. So the standard way  
14 of thinking about agents' beliefs in a dynamic  
15 oligopoly model is to assume that firms know the true  
16 data-generating process. So in this environment, the  
17 only source of uncertainty would be about what exact  
18 amount of realization I'm going to receive today.  
19 Okay?

20 In addition to this type of uncertainty in  
21 this paper, I'm going to incorporate uncertainty about  
22 the demand process itself. So why do I think that  
23 this is an important factor? So a lot of industry  
24 experts were trying to understand what was going on  
25 and what drove this oversupply problem, and a lot of

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1 them attributed it to a firm's limited information.  
 2 So this one particular quote says, "The industry  
 3 extrapolated the good times and foresaw an  
 4 unsustainable rise in demand."

5 There are also a growing body of studies  
 6 that use learning models to describe agents' beliefs  
 7 with respect to macroeconomic shocks and trade demand  
 8 are highly correlated with these shocks. Lastly, of  
 9 course, the benchmark rational expectations,  
 10 assumptions are appropriate for many of the settings  
 11 that we study; however, there are also many settings  
 12 where this may not be the case. So firms may be new  
 13 to the environment, for example, or the environment  
 14 itself may be subject to some structural changes due  
 15 to policy shocks or other exogenous shocks.

16 So in this paper, I'm going to try to  
 17 address these questions. So first of all whether a  
 18 model that incorporates learning about this aggregate  
 19 demand process can help us understand the -- how firms  
 20 are investing. And, also, how this learning in  
 21 agents' beliefs interact with strategic incentives of  
 22 the firms. Lastly, I'm going to think about whether  
 23 the modeling choice of firms' expectations matter when  
 24 we do policy evaluation or welfare analysis.

25 So here is the overview of my approach. I'm

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1 going to first propose a dynamic oligopoly framework  
 2 where agents are forming and revising expectations  
 3 about the aggregate demand using information that's  
 4 available to them at the moment they're making their  
 5 decisions. Agents may believe that the process itself  
 6 is changing over time, so the natural way to model  
 7 agent beliefs in this case would be to allow them to  
 8 put heavier weight on more recent observations. So  
 9 I'm going to allow for this.

10 I'm also going to look at various other  
 11 alternative models of firm beliefs. I'm going to  
 12 compare predictions of my model to those of the other  
 13 models. I'm going to estimate this model using firm-  
 14 level data from the container shipping industry and  
 15 then conduct counterfactuals with respect to  
 16 combination, demand volatility, and scrapping  
 17 subsidies.

18 So the first set of counterfactuals, which  
 19 is with respect to competition and allowing  
 20 coordination and investment, is going to highlight how  
 21 strategic interaction plays a part in overcapacity as  
 22 well. And I'm going to do this exercise under two  
 23 different informational regimes, so under the learning  
 24 model and the other one under full information, to  
 25 look at this modeling choice would matter.

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1 So, of course, one of the biggest challenges  
 2 in thinking about selecting an appropriate information  
 3 structure is that as researchers we do not observe  
 4 agent beliefs directly. And as Manski points out,  
 5 it's hard to identify information and model parameters  
 6 simultaneously.

7 So the strategy I'm going to take in order  
 8 to tackle this problem is the following. So, first of  
 9 all, the standard approach in estimating this type of  
 10 dynamic oligopoly model is to look for objects like  
 11 investment costs, entry costs, or exit values that can  
 12 rationalize firm behavior that we observe in the data  
 13 while imposing the full information structure.

14 For my setting, I have data on shipbuilding  
 15 prices, as well as prices on scrapping, so scrapping  
 16 values basically. So I'm going to use this data  
 17 directly and then instead I'll focus on identifying  
 18 the model of firm beliefs. So taking the investment  
 19 costs and the scrapping values in the data as given,  
 20 patterns in the data such as investment volatility and  
 21 the correlation of -- between investment and demand  
 22 will tell us something about agent beliefs.

23 I'm also going to, as I said, consider  
 24 various alternative models of firm beliefs. Of  
 25 course, these two things are highly reliant on

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1 structural assumptions that I make in various parts of  
 2 the model. So as a more model-free way of thinking  
 3 about this, I'm going to rely on GDP forecast data.  
 4 And, so, the idea is the following: The GDP in the  
 5 destination region is highly correlated with trade  
 6 demand. And, so, the idea is that the correct model  
 7 of firm belief should yield demand forecasts that are  
 8 highly correlated with or consistent with the GDP  
 9 forecast.

10 Okay. So I'm not going to be able to get  
 11 into all the details of the model and the estimation,  
 12 so let me just highlight some main findings that I  
 13 have. So, first of all, I find that learning raises  
 14 the volatility of investment and the correlation  
 15 between demand and investment. And this is going  
 16 to -- what's going to help me predict these boom and  
 17 bust patterns that we see in the data.

18 In particular, I find that agents put  
 19 heavier weights on more recent observations, such that  
 20 the relative weight on an observation from ten years  
 21 ago is around 45 percent compared to the weight on the  
 22 most recent observation. And this is also confirmed  
 23 with a validity test that I conduct using GDP forecast  
 24 data.

25 I find that strategic incentives increase

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1 both the level and the volatility of investment. And  
2 learning intensifies these forces. So, in summary,  
3 learning amplifies investment cycles, both through,  
4 first of all, leading agents to revise their beliefs  
5 as they face demand volatility, but also through  
6 intensifying the strategic incentives.

7 Lastly, I find that the modeling of firms'  
8 expectations has policy implications. So, in  
9 particular, the full information model underestimates  
10 welfare gains from a particular merger that I consider  
11 between the top two firms in this industry.

12 So the key ingredients in the data that I  
13 use is the following. I have route-level data on  
14 prices and quantity, and I have firm-level data on  
15 capital investment and deployment and the firm routes  
16 that they operate on, as well as some data on  
17 shipbuilding and scrap prices.

18 So I'll focus on describing the model for  
19 firms' expectations and the dynamic problem that the  
20 firms face. And, so,  $Z_t$  is the demand state for the  
21 Asia-Euro market, and  $Z_t$ -tilde is for the outside  
22 market. And Asian firms here consider an AR(1)  
23 process for the demand in the Asia-Euro market and the  
24 outside market, so this is the how demand states  
25 evolve over time.

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1 And, so, the assumption of this learning  
2 model that I consider is that the parameters in  
3 this -- in these AR(1) processes are unknown to the  
4 agents. So agents update their beliefs by  
5 reestimating these parameters in every period using  
6 the demand realizations up to that date. Okay? So --  
7 and, again, I'm going to consider -- or I'm going to  
8 allow agents to put heavier weights on more recent  
9 observations, and so consider various weighting of the  
10 past observations.

11 So in the figure that you're looking at, the  
12 case with the flat line on the very top is the case  
13 where agents put this equal weights on all  
14 observations and other cases where the weights are  
15 falling dramatically with the age of the observations.  
16 Okay? And this is, again, the case where agents are  
17 concerned about structural breaks and unknown dates.

18 So firms decide whether to invest and also  
19 whether to scrap their ships in each period. The  
20 state that they -- the pair of relevant variables are  
21 their current capacity, their order of book, that's  
22 how much they're waiting to get built, and the sum of  
23 everyone's capacity in the market, as well as some --  
24 the industry order book. Also, there are two demand  
25 states.

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1 In the static product market competition  
2 stage, firms choose how much to charter, that's how  
3 much to lease from third-party companies, and they  
4 choose how much to deploy in different markets. And  
5 they face constant elasticity demands for shipping  
6 services.

7 So here is our implement -- the model of  
8 firm beliefs. Now, for each of these weighting  
9 parameters,  $\lambda$ -t is the parameter that governs how  
10 much firms discount older observations. So for each  
11 of these parameters, I estimate the parameters in the  
12 AO(1) model using demand realizations up to that  
13 point. So this would correspond just to fitting like  
14 least squares on the growing sample and weighting --  
15 weighted least squares if you have a case where agents  
16 are discounting all their observations.

17 And, so, what you're looking at is the  
18 estimates, the beliefs under learning model for the  
19 Asia-Euro market for one particular value of  $\lambda$ .  
20 And, so, the figure on the very left side shows the  
21 volatility estimate. So you can see that it jumps  
22 dramatically around 2009 -- 2008 or '09. And, also,  
23 the persistent parameter in the AR(1) model, which is  
24 the  $\rho$ -1, tends to fall steadily after 2007. Okay?  
25 And how much this volatility measure jumps or this

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1 just persistent parameter changes is going to depend  
2 on  $\lambda$ , which is how much they discount their older  
3 observations and also the model of firm beliefs, and  
4 this variation will help me identify the model. Okay?

5 So the estimation proceeds in different  
6 steps, but I'm just going to focus on the last step,  
7 where I basically estimate the dynamic parameters and  
8 the parameter in the model of firm beliefs. The other  
9 steps are quite standard, but I just want to point out  
10 one thing, which is that I estimate the investment  
11 costs and scrap values outside of my dynamic model  
12 using this shipbuilding cost data and then do the last  
13 step.

14 So I use the method of simulated moments to  
15 estimate this model, matching the moments in the data  
16 including the average investment in the period before  
17 2008 and after 2008. And the total capacity in the  
18 industry, total capacity in the order book, and the  
19 correlation between demand and investment and the  
20 volatility investment.

21 So the main result is that I find that the  
22 adaptive learning model where  $\lambda$ -t is equal to .02  
23 fits the data the best. It's sort of interesting to  
24 think about this, so there are a couple of other  
25 papers that try to estimate this model in the macro

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1 literature using either survey data on some microdata  
2 on expectations, and it seems that the value that I  
3 estimated is quite close to their estimates.

4 One other parameter that I estimate in this  
5 step is a fixed cost, though this is fixed costs of  
6 holding onto capital. That does not vary with how  
7 full the ships are. So it would be maintenance costs,  
8 port charges, or, like, labor -- basic labor costs.  
9 And it's substantial. So it's going to be about 36  
10 percent of period profits.

11 So here are just -- it's just the model but  
12 in terms of the yearly investment. I'm just  
13 aggregating at the year level, and the solid line is  
14 data, and then the line with circles is the model  
15 predictions. And as you can see, it does a pretty  
16 good job at predicting the boom in 2007 and then also  
17 the bust afterwards.

18 So I just want to briefly talk about the  
19 alternative models that I consider. So the full  
20 information benchmark is the one where parameters in  
21 this AO(1) model are known to the agents. And, so,  
22 here as a researcher, we would estimate this model  
23 using the maximum data available to us, so the full  
24 sample of data. And they endow those beliefs to the  
25 agents. I also consider Bayesian learning model and

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1 also some more flexible specification of the full  
2 information model.

3 So here are the model fits under alternative  
4 models. Again, the solid line is the data, and the  
5 line with the circles are model predictions. And I  
6 just want to draw your attention to the figure on the  
7 left side. So that's the full information benchmarks  
8 case. As you can see, it does a really poor job at  
9 predicting the correct timing and quantity of  
10 investment. So as you can see, the firms are actually  
11 investing less during 2006 and '07, the investment  
12 boom period.

13 And, so, why -- what's driving this?  
14 Basically there were two forces that are going on.  
15 When demand increases. This has two effects. One is  
16 that, of course, the returns in investment gets higher  
17 and firms want to invest more. But at the same time,  
18 demand for ships increases, this raises the price of  
19 ships, and that's going to decrease investment.

20 And, so, in the full information case, this  
21 negative effect dominates and actually the correlation  
22 is negative between the investment and demand. In the  
23 learning case, when demand is good, agents also become  
24 more collectively optimistic so that this positive  
25 effect is going to dominate. As you can see, Bayesian

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1 learning model does a better job, and also the  
2 flexible model of GARCH, but not as well as the  
3 baseline learning model that I showed you.

4 Okay, so, the remaining time, I want to talk  
5 about counterfactuals that I think about. So the  
6 first one is about competition. And, so, the question  
7 that I have in mind is whether strategic incentives  
8 increase the level and the volatility of investment  
9 and what happens if we increase consolidation in this  
10 industry. And, so, why do I care about this? First  
11 of all, there is quite big theory literature on how  
12 strategic incentives such as business stealing effect  
13 or preemption effect can also lead to overcapacity.  
14 And, also, in this industry, there has been a trend  
15 towards consolidation. So there's all kinds of  
16 proposed mergers and alliances that are happening.

17 In the model, there are at least two sources  
18 of strategic incentives. So, first of all, as a firm,  
19 as I deploy more capacity, that's going to increase my  
20 own market share, but it's going to have a negative  
21 effect on my rival's profits and market share. Okay,  
22 so that's going to lead to the business stealing  
23 effect.

24 But, also, when I increase my order, that's  
25 going to increase the aggregate order book, which is

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1 going to raise the shipbuilding prices. So this is  
2 going to lead to the preemption effect where when  
3 demand is good, I want to be the one that's first to  
4 invest. Okay?

5 So the two things that I consider is that  
6 monopolization, which gets rid of strategic  
7 interaction between all firms, so it's a multi-plant  
8 monopoly where the market shares of the firms are  
9 fixed, but they, you know, make coordinated investment  
10 decisions. So that's the line in the bottom. And  
11 then the intermediate line is a merger case where I  
12 allow the merger between the top two firms. And then  
13 the top line is the baseline learning case.

14 And, so, what I find is that both  
15 monopolization and a merger decreases the level and  
16 the volatility of investment. So in the monopoly  
17 case, something like 34 percent and the volatility  
18 goes down by 21 percent.

19 So in terms of the welfare, what does it  
20 imply? It leads to a huge gain in producer surplus --  
21 for the producers and some consumer surplus loss. So  
22 I just want to point out that the consumer surplus is  
23 incomplete, so it's only with respect to one big  
24 market, which is about 30 to 40 percent market share  
25 in this industry. But nonetheless, if you look at the

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1 merger case, it's likely the case that the producer  
2 surplus gain is going to dominate the consumer surplus  
3 loss because they're going to be not only reducing  
4 investment, but these merged firms will know when to  
5 invest. So they're going to try to invest more  
6 efficiently when price is lower, okay?

7 And, so, the last thing that I consider here  
8 is whether the modeling choice would matter when I do  
9 this type of policy valuation. So I do this merger  
10 exercise under the learning model and under the full  
11 information model and find that the learning model  
12 predicts a much higher change in the investment --  
13 both the changes in the investment rate and also the  
14 welfare.

15 So the rough intuition is the following:  
16 When there is high demand, that's when there is high  
17 incentives to steal business or preempt your rivals,  
18 but under learning, agents are also becoming more  
19 optimistic during this period. So learning reinforces  
20 this preemption in business stealing effects and so  
21 intensifies the strategic incentives. And, so, it's  
22 going to predict a larger welfare gain from this  
23 merger. In other words, the full information model  
24 underestimates welfare gains from this particular  
25 merger.

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1 So the last set of counterfactuals that I  
2 want to talk about today is with respect to demand  
3 volatility. And, so, I do this exercise under the  
4 learning model and full information model, and in both  
5 cases, increasing demand volatility is going to  
6 decrease investment slightly. And, so, this is  
7 actually consistent with some of the previous studies,  
8 like Bloom in 2009 and Collard-Wexler in 2013 that  
9 shows that increased volatility reduces investment.

10 However, if you look at the volatility of  
11 investment, you will see that there's also -- it's  
12 also the case that when demand volatility goes up, the  
13 investment volatility goes up. So there are two  
14 reasons why this is happening. First of all, as  
15 demand volatility goes up, the price of input, the  
16 shipbuilding price is also becoming more volatile, so  
17 that's going to lead to more volatility in investment,  
18 but also under learning, there is a second channel  
19 where higher demand volatility leads to more drastic  
20 and more frequent revisions and beliefs, and this is  
21 going to lead to more volatile investment.

22 Okay. So I just want to conclude by saying  
23 that, okay, this paper analyzes boom and bust cycles  
24 of investment under demand uncertainty. It builds an  
25 estimate of the dynamic oligopoly model with

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1 uncertainty about the demand process itself. I show  
2 that a learning model can help us understand this type  
3 of firm behavior where they're investing a lot when  
4 investment is expensive. And I also show that  
5 strategic incentives increase the level and the  
6 volatility of investment learning sort of intensifies  
7 these forces.

8 And, lastly, I show that the modeling choice  
9 for firms' expectations has policy implication. Thank  
10 you.

11 (Applause.)

12 MR. RAVAL: So Allan is doing double duty  
13 today, and he's also going to discuss this paper.

14 MR. COLLARD-WEXLER: Okay. I'm not thinking  
15 what if I had presented after the discussion.  
16 Anyways...

17 So I want to start off by telling you why  
18 you should care about container shipping. So there's  
19 this great book by Marc Levinson called The Box,  
20 which, you know, read that, and, like, don't read my  
21 paper, be like read that book first because it's  
22 amazing. The kind of transformation of international  
23 trading relationship because of container shipping is  
24 enormous, and it's beautifully documented there.

25 And, you know, what I think is interesting

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1 is most of you probably know Myrto Kalouptsidi's work  
2 on bulk shipping. And, you know, you might think,  
3 well, oh, this is another shipping, you know, paper.  
4 But bulk shipping and container shipping are really  
5 different, so my summary here is bulk shipping, like  
6 shipping coal or whatever, phosphates, from one place  
7 to another, that's like a taxi. You know, you just  
8 call one up, it's perfectly competitive. And  
9 container shipping is like airlines, so there's  
10 regular routes, and the issues of market power are  
11 first order, and there's been some cartel activity on  
12 -- in this world. It's quite concentrated.

13 So I think -- I mean, Myrto's even told me  
14 this, that, you know, container shipping of the two is  
15 the more interesting part of the global shipping kind  
16 of industry. And, so, I think this is why -- I think  
17 this is why from an antitrust perspective we'd really  
18 like to understand this market. And, you know, like  
19 other large commodity markets, it's had very large  
20 swings in total capacity, and people can tell you what  
21 China was expected to produce or not and what that did  
22 around the financial crisis.

23 So there are also this large amount of  
24 cyclicalities in this industry. So let me just tell  
25 you, you know, what are the -- the components of this

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1 paper are, you know, a computational Ericson-Pakes  
2 dynamic oligopoly model. There's some kind of --  
3 there's limited data here, and she's doing like a  
4 combination of estimation and calibration and kind of  
5 dynamic estimation to get different parameters of  
6 profits, investment costs, and so on.

7 And then the other twist is that rather than  
8 just using kind of simple Markov process for demand,  
9 she's using an adaptive -- adaptive expectations  
10 model, where the process gets updated when you see  
11 different realizations. So this is what this paper is  
12 combining in the model section.

13 So the first thing I want to push on is that  
14 it strikes me that what has to be done here is taking  
15 a lot of different price information and kind of  
16 reducing it down to kind of a single price on Asia-  
17 Europe in terms of that market, which now that I've  
18 told you that ship -- you know, container shipping is  
19 like airlines, you realize that there's going to be  
20 some heroic assumptions that go into that.

21 And, so, there's a lot of aggregation  
22 across, you know, this is a spot contract, this is a  
23 charter contract that needs to be done, and, you know,  
24 I think it works better as a "we really want to  
25 understand shipping, and this is going to be like the

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1 market for taxis in New York," which is just a great  
2 example. You know, we do this because getting the  
3 numbers right is going to matter, rather than because  
4 the data is particularly great.

5 Volumes are easier to get information on.  
6 You see the ships. You see how loaded they are. And  
7 the demand system, basically, in my mind, I was  
8 thinking like Porter '83, you know, a CES demand and  
9 then some kind of increasing marginal cost  
10 specification.

11 And, so, the first question is just, you  
12 know, how much are we losing by this aggregation into  
13 a homogenous product to Asia-Europe. And this got me  
14 more worried because you've got this outside Asia-  
15 Europe market as well. And, so, if my first model was  
16 that, whatever, you could just put all these ships  
17 together, put all the demand together and that's like  
18 a homogenous good, then I don't understand why there's  
19 two markets that you're focusing on.

20 So these are heroic, but this is the only  
21 way we're going to get there. And, so, it just --  
22 whatever the assumptions are, it would be nice to know  
23 what's the violence of the data that's going on here.  
24 But this is -- this is the first paper to attempt  
25 this.

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1 I'll move on. There's some nice bits in  
2 terms of how the model is being estimated and solved.  
3 So, again, unlike Myrto's work, you know, there's  
4 companies like Maersk that are, like, whatever 20 or  
5 30 percent of the global container ship volume. And,  
6 so, you know, the state of the market is going to be,  
7 you know, how big these different firms are and how  
8 many ships they have.

9 Now, the problem is if you're going to keep  
10 track of 10 firms' capital, which is how many ships  
11 they have, you're going to quickly run out of space in  
12 the computer to keep track of what everybody is doing.  
13 The state space is too big, and so there is some nice  
14 stuff on moment equilibria from Ifrach and Weintraub  
15 that's being used, you know, quite carefully in this  
16 paper.

17 I like this bit. My one piece is is that  
18 what's happening is in the paper I keep track of how  
19 many ships I have and then what's the total amount of  
20 capacity to everybody else has, so that's an  
21 approximation. And I think this industry -- you know,  
22 this kind of technique needs like an industry standard  
23 of how do we check robustness. You know, I could  
24 equally do one where I don't keep track of everything.  
25 You know, that's also a moment-based equilibria, but

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1 maybe I don't like it.

2 And, so, being able to tell us why I should  
3 like using total capacity as the state of the rest of  
4 the market would just help evaluate, you know, is this  
5 working or not. And I just think we just need to get  
6 used to doing that when we're using these methods.  
7 Just we haven't used them that often so far.

8 All right, but again, this stuff let's you  
9 estimate a game for this industry with lots of -- lots  
10 of firms and concentration, and that's why she's doing  
11 it. And then I'll just say two things about the  
12 estimation. So one piece that she's doing is she's  
13 using the prices for scrapping ships and also the  
14 prices for ordering new ships to basically pin down  
15 entry and investment costs. And then the things that  
16 are being estimated are these variances of those  
17 scrapping costs and investment costs. And you can  
18 think about it that, you know, she knows the mean, but  
19 she wants to get the elasticity of, say, entry with  
20 respect to profits. So you need some variance around  
21 the scraps to get an elasticity.

22 So it's really the right thing to use the  
23 dynamic model to get elasticities rather than means,  
24 given the data is so good. One comment would be if  
25 these things are moving around year to year, is that

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1 part of resolving -- you know, once I start thinking  
2 about endogenous input costs, you know, should that  
3 also be part of the model, given that they move around  
4 so much from year to year. But, again, using time-  
5 varying entry costs because in this industry that's a  
6 big deal, that -- I think that's a nice innovation  
7 here.

8 Let me move on to the learning process. So  
9 this seems -- this adaptive learning process has been  
10 around forever, so Jan Tinbergen's work has that from  
11 like the thirties. The caveat you should know about  
12 is -- and correct me if I'm wrong -- but firms don't  
13 have any awareness that they don't know things. It's  
14 just they had, like, one AR(1) process and then they  
15 updated, but they're not thinking about, well, maybe I  
16 don't know the AR(1) process. So it has some severe  
17 kind of constraints on, you know -- it's not like the  
18 uncertainty is part of the state in this model. Let  
19 me put it that way.

20 And the thing that this thing does that you  
21 might not be aware of is that you need, like, slow  
22 updating. And Bayesian learning models do very badly  
23 when macroeconomists have used these. You know, the  
24 shock happens, everybody gets it, and then it's over.  
25 Here, you get some kind of persistence, so there's --

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1 this is not just a simple functional form. It also  
2 kind of yields things that are nice in terms of how  
3 quickly kind of new information percolates into the  
4 economy. And, so, I think that's what's good.

5 If there's any way other than using the full  
6 structural model to validate your estimates, that  
7 would be great, like resale value of ships or other --  
8 there are some surveys, but not for shipping in this  
9 paper, but it -- at some point, there was a kind of a  
10 "how do I know this," other than the, you know, GMM  
11 criteria is a little bit higher for Lambda equals .002  
12 versus .00, for instance. And, so, that -- I think  
13 that would help kind of shore up the evidence there.

14 So there's a number of different  
15 counterfactuals -- mergers, demand fluctuations, scrap  
16 subsidies -- so also related to different papers that  
17 have come before in the literature. I really think  
18 that, you know, the three -- the merger, you know --  
19 the thing that I think this paper wants to do is  
20 distinguish what are the counterfactuals that I need  
21 the learning model for, and what are the  
22 counterfactuals that I kind of could have done without  
23 it.

24 And likewise, what other counterfactuals,  
25 what I could have used kind of a competitive model,

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1 whereas what other the counterfactuals we're having in  
2 this whole oligopoly interaction means something,  
3 because that's -- that's really what this paper is  
4 combining. And, you know, I have to say of all of  
5 them, you know, it's really the does cyclical of  
6 the industry change when you have -- when you have,  
7 say, investment, when you have a merger, given this  
8 learning story.

9 You know, that's the one that I think really  
10 combines the two pieces very nicely. And just given  
11 the amount of work put into getting these two  
12 components -- dynamic oligopoly and learning -- into  
13 one paper, you should kind of focus on the thing that  
14 -- at least I would focus on the thing that kind of  
15 brings them together.

16 One of the -- you know, some questions. So,  
17 like, you're estimating the learning model to get a  
18 sense of the -- and then using the estimates from the  
19 learning model, you're looking at the prediction is a  
20 rational model. It kind of struck me that if I'm  
21 worried about any type of misspecification of using  
22 the wrong parameters in the rational model, like, what  
23 would that do. So I think one suggestion here is just  
24 if you estimated the parameters with the no learning  
25 model, you know, how would those predictions work.

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1 The other piece, and I don't know if there's  
2 much you can do, but it would be nice to get some  
3 sense of, you know, does parameter uncertainty in the  
4 sense of statistical significance of these things,  
5 does that affect these comparisons that you're doing.  
6 I just can't tell if the numbers are largely different  
7 or small. And, so, just getting an idea of, you know,  
8 if you drew from the distribution of parameters in  
9 some way, the dynamic parameters are hard to draw from  
10 because there aren't standard errors on those, but if  
11 you drew from all the other parameters here, would  
12 these effects be robust. And I think that would help  
13 kind of emphasize what's going on.

14 There's a lot to like. We want to know  
15 about container ships, and this paper does a good job  
16 at getting a first pass at what we can learn from this  
17 market. There are some nice things about the modeling  
18 of the industry, large state spaces, time-varying  
19 costs of ships. And there's also this kind of  
20 learning model which just says, you know, we can -- we  
21 can be more flexible about the other components of  
22 these dynamic oligopoly models and, you know,  
23 accounting for these kind of large swings in  
24 investment might be one way we can make our dynamic  
25 oligopoly models kind of match data better.



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1 Okay, and that's it.  
 2 MR. RAVAL: All right, we have time for one  
 3 last question.  
 4 MS. JEON: If there is no question, I can  
 5 just address, like, some of the comments that Allan  
 6 gave. Thank you so much again. I just want to say in  
 7 a very limited sense, I did look at robustness of,  
 8 like, changing the moments that firms care about, so I  
 9 try to put in, like, the biggest firm states into the  
 10 state space. And it didn't seem to change much.  
 11 And then, oh, for the full information  
 12 counterfactuals, I reoptimize everything so that I  
 13 found the parameters for the -- that works for the  
 14 full information case, but otherwise, really great  
 15 comments. Thank you.  
 16 (Applause.)  
 17 MR. ROSENBAUM: All right, thank you all.  
 18 We'll take a 20-minute break and come back for Steve's  
 19 keynote at 11:40.  
 20 (Recess.)  
 21  
 22  
 23  
 24  
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1 KEYNOTE ADDRESS:  
 2 "MARKET STRUCTURE AND COMPETITION, REDUX"  
 3 MR. ROSENBAUM: We'll get started.  
 4 Okay. Steven T. Berry is the James Burrows  
 5 Moffatt Professor of Economics at the Yale School of  
 6 Management, a research associate at the NBR, and a  
 7 fellow of the American Academy of Arts and Sciences.  
 8 He specializes in econometrics and industrial  
 9 organization and is a fellow of the Econometric  
 10 Society and a winner of the Frisch Medal.  
 11 Berry has previously served as the chair of  
 12 the economics department and director of Division of  
 13 Social Sciences at Yale and received his undergrad  
 14 degree from Northwestern and his Ph.D. from the  
 15 University of Wisconsin at Madison. Most  
 16 significantly for me, he was my dissertation advisor.  
 17 Steve.  
 18 MR. BERRY: Significant for me, too.  
 19 Okay, so we've seen two nice keynote  
 20 addresses, and they were, I think, the very best kind  
 21 of keynote address, where someone gives us a concise,  
 22 30-minute summary of a body of their research. And it  
 23 turns out I don't have a body of research right now I  
 24 want to summarize in 30 minutes, so instead I'm going  
 25 to give -- I'm going to give an old man speech, which

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1 is along the lines of what's going on and what should  
 2 we do about it in our field.  
 3 Very good. So when you talk to IO  
 4 economists, there's something a little surprising,  
 5 which is that of all the applied micro fields, in many  
 6 cases, we're the one that often gets the least  
 7 attention in the newspaper, that there's a lot of talk  
 8 about, you know, taxation and public finance and, you  
 9 know, labor issues and the minimum wage, and yet if  
 10 you looked out right now at the debate in the paper,  
 11 you'll see all kinds of things saying that the country  
 12 is in the midst of a crisis of market power.  
 13 Joe Stiglitz has an article just entitled  
 14 "America has a Monopoly Problem." The Council of  
 15 Economic Advisors, you know, put out a report on this  
 16 about, you know, the problem with markups. And, you  
 17 know, you see kind of debates about hipster antitrust  
 18 and IO economists have noticed this, and Carl Shapiro,  
 19 for example, is giving, I think, a nice set of  
 20 speeches where he says what should our policy response  
 21 to this be.  
 22 And I want to talk about something more  
 23 boring but much more dear to my heart, which is what  
 24 should be the response of empirical IO economists, how  
 25 should we think about the questions which are being

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1 raised, and is it true that since we are, after all,  
 2 the world's experts in markups that we have an answer  
 3 for the questions that are being raised so prominently  
 4 in the press and the policy debate and by our  
 5 colleagues who are outside of industrial organization.  
 6 And I think the answer is so far we have not  
 7 answered this at all, as near as I can tell, within  
 8 empirical IO. And it's a little surprising. I've  
 9 said to some people, it's a little bit like, you know,  
 10 someone finds out their wife has cancer and runs to  
 11 the biochemist next-door and says, you know, can you  
 12 tell me how to treat the cancer, and the biochemist  
 13 says, well, you know, I don't know, but there's this  
 14 protein I'm investigating and maybe 30 years from now  
 15 I'll tell you something about whether there's a  
 16 treatment there.  
 17 So people have come out and said that maybe  
 18 there is this aggregate problem in the economy that  
 19 markups are very high, that we -- as Stiglitz says, we  
 20 have a monopoly problem, that we have a market power  
 21 problem and important enough for the Council of  
 22 Economic Advisors to issue reports about it, and we  
 23 have almost nothing to say about it. When I ask my  
 24 colleagues in a room like this, you know, are markets  
 25 -- are markups going up in general? Right, in

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1 general, are markups higher in the economy -- we're  
2 the markup experts, right, that's our field, that's  
3 what we study. We study, like, pricing and markups  
4 and competition. Are markups going up in general in  
5 the economy, and they say the same thing that I do.  
6 They have exactly the same answer I do, which is how  
7 would I know that.

8 So it turns out, though, people are  
9 interested in this question, and they're doing a ton  
10 of research on it, and they're publishing a lot of  
11 papers. And these papers get hundreds of citations,  
12 and these papers are almost exclusively by non-  
13 industrial organization economists. They're macro  
14 people, they're trade people, they're labor people who  
15 spin a big theory about competition, and they collect  
16 some aggregate data and they find some correlations  
17 and some regressions. And they will give an answer to  
18 the policy people.

19 And the question, I think, is whether --  
20 kind of how do we respond to that. Do we just say,  
21 well, it just turns out that part's macro and we'll  
22 just stay silent? Or is there some kind of response  
23 that we should have?

24 So one of the things I want to point out is  
25 that a lot of these papers by non-IO economists

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1 Policy." And there's a Schmalensee paper from the  
2 '80s that's another structure-conduct-performance  
3 paper. And other than that, I mean, I didn't -- maybe  
4 I missed somebody, but I don't think it cites any  
5 empirical work by current members of the NPR program  
6 except in reference to the estimation of productivity.  
7 It's a paper about competition and markups. And their  
8 claim is we have nothing to say, or at least nothing  
9 that's worth citing when they write the paper. And  
10 it's a pretty well-known paper.

11 Okay, so, part of what I want to do is I  
12 want to think of how should we think about, well, you  
13 know, this new structure-conduct-performance  
14 literature, which is being kind of reinvented by  
15 people in other fields. You know, so what could we do  
16 with it? We could ignore it. That would be one thing  
17 to do. We could pretend it's not happening and just  
18 say our -- you know, the way we treat a lot of macro,  
19 like, wow, interesting things happen in macro, that's  
20 crazy, okay. Wow.

21 Maybe I'll collect some more data. We could  
22 critique it. Okay? We could say -- we could remind  
23 them why we thought this was bad or at least try to  
24 say what the pitfalls are of doing it. And in some  
25 sense, maybe try to take the literature back to where

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1 recreate various aspects of the old and supposedly  
2 discredited structure-conduct-performance paradigm,  
3 which I'm actually old enough to have taught. I don't  
4 know if anyone else in the room took a course both  
5 from Mike Scherer and from Len Weiss. If -- very  
6 good, yeah. I was going to say, if Mike was here, I  
7 got at least 50 percent.

8 And, so, a few of us remember that and  
9 remember actually that it had some strengths, even  
10 though it got -- even though it got killed off. You  
11 know, so, you know, I want to talk about that, too,  
12 sort of how should we think about the use of  
13 techniques that would seem very familiar to empirical  
14 industrial organization economists of the 1970s, and  
15 here we're using the second decade of the 21st  
16 Century, and these are the answers which are -- these  
17 are the methods and the answers which are being  
18 presented to policymakers.

19 So, you know, it's almost a little worse  
20 than I thought. I actually kind of like this Autor  
21 paper on superstar firms, although, you know, from the  
22 IO perspective it has some crazy elements to it, but,  
23 you know, one thing is I just looked through for the  
24 cites to empirical IO. So, you know, there's Demsetz  
25 73, Industry Structure, "Market Rivalry and Public

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1 it was in the late 1980s where the structure-conduct-  
2 performance people were trying to improve their  
3 regression before they got buried under a tidal wave  
4 of a game theory and empirical IO disappeared for five  
5 or ten years, only to come back in a different form.

6 We could talk about improving it. Are there  
7 aspects of it or some parts that are better than  
8 others? Maybe we'd actually like to be a little more  
9 positive than critiquing it and say, well, maybe you  
10 should do this rather than that, or here are the  
11 things that are particularly bad, but here are the  
12 other things that make sense. We could try to improve  
13 it.

14 And/or we could propose alternatives. We  
15 could say actually within modern empirical IO we would  
16 actually -- we confess these are good questions, and  
17 here's how we think we should go about it. Okay.

18 So I'm going to take all of these bullet  
19 points seriously except for the ignore. I just think  
20 that's a mistake. I think, you know, we should care  
21 about questions about markups in the economy, in the  
22 American economy, in the world economy, and so I want  
23 to think a little bit about critiquing it. I want to  
24 think a little bit about improving it, and I want to  
25 propose some extremely tentative alternatives and

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1 maybe just do that as a way of trying to get some  
2 conversation going. Okay.

3 Okay, so what was structure-conduct-  
4 performance? As I say, some of us are old enough to  
5 remember it, and then some of you are young enough  
6 that they still taught it to you in a graduate class,  
7 and some of you may be young enough it never came up  
8 because it's why should you study economic history in  
9 a second-year graduate class.

10 I would say the broad question here is very  
11 much the same question that a lot of the papers today  
12 are answering, and it was asked for the same first-  
13 order important reason, which is people wanted to know  
14 what is the effect of market structure, often called  
15 concentration, on various outcomes, which were most  
16 often prices or products or profits but other aspects  
17 of conduct in the performance of the industry. And  
18 I'm going to say causal effect, which people in the  
19 '70s would not have said, or the '80s would not have  
20 said, but I think that's what they meant.

21 They meant it in the same sense that Josh  
22 Angrist means causal effect, right, that there's a Y  
23 variable like price or markup and there's an X  
24 variable which is concentration, and I want to know  
25 the causal effect of X on Y. I think that was very

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1 much what that literature was about, right? And then  
2 you could ask, you know, what are the problems with  
3 that.

4 But it seems like a decent question, which  
5 is why it dominated empirical IO for a few decades and  
6 generated -- again, Mike and I had Len Weiss. I think  
7 he counted at one point something like 2,000 published  
8 structure-conduct-performance papers in the  
9 literature.

10 What was the typical method? The typical  
11 method was cross-industry, usually OLS regression  
12 of -- I think I actually reversed my sentence there --  
13 of accounting measures of markups like the Lerner  
14 index or profits and other market outcomes on the  
15 Herfindahl index, which would be treated as the market  
16 concentration measure most commonly. And we can come  
17 back to why that was done.

18 So a classic regression would be an  
19 accounting measure Lerner index on the Herfindahl  
20 index. And you want to know is the coefficient  
21 positive, and if that is, that means that  
22 concentration raises markups. That's the causal  
23 effect of concentration on markups. And you could  
24 have a bunch of controls. Again, maybe you don't want  
25 to use Lerner -- accounting -- an accounting Lerner

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1 index, which was typically revenue minus variable cost  
2 over revenue. Maybe you want to use a direct measure  
3 of profits. You know, maybe occasionally we had  
4 price. You could also think of other market outcomes,  
5 you know, and put them on the left-hand side of your  
6 concentration regression.

7 Now, at the time, it was controversial, even  
8 though there were 2,000 -- even though there were  
9 2,000 published papers. It was, nonetheless, a  
10 controversial thing. And a lot of the controversy at  
11 the time focused on what was called the Chicago  
12 critique. And, you know, there are various ways of  
13 thinking of the Chicago critique, but a lot of it  
14 really had to do with the theoretical endogeneity of  
15 market shares and that if you think of the Herfindahl  
16 index, which is, in fact, just a transformation of the  
17 market shares within the industry, so somehow the  
18 market shares are leading to concentration, right?  
19 And Chicago liked to emphasize reverse causality, that  
20 if you get a big firm, you know, a Cournot model or in  
21 lots of models, that would be a low-cost firm. Low  
22 cost leads to high shares for that particular firm.

23 So take an industry that's relatively  
24 deconcentrated, have one of the firms invent a new  
25 technology, which makes them much more efficient, it

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1 drops their marginal cost, the Herfindahl -- that firm  
2 will gain market share and now you'll have an  
3 asymmetric industry with an efficient firm and a bunch  
4 of inefficient firms. That share will go up and the  
5 Herfindahl index will rise. Right, the Herfindahl  
6 index will rise. So they said really all of this  
7 concentration is a result of reverse causation, is  
8 really about endogenous market shares. And sometimes  
9 even though they had said they were endogenous, they  
10 would do things like regress a firm-level Lerner  
11 index to the market share, right, and say, well, gee,  
12 firms with big market shares have low markups.

13 Now, again, if it's theoretically  
14 endogenous, there's a question of why he just ran OLS,  
15 but that's the kind of thing people would do. What  
16 were some other critiques? And another one that's  
17 come back? You know, accounting data are terrible in  
18 many -- in many ways. There's a ton of  
19 mismeasurement, capital is very -- extremely difficult  
20 to measure. Everything's aggregated. You don't have  
21 detailed product measures. You often have no price  
22 variable at all. You're only seeing revenue, which is  
23 why you get some kind of accounting profit or  
24 accounting margin that you're using because you don't  
25 know how to have a cross-industry measure of price.

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1 So there was a lot of the critique of  
2 structure-conduct-performance would be about the  
3 problems of accounting data. Now, the advantage of  
4 accounting data -- and what I'll come back to is that  
5 it exists across industries and across -- so if you  
6 want to do something cross-industry, it's very  
7 difficult to avoid accounting data because there just  
8 aren't consistent sources of data that, you know, have  
9 price and things that modern empirical people use,  
10 right?

11 Another critique is that there was really no  
12 single cross-industry theory of markets, and I think  
13 that's a hallmark of a lot of empirical IO people. We  
14 don't really think there is "the" theory of "the"  
15 market, right? We think that you have to match the  
16 theory to the market, that different things happen in  
17 different places and sometimes product differentiation  
18 is important and sometimes it's not.

19 And sometimes there's collusion and  
20 sometimes there's not. And sometimes capacities are  
21 really relevant, and sometimes they're not. And  
22 sometimes the dynamics of the market are important,  
23 and sometimes they're not. We think there's a just  
24 different theory for every market, and so how do you  
25 possibly run a cross-industry regression when you

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1 don't even have a single theory that you think runs  
2 across markets, right?

3 And, of course, implicitly in structure-  
4 conduct-performance, there was something like a  
5 Cournot model always running behind it, which I'll  
6 come back to. The question is how bad is that. Okay,  
7 so Mike and I had courses with Len Weiss. Len, by the  
8 end of his career, was trying to save structure-  
9 conduct-performance, said, okay, you know, Chicago  
10 says shares are -- and Herfindahl's are theoretically  
11 endogenous, you know, let's treat that seriously as  
12 econometric endogeneity and, you know, now maybe we're  
13 really, really, really in Josh Angrist's world where  
14 we have a Y and an X and a Z, right? So we're looking  
15 for the causal effect of X on Y, but X is endogenous,  
16 and so we have an instrument Z, and could you possibly  
17 do this as a Y-X-Z model within instrument Z. And  
18 what would the instrument be, right?

19 And, so, I want to come back to that a  
20 little bit. Is that a possible solution that we have,  
21 you know, kind of instruments or how often is it a  
22 solution, at least to this -- at least to the Chicago  
23 school -- at least to the Chicago school problem.

24 Okay, so what was the -- what was the --  
25 what happened? As I say, well, game theory came in,

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1 and then Bresnahan proposes the acronym that fell out  
2 of use, the New Empirical IO, partly because it wasn't  
3 new, partially because NEIO is not a great thing to  
4 say out loud anyway. And what he suggested was that  
5 we have single-industry studies. Why? Because you  
6 could get much more carefully measured data.

7 You could actually maybe get price within an  
8 industry. You could get price separated from quantity  
9 within an industry. You could start to get product  
10 characteristics. Occasionally you might get cost  
11 data. You would know what theory to tie to this  
12 market, one would hope, and you could start putting it  
13 in an oligopoly context, which was closer to classic  
14 supply-and-demand analysis in the sense that your  
15 analysis of endogeneity and identification and  
16 instruments could be based on, you know, ideas that  
17 demand shifters are excluded from the cost function or  
18 cost shifters are excluded from the demand function  
19 and so forth.

20 And you could go back to a much clearer kind  
21 of classic supply-and-demand style notion of  
22 instrumental variables and endogeneity and  
23 identification. So only for the purpose of these  
24 slides and nowhere else I'm going to jokingly call  
25 this the dominant empirical IO algorithm. I don't

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1 think we should adopt that anymore than NEIO,  
2 actually.

3 But this really is the dominant algorithm,  
4 which -- within empirical IO in a broad sense that  
5 we're single -- we're crafting studies of single  
6 industries with the theory guided toward that industry  
7 with an industry-specific data collection and  
8 identification tied to the cost and demand shifters  
9 and equilibrium assumptions of that industry, and  
10 we're handcrafting all of these little individual  
11 industry studies, right, in a way that we think is,  
12 you know, other people say we're making too many  
13 assumptions, but in a way that we think is pretty  
14 careful, say, compared to structure-conduct-  
15 performance.

16 So my colleague, Bill Nordhaus, pulled me  
17 aside one day, and he said, you know, the thing about  
18 you guys is it's like -- it's like house-to-house  
19 combat for you guys. You know, it's just like --  
20 there's this big battle and you just took like a  
21 house. He said, you know, macro is -- in a good way,  
22 it's like carpet bombing. We just solve all the  
23 problem at once. I'm like, okay, is that good, carpet  
24 bombing? But, okay. It kind of is the way I think  
25 about macro, but okay.

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1 You know, but here's the critique, and I  
2 think we should take it seriously, which is that macro  
3 studies the economy and we're interested in a  
4 particular part of learning about marketing for  
5 yogurt. Right? The Journal of Economic Perspectives,  
6 once asked me to write an article on what has IO  
7 learned about markets in general.

8 They're like, oh, you can't write that, huh?

9 Now, you know, okay, the interesting thing  
10 is while the macro economists are moving in behind us  
11 with structure-conduct-performance, I actually think  
12 we've done a good job over time of going into markets  
13 that are actually pretty important and incorporate a  
14 bunch of the economy, like health and education and  
15 environment and in addition to the broad studies of  
16 antitrust that ought to be directly relevant to these  
17 questions that everybody is asking right now.

18 So I don't want to -- you know, I actually  
19 think we've done a lot of important of policy-relevant  
20 stuff, and in some sense, as we have been sort of  
21 colonizing big areas of what used to be public  
22 economics, precisely because we can do supply and  
23 demand equilibrium studies that used to be the  
24 theoretical hallmark of public economics, they --  
25 public economics, meanwhile, has adopted this kind of

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1 Y-X-Z strategy, where you're not doing equilibrium  
2 studies, but you're looking for causal effects. And I  
3 think it's been a big success.

4 But, you know, despite that, I think  
5 actually pretty big success and that kind of policy  
6 success that has made IO I think increasingly policy-  
7 relevant in many parts of micro, very few people, and  
8 actually I say Allan's a bit of an exception here,  
9 have been doing things that are sort of geared toward  
10 the macro aggregate conversation about markups and  
11 competition in the economy as a whole, and I think  
12 this is why people have gone back to structure-  
13 conduct-performance because that's -- that literature  
14 was an attempt to answer that question and maybe is  
15 the first thing you would do if you weren't steeped in  
16 modern IO and wanted to answer that question. It's  
17 just not -- not as insane as, you know, I'd sort of  
18 like it to be.

19 Okay, so, you know, I didn't do a full  
20 literature review, right? You know, I think -- on an  
21 earlier slide, I think I had that, you know, you just  
22 look up that Council of Economic Advisors report and,  
23 you know, just alphabetically you get a reference, you  
24 get another reference. Both of those are regressions  
25 on Herfindahl, right? Modified Herfindahl, innovation

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1 on Herfindahl, something on the Herfindahl, something  
2 in concentration, right? Just stop -- at the moment  
3 we -- most of us in this room would not do any more.

4 I guess the one -- I'm sorry, the one on the  
5 earlier slide was that, you know, that -- the Demsetz  
6 thing, that, you know, they're just not citing us, and  
7 they are citing the structure-conduct-performance  
8 literature or this modern structure-conduct-  
9 performance literature that is stuff on Herfindahl's,  
10 stuff on H.

11 I really thought that that -- that that  
12 highly cited paper on innovation under Herfindahl, I  
13 was really pretty sure that was in Mike Scherer's 1980  
14 textbook, but it's a fat book and I couldn't find it.  
15 Maybe he just sketched it on the board, but I don't  
16 know.

17 Okay, so, you know, not all of these are all  
18 -- not all of these sort of new structure-conduct-  
19 performance papers have all the features of structure-  
20 conduct-performance, but, you know, they have some of  
21 the features and/or all of them, which is you're using  
22 cross-industry data rather than, you know, our  
23 strategy of single-market data and/or they're using  
24 accounting data so that they can run cross-industry  
25 rather than kind of carefully crafted prices and other

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1 things. They're throwing concentration in. They're  
2 just trying to get direct measures of markups, maybe.  
3 And sometimes they're treating market structure as  
4 exogenous, as just this exogenous thing that's out  
5 there, even though they're using H; and/or sometimes  
6 trying to use ad hoc instruments. In other words,  
7 they're sort of doing the Y-X-Z thing of recalling a  
8 variable that was not in X and sort of conjuring it  
9 out late in the paper and saying, oh, it's an excluded  
10 instrument and you're not quite sure why except they  
11 forgot to put it in earlier, and so it wasn't in X.

12 Okay. So, okay, here's the critique. I  
13 still think that as well as intended as it is that  
14 straight-up causal effect structure-conduct-  
15 performance is still pretty hopeless, right? I don't  
16 think you can directly say this. You know, so let's  
17 say you had a really good price or a markup, right,  
18 and you're going to regress it on H to get the casual  
19 effect, but what is that thing? It's not a demand  
20 curve. It's not a cost function. What is it?

21 I think it has to be the first-order  
22 condition from an oligopoly model. What else creates  
23 the relationship between price and fundamentals in an  
24 oligopoly? It has to be the first-order condition  
25 from an oligopoly model. Now, just thinking about

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1 them in general, without the structure of a particular  
2 model, first-order conditions include the effect of  
3 demand and supply because there are markups, and  
4 markups depend on demand, so demand is in there. And  
5 prices also depend on cost, so cost is in there.

6 So what is excluded from that relationship  
7 that could possibly be an instrument? Right? People  
8 -- I've been at talks; people say, oh, don't worry, I  
9 instrumented for H. This just happened at the Searle  
10 conference. Don't worry, I instrumented for H. I  
11 understand it's endogenous; I instrumented for it.

12 What variable is excluded from the price  
13 Herfindahl equation? Right? What's excluded from  
14 that? Okay, if it's a first-order condition, the pure  
15 measures of fixed cost, maybe, but I've never seen  
16 people do that. But fixed cost is excluded from  
17 pricing decisions. We teach the undergraduates that.

18 Something about exogenous merger policy, I  
19 guess maybe? I haven't really seen that done well.  
20 And part of that is that -- you've got to get a lot of  
21 variation cross-sectionally from these things.  
22 There's not that many time periods, and, you know,  
23 even if you thought the merge policy changed in year  
24 X, well, that's like one change in the variable. How  
25 much cross-section -- do you have real cross-sectional

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1 variation in that? Right, if we had regional, I don't  
2 know, maybe if we had regional DOJs or something,  
3 policy instruments.

4 And just more fundamentally, there just  
5 isn't a direct model that has an effect of H in it.  
6 If you look at a sensible first-order -- and there's a  
7 second, if you just remind everybody, everybody knows  
8 this, if you just look at a model that has H in it  
9 because you did something that generated H, there is  
10 no effect of H in that model. H is just a joint  
11 endogenous outcome. As Chicago said, I don't know,  
12 did the demand elasticity go up, or did a marginal  
13 cost go down? Right?

14 That will affect price, and it will affect  
15 H, but not via the effect on H. Right? They're both  
16 just endogenous outcomes. Right? This is a lot like  
17 saying, you know, imagine another Y-X-Z paper, you  
18 know, I want to find out the causal effect on price of  
19 quantity, right? All the quantity -- and there are  
20 many theories of why quantity affects price. All the  
21 quantity's endogenous. What instrument should I use  
22 in the pricing equation? Right? Now, everybody knows  
23 that's a huge mistake. There's no such thing as the  
24 pricing equation, and there's one thing called a  
25 demand function, and there's another thing called a

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1 supply function. There is no such thing called the  
2 pricing equation. And I'm going to argue there is no  
3 such thing as the H equation.

4 Right? So I really still think this is  
5 fundamentally a problem with kind of the regression on  
6 H. Okay, so let me hammer it home, okay? So, okay,  
7 so the only way you can get H in a model that I know  
8 of, and everybody knows this, is Cowling and Waterson  
9 in '76 or something, is via the Cournot model, right?  
10 So Hugo had the Lerner index, price minus marginal  
11 cost. The J -- M is market, J is firm. I should have  
12 had a J index on that marginal cost there, I see. I'm  
13 just multiplying his equation through by price so I  
14 get an inverse semi-elasticity instead of an  
15 elasticity.

16 Let me give a little econometric structure  
17 to marginal cost. Really that beta is not a  
18 coefficient that ought to be varying. It ought to be  
19 varying with market quantity. It ought to be varying  
20 with demand shifters and stuff, but, you know, given  
21 that it's constant if you're going to do structure-  
22 conduct-performance or something. It should still  
23 vary across every market, by the way. There's no  
24 reason for it to be constant across markets, and I  
25 would get like a -- I would get like a Chicago

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1 regression a little bit here, which is price on market  
2 structure, right?

3 But, again, is that the causal effect of  
4 market structure on price? No, it's just putting two  
5 endogenous variables in the same first-order  
6 condition. Right? Furthermore, demand stuff should  
7 enter beta, really. All the cost stuff is already in  
8 the equation. There's a huge endogeneity problem, and  
9 the Cournot model -- the cost shock is determining the  
10 share. Indeed, it's the only determinant of the  
11 within-market variation and share as marginal cost.  
12 Right, it's just one-to-one within market.

13 And everything else is demand, right? So,  
14 you know, this is Bresnahan's point. And by the way,  
15 you know, share is really just quantity divided by  
16 industry share. And if marginal cost slopes up,  
17 quantity also enters marginal cost. This is  
18 Bresnahan's point. Quantity is in there twice. Give  
19 me one instrument. Give me as many instruments for q  
20 as you want. How do I distinguish the effect via  
21 demand and the effect via quantity? That's  
22 Bresnahan's point. You can't distinguish these  
23 things. Bresnahan's point was, well, fix beta, and I  
24 can tell you -- and I can tell you the effect of q on  
25 -- fix the model, fix beta, and I'll tell you the

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1 effect of  $q$  on marginal cost.  
 2 Without saying this a Cournot model, without  
 3 saying that I have an estimate of demand to learn  
 4 something about  $\beta$ , and without specifying marginal  
 5 cost, this equation is hopeless. There's no causal  
 6 effect of share. Even the Chicago guys are wrong.  
 7 There's no causal effect of share here. So what are  
 8 you supposed to do? You're supposed to average that  
 9 equation, and then you get -- you get concentration  
 10 comes out.  
 11 Right? So if you take a simple market  
 12 average, the average share is always one over  $N$ ,  
 13 right? So then I get an equation that relates price,  
 14 I've got the same semi-inverse -- inverse semi-  
 15 elasticity to one over  $N$ . I've got the average cost  
 16 shifter now, and I've got the average output, right,  
 17 to tell me to learn about economies are just economies  
 18 of scale, and I've got the average cost shock, right?  
 19 So, now, the SCP folks hated  $N$ . And why do  
 20 they hate  $N$ ? Because every industry they looked at  
 21 there was some gigantic tale of tiny, little firms and  
 22 how do you count  $N$ . On the other hand, I got to say  
 23 that  $N$  is responding at least at lower frequency to  
 24 cost shocks probably, right? And I can almost imagine  
 25 some instruments for  $N$  if I could measure it and some

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1 correlates of  $W$ -bar. I object to this less than the  
 2 Herfindahl one, but it's really got all the same  
 3 problems, right?  
 4 And, again,  $N$  shows up twice. It's  
 5 affecting economies or diseconomies of scale, and it's  
 6 also having this competitive effect via the demand  
 7 side moving down the demand curve in the Cournot  
 8 model.  
 9 So I don't know. The next one is worse,  
 10 though, which is the classic one, which is the Cowling  
 11 and Waterson one, where you take a share-weighted  
 12 average, and the share-weighted share is the  
 13 Herfindahl index. I get the share-weighted cost  
 14 shifter, and, you know, effectively the share-weighted  
 15 quantity or you can think of that as  $Q$  times  $H$ ,  
 16 classic thing. And then I have the share-weighted  
 17 cost shock.  
 18 But now that cost shock has shares in it,  
 19 right? So now when one of the individual cost shocks  
 20 goes up, mechanic -- when the share of a low-cost firm  
 21 goes up, the weight you put on its shift -- on its  
 22 weight goes up, which actually changes the shock. You  
 23 get this mechanical relationship now between  $\nu$  and  
 24 everything else.  $W$ -tilde there, the share-weighted  
 25 cost shifter is endogenous now. It's got share in it,

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1 right?  
 2 The share-weighted first-order condition,  
 3 right, is a tough thing to instrument because it's a  
 4 function of shares everywhere. And this is the only  
 5 way that anyone knows how to get  $H$  in a regression  
 6 that has price in it. Okay.  
 7 It does not get easier with product  
 8 differentiation or different models of competition or  
 9 anything else, and this is why we gave up on it. And  
 10 we were right. Okay.  
 11 Okay, one thing. If you want to regress  
 12 price on concentration and just tell me it's the  
 13 descriptive regression, I have to accept that because  
 14 you have described the data to me. Right? So I would  
 15 actually rather see the OLS regression of price or  
 16 markup on Herfindahl and just say, look, it's a  
 17 correlation, it's not a causal effect, and I'm just  
 18 describing my data set to you in this particular way,  
 19 and we can talk about what -- you know, if there's  
 20 some model or something.  
 21 So I would rather you not instrument, right,  
 22 and just give up on the idea that it's the causal  
 23 effect. It's a descriptive regression, and it's a  
 24 fine thing to do. And, actually, you know, Autor's  
 25 paper comes kind of close to that, to tell you the

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1 truth. They're thinking of a hidden third factor  
 2 that's kind of moving both.  
 3 On the other hand, if there's a hidden third  
 4 factor, maybe we should just look at the reduced form.  
 5 Why not look at the reduced form effect of that third  
 6 variable on price or markup and on concentration?  
 7 Right? Why are we sort of going indirectly through  
 8 these two endogenous variables? Maybe it's all we  
 9 got. Maybe we don't see the third factor. But that's  
 10 the only excuse I can think of.  
 11 Okay, I'm going to have two possible non-  
 12 structure-conduct approaches to the question -- again,  
 13 the question I think we're being asked, which is are  
 14 markups going up in general. Okay, so, one, this  
 15 paper got a lot of attention, Jan De Loecker and Jan  
 16 Eeckhout. Okay, so they're going to do something a  
 17 little SCP, because they're going to say just up  
 18 front, and I've seen Jan talk about it, he says, I'm  
 19 going to use accounting data. He says, I'm going to  
 20 use the worst accounting data there is, which is  
 21 Compustat data, and I have for years told my students  
 22 never to use the crappy accounting -- Compustat  
 23 accounting data. But, you know, manufacturing isn't  
 24 that big a part of the world anymore, and this is  
 25 accounting data that will tell you the economy, not

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1 just manufacturing. You know? So maybe you got to  
2 compromise sometimes.

3 And they're going to go for the macro  
4 markup, cost over price or price over cost. And  
5 they're going to do it without any of the demand data  
6 and without an oligopoly equilibrium assumption,  
7 purely through cost minimization. Right, so two  
8 things, accounting is not very good. Jan's very aware  
9 of that, and he's very aware of the other thing, too,  
10 which is the Chicagoans called from 1975 to say that  
11 high markups might reflect low cost.

12 Okay, so, you know, most people know this  
13 math. You start off with the Lagrange multiplier for  
14 the pure cost minimization of a variable input that  
15 caused the -- the Lagrange multiplier is  $\lambda$ . We  
16 recall that  $\lambda$  in the cost minimization problem is  
17 equal to marginal cost. And we get that marginal cost  
18 equals the wage divided by the marginal productivity  
19 of labor, and we just rearrange that problem, we  
20 multiply everything by  $L$ , and we divide everything by  
21 revenue, and we rewrite the whole thing and we take it  
22 to the other side, and we get this Hall markup, which  
23 is the input elasticity of output of the variable  
24 input divided by the input revenue share is equal to  
25 price over marginal cost. That's just a fact about

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1 cost minimization, by the way. And the input revenue  
2 share is actually probably not so badly measured in  
3 the accounting data, and so kind of the only problem  
4 is that we need to know the input elasticity of a --  
5 of a variable input. So Bob Hall would have said,  
6 well, it's cost that returns to scale, it's Cobb-  
7 Douglas, so the input elasticity is the cost share of  
8 labor, so it's the cost share of labor divided by the  
9 input share of labor, so it's just cost over revenue.  
10 Right? And that's kind of the macro approach, is  
11 marginal cost over price or price over marginal cost.

12 So the key question here is then -- it flips  
13 to a nice supplied micro question, which is this is a  
14 technology adjusted input revenue share, and the  
15 question I think is are we really sufficiently  
16 allowing for heterogeneity in technology, right?  
17 Because the question is going to be are prices  
18 changing over industry over firm over time. And we're  
19 going to get the right industry -- answer to the  
20 degree that we have estimated this input elasticity  
21 not correctly on average but correctly over firm and  
22 industry and time.

23 Okay. Now, I mean, this is kind of nice,  
24 and Jan's point is that markup is a residual here,  
25 just as in many of our models where we don't see any

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1 cost data, marginal cost is a residual of the first-  
2 order condition. So it's -- you know, it's kind of  
3 nice. It's not really a dual, but it's a similar kind  
4 of notion.

5 As I say, it's really -- just as our  
6 measures of marginal cost depend critically on us  
7 getting the own firm elasticity or the cross-  
8 elasticities, this depends really critically on  
9 getting -- getting the beta right, getting the input  
10 elasticity right. And against that, you have to put  
11 the advantages of cross-industry data. This seems  
12 like a good complement to me. That's not really going  
13 to answer people's questions in the end, as John has  
14 said, because people want to know whether it's price  
15 going up or costs going down.

16 Right, but it's a nice complement. I mean,  
17 it's -- and it uses accounting data. What can you  
18 say? For example, what do they find? They get a big  
19 increase of markups, which we should at least say,  
20 okay, that's a possibility, that's what they found.  
21 Big increase in markups beginning about 1980. High-  
22 market firms tend to be smaller, which goes against a  
23 ton of other theories and makes me worry that they're  
24 not getting the input elasticity right for small  
25 firms. It worries about that.

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1 And it's mostly within industry. So that's  
2 interesting because it doesn't sound like we're  
3 failing to, you know, enforce the antitrust law  
4 someplace and doing it other places or things like  
5 that.

6 Okay, I've got a minute. Here's the other  
7 idea that I just want to point out. So another thing  
8 is we could do what we do, but we could compromise a  
9 little bit, which is can we do some studies that are  
10 bigger aggregates of the -- could we do some studies  
11 that are on bigger aggregates of the economy and ask  
12 this question using our best tools. We might  
13 occasionally have to bring some accounting data, or we  
14 might not be able to do our fanciest model because  
15 we're going to do it -- you know, we're going to have  
16 to assume some things are constant.

17 Maybe the theory is constant across a little  
18 bit bigger set of industries than we, you know, had  
19 thought of. We have our workhorse industries. I  
20 don't even think we've done it within our workhorse  
21 industries. What about airlines? What about  
22 automobiles? What about the healthcare sector? What  
23 about supermarkets? Are markups going up there? We  
24 could at least say that. It seems like we owe people  
25 that, actually, if you ask me. I told Marty -- or I



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1 told somebody yesterday I was giving this talk, and I  
 2 said it was going to be about what we should do, and  
 3 he said, no, you mean what young people should do.  
 4 So one example of this would be we have a  
 5 student -- and actually I think he's showing up in DC  
 6 next year at Georgetown, he's at Dartmouth now -- who  
 7 did -- took the accounting data plus some geographic  
 8 data from the census of wholesaling and kind of just  
 9 did really standard IO on it. And he starts with some  
 10 interesting facts, which sound a little bit like what  
 11 people are saying in a way. The wholesale sector is  
 12 growing, by the way. I was super surprised by that.  
 13 I thought Walmart had disintermediated the wholesale  
 14 sector. It turns out it's growing really a lot.  
 15 There are fewer but larger firms. It sounds  
 16 like an increase in concentration. They have many  
 17 domestic locations. They're offering an increasing  
 18 variety of products. That's interesting. That's not  
 19 like mergers or something. That's maybe a better  
 20 output. They're often sourcing both domestically and  
 21 internationally, and there may be some fixed costs to  
 22 that. Accounting markups are growing, and IT spending  
 23 is growing.  
 24 Okay, so what story is that? So what he did  
 25 is he just took a set of really standard IO tools and

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1 in some sense just explained this data through the  
 2 lens of those tools, right? And there was no  
 3 alternative theories. It was not like testing  
 4 something, really, more like a decomposition. If you  
 5 took the standard -- really long standard IO stuff and  
 6 just passed this data through those tools, what came  
 7 out of the other side, right? So he's got nested  
 8 logit demand and price-setting Nash, and there's  
 9 geographic competition, and there are some fixed costs  
 10 of variety and foreign sourcing and some other stuff  
 11 and some really crude free entry model.  
 12 He doesn't solve all the endogeneity  
 13 problems because you don't see the detailed cost and  
 14 demand shocks when you enter, but like a lot of people  
 15 do that. He does consider the endogeneity of the  
 16 pricing decisions, supply and demand, and so forth.  
 17 Really, really standard, standard, standard, standard,  
 18 standard stuff.  
 19 And what does he find? You know, okay,  
 20 you're selling more with bigger markups, and the  
 21 model's going to explain that through an increasing  
 22 demand for wholesaling, particularly for firms that  
 23 have a lot of variety, a lot of locations, and also  
 24 foreign sources as well as domestic, okay?  
 25 Marginal costs are decreasing. Prices

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1 aren't going up that much. And the entry model,  
 2 therefore, suggests increasing fixed costs. Right?  
 3 Together, demand is up and costs are down. The  
 4 markups are increasing a lot. Firm size is increasing  
 5 a lot because of the importance of the fixed costs.  
 6 And the markups aren't competed away. It's consistent  
 7 with this being an effect of IT driving up the  
 8 importance of logistics, fixed investments and  
 9 software that give you better geographic cost as you  
 10 deliver your goods, fixed costs of opening operations  
 11 in China, and it's an interesting story. I think I  
 12 just said all those.  
 13 And I think it's a good question of, you  
 14 know, how common is this, for example. I suggested it  
 15 for airlines a long time ago, that networking lowers  
 16 marginal cost, drives up demand, drives up demand for  
 17 some reasons which might be good and some reasons  
 18 which might be more like marketing and bad things,  
 19 right, but they both lead to higher markups.  
 20 Increased demand, lower costs, higher fixed costs.  
 21 You get higher margins in variable profits. Fixed  
 22 costs are naturally limiting the amount of entry.  
 23 Right? That would explain higher markups.  
 24 Is it true for a lot of industries? Could  
 25 we figure it out for a lot of industries? And the

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1 last point I want to make is that a lot of the  
 2 interest -- if you look at the Autor paper, which  
 3 comes very close. He has a quote, unquote theory of  
 4 superstar firms, which isn't well elaborated, but it's  
 5 a little bit like what I just said. And he says,  
 6 okay, the superstar firms are employing less labor.  
 7 A lot of the interest in this has to do with  
 8 distribution, which we might think of as input demand,  
 9 and we have a tendency to skip over that. So what are  
 10 the implications of our even market-by-market  
 11 competition models for input demand, which is the --  
 12 which is getting toward the distributional impact.  
 13 Are the returns to labor and the use of labor changing  
 14 relative to the returns to software and capital and so  
 15 forth? Those are questions it seems like we could  
 16 answer maybe in there.  
 17 (Applause.)  
 18 MR. ROSENBAUM: All right, thank you, Steve.  
 19 We'll take one question and then can continue the  
 20 conversation after the panel.  
 21 Ginger?  
 22 MS. JIN: Thank you. I really appreciate  
 23 the keynote here. I just want to ask probably a  
 24 simpler question than you're asking. Does market  
 25 concentration go up over time? This is not sort of a

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1 question of what's the effect of X on Y, just sort of  
 2 what's the trend on X.  
 3 MR. BERRY: Yeah, so really I think there  
 4 are some competing papers on this. And, again, if you  
 5 went back to Scherer's text book, that would be like,  
 6 you know, table one, concentration, concentration over  
 7 time, concentration over industry, right? We kind of  
 8 stopped doing this a while back. So Autor's paper  
 9 claims yes. I think the two-Jan paper, De Loecker and  
 10 Eeckhout, claims no. So there's a measurement issue  
 11 there, I think.  
 12 MR. ROSENBAUM: Okay, now I'm going to turn  
 13 it over to my colleague, Doug Smith, for our final  
 14 panel on privacy and data security.  
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1 PANEL: PRIVACY AND DATA SECURITY  
 2 MR. SMITH: Maybe the panelists wanted to  
 3 sit down.  
 4 So thanks, everybody, for staying for this  
 5 last session. Hopefully it will be a lively one. You  
 6 know, privacy and data security is not really an area  
 7 where I think I need to elaborate on why -- a lot on  
 8 why people are interested in it. It's kind of a big  
 9 topic these days, but the FTC has a particular  
 10 interest because, you know, it falls under our  
 11 consumer protection mission. And, so, you know, we're  
 12 really delighted to have four panelists today who can  
 13 speak to both the state of economic literature and  
 14 also talk about their own contributions to it.  
 15 So before we get started on that, though, I  
 16 just want to do a quick plug for our PrivacyCon, which  
 17 is happening February 28th of next year. This is a  
 18 one-day conference where the focus is on new research.  
 19 And the -- actually the submission date is two weeks  
 20 from today, so if you're interested, I encourage you  
 21 to look into it quickly and whether you're going to  
 22 submit or not, you know, it might be an interesting  
 23 conference to attend.  
 24 So with that, I think I'll just plunge right  
 25 into introducing the panelists. So the way we're

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1 going to start this off is each panelist is going to  
 2 get a little bit of time to discuss their own  
 3 research. And, so, I'll sort of do the presentations  
 4 as we go along -- sorry, do the introductions as we go  
 5 along.  
 6 So first we have Frank Nagle. Frank Nagle  
 7 is an assistant professor in the Management and  
 8 Organization Department of the Marshall School of  
 9 Business at USC. He studies the economics of IT and  
 10 digitization with a focus on the value of  
 11 crowdsourcing and cybersecurity. His work utilizes  
 12 large data sets derived from online social networks,  
 13 financial markets, cyber attack data, and surveys of  
 14 enterprise IT usage.  
 15 Prior to his academic career, Professor  
 16 Nagle worked at a number of startups in the  
 17 information security industry. In these roles, he  
 18 conducted red team tests, responded to credit card and  
 19 intellectual property breaches, and developed a two-  
 20 week course that all FBI cyber agents must pass before  
 21 entering the field.  
 22 So please talk to us about your work.  
 23 MR. NAGLE: Great. Thanks, Doug.  
 24 So, yeah, so my work looks at the value of  
 25 goods that have no price, which in the digital economy

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1 is increasingly a lot more goods. So that kind of  
 2 breaks down into two buckets. One is crowdsourcing,  
 3 and the other is security and privacy. On the  
 4 crowdsourcing side, a lot of my work stemming from the  
 5 dissertation studies the value of open-source  
 6 software, so free software. How do we value this at  
 7 the macro level? We've looked at how it's -- the fact  
 8 that it has no price, has weird effects on calculating  
 9 GDP. We've also looked at the more micro level, at  
 10 the firm level, of how using open-source software can  
 11 impact firm productivity in positive ways but only for  
 12 some subset of firms.  
 13 And then we've kind of dug in a little bit  
 14 more where open-source is a crowdsourced good and  
 15 firms can actually contribute to it, although this  
 16 seems kind of counterintuitive because you're paying  
 17 your employees to write code that your competitors can  
 18 actually use. But what we show is that the firms that  
 19 contribute actually learn while they're doing this,  
 20 and they end up getting more productive value out of  
 21 using their open-source.  
 22 And, so, now we're starting to do some more  
 23 things related to regulation, technology procurement  
 24 at the federal level, to better understand the role of  
 25 the Government in these types of things. And we're

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1 also thinking about -- there's some bills before  
2 Congress right now, and there's a push from the White  
3 House that's been going on for the past few years to  
4 increasingly use open-source and open-source  
5 governance mechanisms as a way to increase  
6 transparency within the software supply chain.

7 And, so, this leads naturally into kind of a  
8 better security, if we have a better sense of what's  
9 actually being used in our firms, in our  
10 organizations, in our federal agencies, then we can  
11 better actually secure it and invest in the right  
12 amount of defense against these things.

13 And, so, on the other side, in the security  
14 and privacy side, as Doug mentioned, that was really  
15 my background before going back into the academic  
16 world. And now we're looking at some large data sets,  
17 about a hundred million observations of various  
18 security events against the Fortune 500 companies.  
19 And we're using this to show a couple things. One is  
20 the importance of actually fixing the low-hanging  
21 fruit, so simple things like patching and closing  
22 ports and having good password policies. As it turns  
23 out, those actually matter. And there are still a lot  
24 of firms that are not fully investing in those kind of  
25 low-hanging fruit as they should be.

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1 And the other thing we're looking at is  
2 competitive response. So one of the things we see is  
3 perhaps unsurprisingly, but we've -- you know,  
4 nobody's shown this before, is that when a company  
5 like Target gets hacked, Walmart and all the other big  
6 retailers start investing more heavily in security.  
7 And we're trying to kind of tease out as to whether  
8 this is something that's just awareness, so, wow,  
9 Walmart knows that they can be hacked, or is it some  
10 other kind of raising the bar and something that they  
11 actually advertise to their customers, you know, we  
12 have better security than Target, so you should come  
13 shop at us rather than at Target. And we're digging  
14 into that right now.

15 So that's kind of the high-level overview of  
16 the things I'm working on right now.

17 MR. SMITH: Thanks, Frank. So that was  
18 great.

19 So, Sasha Romanosky is our second speaker.  
20 He's a policy researcher at the Rand Corporation and a  
21 former cyber policy advisor at the Department of  
22 Defense. He researches topics on the economics of  
23 security and privacy, national security, applied  
24 microeconomics, and law and economics.

25 His research has examined questions such as

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1 whether or not state-level data breached disclosure  
2 laws and reduced consumer identity theft, when and how  
3 firms are more likely to be sued when they suffer a  
4 breach, and when they're more likely to settle legal  
5 actions. He's also studied the cost of data breaches  
6 in order to understand whether corporate losses are  
7 really as severe as is commonly believed.

8 And most recently he has collected a data  
9 set of cyber insurance policies to examine how  
10 insurance carriers measure and price cyber risk. So  
11 Sasha.

12 MR. ROMANOSKY: Thanks. So it's been an  
13 interesting exercise to try and summarize my body of  
14 work. It's probably something we should all do every  
15 few years. But as I was -- so actually, earlier  
16 today, as I was sitting and listening, I was doing a  
17 bit of that. Hopefully no one will begrudge me for  
18 it. But I think I'll characterize it like this. I  
19 think I started out being very interested in  
20 understanding different kind of policy interventions  
21 that can be applied at a federal level, even at a  
22 state level, to try and incentivize firms and  
23 consumers to adopt better behavior.

24 So firms invest in security. They have many  
25 different reasons for doing so -- regularity, peer

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1 pressure, shocks to the industry, say because of a  
2 data breach, and certain different kinds of regulatory  
3 interventions. And, so, the way I have tried to  
4 characterize that, or at least the way I was framing  
5 it in my mind was in terms of just very simply ex ante  
6 regulation.

7 We're going to apply compliance regulations  
8 to these firms to try and get them to at least reach a  
9 minimum standard versus ex ante liability. We're  
10 going to allow the accident to happen, the data  
11 breach, the security incident, and create a framework  
12 for injured parties, consumers, to bring actions to  
13 make themselves whole, so these data breach lawsuits.

14 In the middle somewhere is information  
15 disclosure. So an event has happened. It hasn't  
16 really caused any kind of demonstrable loss yet, so  
17 we're going to inform people. We're going to empower  
18 these consumers. And that's where these data breach  
19 laws really fit in. And, so, I guess I've tried over  
20 the years to try and understand those different  
21 components to understand whether or not firms are  
22 really incentivized to do the right thing and are they  
23 actually doing that, how are consumers reacting to all  
24 of that, and are we better off by any kind of -- any  
25 measurable factor.

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1 And, so, as you heard, I've looked at the  
 2 effect of these breach disclosure laws on consumer  
 3 identity theft, which led me into looking at the  
 4 litigation. It was always the story that plaintiffs  
 5 would bring these actions against firms -- class  
 6 actions or just individually -- but they would always  
 7 fail. And, so, I tried to understand, well, do these  
 8 lawsuits actually fail? Are there any kinds of  
 9 settlements? And what are the characteristics of a  
 10 breach that lead to litigation? What are the  
 11 characteristics of the lawsuit that lead to any kind  
 12 of settlement?  
 13 And that was quite interesting. And that  
 14 took me into the story of the cost of data breaches.  
 15 If we think cyber is really a big deal, if we think  
 16 these security incidents are really a big deal, like  
 17 we always hear about, is that actually true? And, so,  
 18 I was able to collect the data set to try and  
 19 understand what these costs are. And what shook out  
 20 of that was the notion that, well, maybe they're not  
 21 quite as intense as we all think. From the data that  
 22 I looked at, they really only represented less than  
 23 half a percent of firms' revenue, which I think is  
 24 quite telling. If true, that suggests that relative  
 25 to other kinds of risks that a firm faces --

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1 operational, regulatory, environmental, liability,  
 2 employment, everything -- cyber may not be such a  
 3 costly thing for them.  
 4 We had done other research asking consumers,  
 5 how do you feel about firms' behavior in response to  
 6 these data breaches? Are you happy? Are you not  
 7 happy? And for the most part, they didn't -- they  
 8 didn't seem to object. They were relatively happy  
 9 with firms' responses, what these letters looked like,  
 10 the kinds of information that were included, and the  
 11 suggestions. No, it's not great, right? These  
 12 disclosure laws can only do so much, and the notices  
 13 can only do so much, but the point is that consumers  
 14 were not objecting as much as we thought they were.  
 15 The customer attrition was not as much as we thought  
 16 they were. So the point is that if the costs to firms  
 17 aren't as great as we think they are, and if consumers  
 18 aren't really as mad as we think they are, then what  
 19 is the incentive for firms to adopt or to improve  
 20 their practices?  
 21 And I would argue maybe that they're doing  
 22 just the efficient amount. Maybe they are investing  
 23 as much as they should in order to minimize their  
 24 costs. Maybe not as much as consumers would want them  
 25 and security advocates and other privacy advocates,

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1 but maybe they are doing the appropriate amount.  
 2 And that had led me to other work on cyber  
 3 insurance, which I can talk about maybe, but I see  
 4 that time is up, so I'll stop.  
 5 MR. SMITH: Thanks, Sasha.  
 6 All right. Well, Rahul Telang -- I'm sorry.  
 7 So your last name -- oh, good. Okay, good. Rahul  
 8 Telang is a professor of information systems at  
 9 Carnegie Mellon University. His research interests  
 10 lie in two major domains. One is the digital media  
 11 industry with a particular focus on the economic  
 12 consequences of the digitization of songs, movies, TV,  
 13 and books. His second area of work is on the  
 14 economics of information security and privacy. He's  
 15 examined the issue of vendors' incentives to improve  
 16 the quality of their products and the role of  
 17 policymaking and standards and changing these  
 18 incentives.  
 19 His earlier work explores the challenges of  
 20 vulnerability disclosure and how competition and  
 21 policymaking affect these patch release decisions.  
 22 Recently, he is examining the role of data breach  
 23 disclosure laws and identity thefts. He was the  
 24 recipient of an NSF career award for his work on the  
 25 economics of information security.

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1 So...  
 2 MR. TELANG: Thank you. Thank you for  
 3 having us. So, you know, broadly in the economics of  
 4 information security and privacy, I'm very interested  
 5 in trying to understand the firms' incentives and then  
 6 particularly trying to understand how the market  
 7 structure -- you know, the market frictions that  
 8 information transparency actually affect both the  
 9 firms' incentives to do the right thing -- and we'll  
 10 define what the right thing is -- and even the  
 11 consumers' incentives.  
 12 So some of my earlier work tried to look at  
 13 why do software vendors create buggy products and what  
 14 are the welfare implications of that. And currently  
 15 that I'm interested in just looking at the data  
 16 breaches broadly. And I'm just using data breaches as  
 17 a proxy because actually getting data on the firms'  
 18 security posture and how much they're investing and  
 19 where they're investing is just very difficult, not  
 20 that we should not go after that. It's just that that  
 21 sort of information is much harder to get.  
 22 So we looked at, you know, the hospital  
 23 industry and tried to understand do hospitals in the  
 24 competitive markets actually do a better job of  
 25 investing in security or having fewer data breaches.

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1 You know, the IO market for hospitals is very well-  
2 defined. People study about the hospital competition  
3 and outcomes very well, so, you know, you can kind of  
4 borrow from that literature heavily.

5 But one other thing that we find is it's not  
6 clear at all that the competitive markets are less  
7 likely to see fewer -- are more or less likely to see  
8 breaches. In fact, we find that it really makes very  
9 little difference. And one other thing that we find  
10 is that in a setting like hospital, data breaches and  
11 information security is the last thing users care  
12 about when they're choosing hospitals. If anything,  
13 the hospital -- the users care about how nice the  
14 building is and what the surgeon is and whether they  
15 have all this equipment. And that just means that  
16 information security is not one of the features that a  
17 hospital can sell in the market and be able to get  
18 demand or be able to try to get higher prices. That  
19 has interesting implications about, you know, what is  
20 the role of policymakers now because the markets may  
21 not necessarily create the sort of incentives.

22 You know, some of the other projects that  
23 I'm looking at is at the consumer level, that do  
24 consumers actually respond to data breaches. And, you  
25 know, one other goal is to actually get the actual

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1 user data, so we are working with a financial  
2 institution. And, you know, there are two things that  
3 we are noticing. Number one, if there is a direct  
4 harm, that is, if the user knows they actually --  
5 there was a direct harm because of some security  
6 incidents, we find evidence that they actually punish  
7 the bank. So they take their business somewhere else  
8 over six to one-year period, with a three to four --  
9 three to five percentage point increase in consumer  
10 churn.

11 But on the other hand, we are also finding  
12 to an extent -- and it's very preliminary -- when  
13 there is no direct harm, so a retailer got breached, I  
14 transact with the retailer but there is no evidence of  
15 a direct loss to me, we are finding very little  
16 evidence that consumers are willing to punish the  
17 retailer. So the longtime impact of the data breach  
18 at the retailer seems, at least in our data, you know,  
19 very minimal.

20 And then there's another piece, which is  
21 sort of more privacy side that I'll just mention and  
22 then pass it on. We are working with -- we ran some  
23 randomized experiment on online advertisement. The  
24 goal is that the online -- you know, the online ad  
25 platforms are using extensive amount of behavioral

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1 data to target us, you know, programmatic advertising,  
2 algorithmic advertising. So they're essentially doing  
3 selection. They're trying to find people who are more  
4 likely to buy and then serve the ad, which is fine as  
5 long as the people who are more likely to buy are also  
6 responding more to the ads, then that's probably at  
7 least somewhat of a win/win.

8 You know, we might still care about our  
9 privacy, bvhrrspat at least the advertiser and the ad  
10 platforms are better off. And, you know, basically  
11 what is our research showing is that that's not true  
12 at all, at least in a series of experiment, people who  
13 are more likely to buy, and we can see they are more  
14 likely to buy from the behavioral data that we have  
15 access to, are not necessarily the people who are  
16 responding more to ad either. So what we are finding  
17 is that the ad platform have all the incentives to  
18 target and select people, and they go back and report  
19 to advertisers look how good my ad campaign is. It's  
20 not clear that the advertisers are necessarily  
21 benefitting from paying premium for this very  
22 extensive targeting.

23 So look forward to the discussion.

24 MR. SMITH: All right, great. Thanks.

25 So our last panelist is Liad Wagman. Liad

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1 Wagman is an associate professor of economics at  
2 Illinois Institute of Technology's Stuart School of  
3 Business and visiting associate professor of executive  
4 education at Northwestern University's Kellogg School  
5 of Management.

6 He works in the areas of information  
7 economics, industrial organization, and  
8 entrepreneurship. His focus is on issues of privacy,  
9 information utilization and trade, and innovation.  
10 His recent works include a study of privacy in  
11 financial markets, a study on the tradeoffs associated  
12 with increased security via government surveillance,  
13 and studies of privacy in oligopolistic markets. And  
14 those studies incorporate data access and information  
15 consolidation as factors in antitrust considerations.

16 MR. WAGMAN: All right, so maybe I'll talk a  
17 little bit about the privacy aspect that us economists  
18 are more used to, that is in the context of price  
19 discrimination. And I started my work on this in a  
20 context-agnostic way by just looking at the standard  
21 models we use like Cournot or Bertrand and so forth.  
22 And I found that the impact of whether there is  
23 privacy or there isn't privacy on a consumer surplus  
24 is not obvious. It's not monotonic. Some privacy is  
25 good; too much is bad.

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1 I then looked at individual consumers and  
2 individual firms in a market, and I saw that the  
3 effect on them is also not obvious. It depends on the  
4 model we use. It depends on the market structure in  
5 question and on the specific context. That means that  
6 even in a given market over time some may benefit and  
7 some may lose from privacy. And, so, privacy  
8 regulation should not be a static thing. It needs to  
9 be adjusted dynamically.

10 I then looked at more context-specific  
11 cases. I looked at privacy and financial markets,  
12 specifically mortgages. And I looked at the  
13 information we disclose as part of our mortgage  
14 application process and whether that information can  
15 be sold or not. And I found that when it cannot be  
16 sold, when we have some degree of privacy there, that  
17 prices tend to go up, i.e., mortgage rates. And when  
18 they go up, firms have less incentive to screen away  
19 consumers. And so standards decrease, and  
20 foreclosures might increase, and denial rates  
21 decrease. So that's one context-specific study in  
22 financial markets.

23 I also looked at cases of antitrust and  
24 whether privacy or lack of can tip the scales one way  
25 or another. And what I found is that when firms have

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1 consumer data, wide access to it, where they can price  
2 discriminate very well, that it's easier to prove  
3 antitrust cases that are marginal, that are just on  
4 the bounds between being rejected and proved, meaning  
5 lack of privacy can intensify competition, which can  
6 be good for consumers. So, again, the relationship  
7 between privacy and consumer surplus is not obvious.  
8 This is not taken into account, any intrinsic value of  
9 privacy or issues of data security.

10 I then looked at cases of government  
11 surveillance, something that might not be a popular  
12 topic here, but I think it's important to note that  
13 even there the relationship between the number of  
14 persons intercepted through wire tapping specific to  
15 the narcotics-related cases, which is the vast  
16 majority of them, and the number of persons that are  
17 arrested or convicted is not linear, it's not  
18 monotonic.

19 And I looked at where states are and where  
20 the Federal Government in terms of law enforcement is  
21 on this nonmonotonic curve. And I found that it's  
22 actually -- if you consider it as a Laffer curve, kind  
23 of a U shape, it's on the left side of the curve,  
24 which is good news.

25 And another interesting context-specific

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1 privacy issue I looked at is physical privacy in a  
2 neighborhood. I looked at the effect of short-term  
3 rentals in a neighborhood which you might argue hurts  
4 neighborhood cohesion and maybe hurts physical privacy  
5 around your home. I looked at the effect that short-  
6 term rentals have on real estate prices, and by proxy  
7 on your physical privacy. And I found that some of it  
8 doesn't hurt it but too much does. So, again, there  
9 is a nonlinear relationship between the effect and  
10 whether you have privacy or not.

11 So -- and to sum, privacy is hard. It's not  
12 easy. There's a lot of aspects to it. If you just  
13 look at data privacy, there is data that is collected,  
14 there's data that is used, there's data is stored, and  
15 there's data that is transmitted. And each of these  
16 steps involves privacy considerations.

17 MR. SMITH: All right, thanks very much.

18 Great. I guess we'll just get to general  
19 questions. So I think, you know, several of you guys  
20 sort of touched on the question of what are firms'  
21 incentives and how will it balance sort of with  
22 efficient outcomes. So, Frank, I think you kind of  
23 said, well, they're not doing a lot of things they  
24 could be fairly easily doing. So I have a question  
25 about that, which is when you say this is low-hanging

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1 fruit, like how low-hanging is this?

2 MR. NAGLE: That's a good question because  
3 much like Liad was just talking, it depends on the  
4 firm and it depends on the industry, right? So for  
5 small firms, low-hanging fruit is actually high-  
6 hanging fruit, right? So, you know, you think about  
7 mom-and-pop, you know, pizza chain -- pizza restaurant  
8 or something like that. For them, investing in  
9 somebody to come in and do a security analysis and put  
10 in a firewall and all these types of things could be  
11 very expensive. For large companies, things like good  
12 password policies, closing ports, patching  
13 vulnerabilities, you know, those types of things,  
14 they're still an investment, but they're comparatively  
15 much cheaper.

16 And, so, you know, something like Equifax,  
17 the breach that's in the news now, that was a known  
18 vulnerability that was, everybody knew it was a bad  
19 thing and should be patched, and it had been gone  
20 unpatched at Equifax for at least two or three months.  
21 And, so, that -- you know, is that free to fix? No.  
22 But is it much cheaper than investing in, you know, a  
23 thousand cyber agents to kind of come and help you out  
24 and protect your whole company? That's a pretty  
25 straightforward thing to invest in.

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1 MR. SMITH: Okay, thanks.  
 2 And, then, Sasha, you sort of suggested that  
 3 consumers don't care that much? Is that sort of a  
 4 fair way to put it? Or --  
 5 MR. ROMANOSKY: Yeah, I mean, this has --  
 6 this has been the story for a while. It's kind of --  
 7 you know, I mean, it's an old problem, right? If --  
 8 you know, if consumers really did care, then the firms  
 9 would start competing on privacy. They would start  
 10 competing on security. And have we really seen that?  
 11 I haven't seen much evidence of that.  
 12 There may be some instances in sort of niche  
 13 examples with browsers and certainly products like Tor  
 14 for anonymizing web traffic, web activity, have  
 15 increased in popularity, but, you know, I don't think  
 16 there's anything across the board that would suggest  
 17 that.  
 18 What was the other question?  
 19 MR. SMITH: Well, that was basically the  
 20 question. But I guess one thing I wanted to ask you  
 21 about in terms of that as well is, I mean, do you have  
 22 any sense, sort of is this because they really -- they  
 23 don't think the outcomes are a big deal, or is it  
 24 because they just sort of don't know how to effectuate  
 25 a different outcome?

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1 MR. ROMANOSKY: Yeah, I mean, again, a well-  
 2 studied area, and you could -- I mean, I think it's a  
 3 lot of reasons, right? We enjoy -- we want the  
 4 benefits now. We can't anticipate the costs later on,  
 5 right? The costs are intangible. It's very  
 6 contextual. What I might feel is a privacy invasion,  
 7 Rahul probably does not and vice versa, right? Change  
 8 your preferences, change over time, and so the  
 9 challenge for policymakers, how do you create a, you  
 10 know, something reasonable, any kind of intervention  
 11 that can address and can accommodate all these people.  
 12 I may not like the advertising. You know, somebody  
 13 else may. And what do you do with that?  
 14 But, yeah, I mean, I'll say in the research  
 15 that we did, asking consumers about their privacy  
 16 interests and their taste, in their responses, they  
 17 were -- I wouldn't say quite -- it's not that they  
 18 were indifferent, and they were, in fact, generally  
 19 quite positive to firm -- to firm practices.  
 20 And, again, if that really is the case and  
 21 you found some examples of consumer attrition and  
 22 churn, how they report, how their industry reports,  
 23 have found a little bit here and little bit there,  
 24 but, look, if there's nothing driving it, right, if we  
 25 as a community, if we as consumers are not driving

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1 that, then, you know, why should a firm respond to  
 2 that?  
 3 MR. SMITH: Yeah, and so you alluded to  
 4 Rahul found this evidence that people's reactions are  
 5 different under different circumstances, right, so can  
 6 you unpack a little bit more on this idea that the  
 7 people react more strongly when they sort of see the  
 8 direct effects?  
 9 MR. TELANG: So I think the problem with  
 10 security or even privacy is that in many, many  
 11 industry, it's like one of the feature. You know, you  
 12 go to Home Depot or you go to Walmart, you know, maybe  
 13 the prices really dominate, you know, your decision-  
 14 making process, whether Walmart has a good data  
 15 control policies are something probably I can -- I'm  
 16 sure most of the people don't care until there is a  
 17 big breach and then maybe we pay a little bit of  
 18 attention at that something.  
 19 But for some other industry, I think like  
 20 for financial, like my bank, maybe we really care  
 21 about it, that is -- are they protecting my  
 22 information. And we probably pay a little bit more  
 23 attention. So maybe the data seems to point that,  
 24 like when there is a breach at the bank or if I'm  
 25 losing -- I can see in my account that there is a \$200

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1 harm, I worry about it, even though actually in our  
 2 data we find the bank actually compensates me, so I  
 3 get my money back. Even then, I feel -- at least the  
 4 data seems to suggest that people are a little  
 5 concerned that why is this fraud perpetrated on my  
 6 account. Why didn't bank do enough or wasn't it  
 7 proactive enough?  
 8 So for some industry, we feel like security  
 9 is an important feature. I think at least the users  
 10 feel it's an important feature. I think financial  
 11 institutions are probably a good example. But I think  
 12 for a retailer or hospitals or some other thing, I'm  
 13 not so sure that consumers -- and can't blame them  
 14 either -- you know, maybe that'd be default. We  
 15 expect them to have it, and that's not something  
 16 that's going to drive the marketing or the pricing  
 17 decision, or you can charge premium for that, let's  
 18 put it this way, but maybe the -- so I think that's  
 19 really what we seem to find, and it's probably  
 20 consistent with what users should rationally behave.  
 21 MR. SMITH: So, actually, you know, you  
 22 raise -- so one of the questions I guess I have about  
 23 that is to what extent when you're asking -- when  
 24 you're looking at this question, to what extent do  
 25 consumers seem to understand sort of what differences

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1 there might be or are they pretty indifferent? Are  
 2 they knowledgeable or --  
 3 MR. TELANG: Yeah, so, in -- I think that  
 4 Sasha's probably had this survey that he did where he  
 5 asked people about -- or at least the research tried  
 6 to ask people about their perception. You know, it's  
 7 -- my research, we actually had the actual behavior,  
 8 but we didn't actually ask them about their  
 9 perception. My suspicion is that it's kind of  
 10 correlated, which is for the retailer, if there's a  
 11 breach, they pay a little bit of attention and then  
 12 kind of ignore, you know, the future transaction when  
 13 they make the decision. For probably financial  
 14 institution and bank where we keep our sensitive  
 15 information, I think people not only behaviorally show  
 16 that they care about it, but perceptually they  
 17 probably care about it. That would be my, I think,  
 18 sensible conjecture.  
 19 MR. SMITH: Liad, I'm going to shift the  
 20 topic a little bit, but sort of still getting to the  
 21 question sort of -- sort of efficiency. You know, you  
 22 talked a lot about the sort of idea of there can be  
 23 too little privacy and too much privacy. Is there any  
 24 sort of way to think about when we might expect that  
 25 to be, you know, on either side?

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1 MR. WAGMAN: Right. So let me give an  
 2 example. If we think about, for example, being able  
 3 to maintain your privacy at some cost, and if we  
 4 imagine this cost as something continuous that a  
 5 regulator can control, the finding is that when this  
 6 cost is too low, consumers end up being harmed and  
 7 firms end up being harmed. And when this cost is too  
 8 high, firms are actually happier, consumers not so  
 9 much.  
 10 Now, once you engage in repeated interaction  
 11 between firms and consumers, these findings change.  
 12 Firms, in fact, might want to commit to a level of  
 13 privacy because they'll be able to retain consumers  
 14 over repeated interactions. So what we find is that  
 15 even in these repeated interactions, having too much  
 16 privacy or too little privacy ends up being bad for  
 17 consumers. And the reason is too little privacy,  
 18 consumers, at least the lower willingness to pay  
 19 consumers, don't get the benefits of price  
 20 discrimination.  
 21 And when privacy is too expensive or too  
 22 hard, then firms don't need to try to give reasons for  
 23 consumers to be tracked to give their information. So  
 24 somewhere in the middle kind of gives a sweet spot  
 25 where consumers are willing to give the information

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1 and willing to be tracked in order to get the  
 2 benefits, and firms are happy as well because they're  
 3 able to price discriminate.  
 4 MR. SMITH: So when you say the middle, is  
 5 that sort of an exogenous dimension of cost or is that  
 6 something --  
 7 MR. WAGMAN: No, so, again, it's market-  
 8 specific, it's industry-specific.  
 9 MR. SMITH: Mm-hmm.  
 10 MR. WAGMAN: And, you know, this is what  
 11 makes it hard. Now, even in a particular market,  
 12 among consumers, there are going to be winners and  
 13 losers. There are going to be some who are happy that  
 14 there is privacy or that there isn't privacy. And  
 15 those groups of individuals might change, depending on  
 16 market structure, which itself can change over time.  
 17 So it's a dynamic question of what's efficient.  
 18 MR. ROMANOSKY: Can I add one thing?  
 19 MR. SMITH: Absolutely.  
 20 MR. ROMANOSKY: So I think that leads to a  
 21 really interesting question, which is whether or not  
 22 privacy regulations, say state laws, actually harm  
 23 consumers or not, are actually in their best interest  
 24 or not.  
 25 And, so, one way you might think of that is

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1 if we want to define privacy as the control over our  
 2 information, the right to control, the ability to  
 3 control our information, say in a financial setting,  
 4 you might wonder about what the effect -- so let's say  
 5 there were state-level laws that allowed for more or  
 6 less sharing of financial information amongst  
 7 financial institutions. So some states were very  
 8 strict and required and permitted very little sharing  
 9 of information between financial institutions; other  
 10 states were very permissive in the sharing.  
 11 And, so, the question is more or less is  
 12 information-sharing better or worse for consumers.  
 13 And, so, privacy advocates would certainly argue that,  
 14 no, I want control over my information, I don't want  
 15 that to be shared amongst financial institutions. On  
 16 the other hand, what that might lead to is higher  
 17 price of credit, right? So the less information the  
 18 bank has about you, the less they're able to assess  
 19 your financial risk, the more likely they're going to  
 20 charge you -- the more they're going to charge you  
 21 higher rates for borrowing money.  
 22 MR. SMITH: Right.  
 23 MR. ROMANOSKY: And, so, I don't know if  
 24 that -- I'm not saying that that's true. I'm just  
 25 saying that that's a reasonable question, and that's a



1 testable question. And I think there are all kinds of  
 2 examples of state-level -- you know, state-level laws  
 3 make for a great sort of empirical study, but I think  
 4 there are all kinds of different ways that we could  
 5 start to think about how state-level variation in  
 6 different kinds of privacy laws drive different kinds  
 7 of outcomes, and maybe those that we wouldn't -- we  
 8 would actually consider.

9 There hasn't been a lot of work in that  
 10 area, but I think if there's really any opportunity to  
 11 pursue that it's -- it would be a dynamite thing to be  
 12 able to show.

13 MR. WAGMAN: So we were able to test  
 14 something along these lines.

15 MR. ROMANOSKY: Okay, there's one great  
 16 paper on that.

17 MR. WAGMAN: In the Bay Area, where some  
 18 counties adopted stricter privacy financial laws and  
 19 some did not. So we had a control group, and we were  
 20 able to test this. And we found that there was an  
 21 effect. There was a significant effect where once  
 22 privacy was enforced in those counties, their rates on  
 23 mortgages increased. They were charging higher  
 24 prices, and they were approving more mortgages. So  
 25 their denial rates decreased. Their standards

1 And, so, even if it's different, you know, it might  
 2 not be what drives consumers to the product. And we  
 3 see this in the market for mortgages with different  
 4 privacy policies and different mortgage rates.

5 MR. NAGLE: And there are some implications  
 6 and kind of externalities beyond just the rates and  
 7 things like that. There's a study by Catherine Tucker  
 8 and some friends that looks at the impact on  
 9 innovation and the ability of the firms to innovate  
 10 and actually shows that increased privacy slows down  
 11 innovation. And, so, if we think of innovation as  
 12 probably a good thing, then this balance and kind of  
 13 the sweet spot of regulation also factors in beyond  
 14 just the individuals but to the ability of firms to  
 15 innovate as well.

16 MR. SMITH: Great. I don't know if there  
 17 are any sort of more general thoughts on the question  
 18 of sort of efficiency and privacy as it happens in the  
 19 market.

20 MR. WAGMAN: So just a quick thought. I  
 21 mean, Sasha mentioned that a lot of privacy  
 22 considerations among consumers involves some form of  
 23 regret where you give your information away and then  
 24 you realize later, oh, what did I do. But most  
 25 regulators' guidelines, at least, pertain to ex ante

1 decreased.

2 MR. TELANG: I mean, don't you feel that if  
 3 people are heterogeneous in their preference for  
 4 privacy or whatever you would think that the firms  
 5 would also be heterogeneous in terms of providing  
 6 that? So some firms would say, okay, you want a lot  
 7 of privacy, here it is, and if you don't want too  
 8 much, then here it is? But we don't see a whole lot  
 9 of that happening. It could be because of the earlier  
 10 talk about the concentration. Maybe there are some --  
 11 you know, we can't live without Facebook, and there is  
 12 really no competition to it possible because of all  
 13 these effects, so then whatever is the Facebook  
 14 privacy policy is really what we have to live with.

15 But you would think, right, I mean, if I  
 16 have heterogeneous preferences, and if I can market it  
 17 to consumers, that, you know, this is what my privacy  
 18 is or this is my security, you would think that the  
 19 market should sort itself somewhat without FTC or  
 20 policymakers intervening too much.

21 MR. WAGMAN: Right. I think this is where,  
 22 you know, privacy is a second-order effect. It comes  
 23 in, and consumers usually treat price as the, you  
 24 know, the driving factor. And privacy just comes as a  
 25 second-order effect, a second-order consideration.

1 consent. Give my consent now or not. Almost none  
 2 talk about ex post consent, where my information is  
 3 already out there and I want it withdrawn. There have  
 4 been some, you know, policy experiments in the EU  
 5 along these lines but not much in the U.S. So, you  
 6 know, that would be interesting to explore.

7 MR. TELANG: So if I take it in a slightly  
 8 different direction, I think we are very interested in  
 9 understanding are firms doing -- you know, investing  
 10 optimally in security. You know, you don't want them  
 11 to spend too much. You don't want them to spend too  
 12 little. And, you know, what is the ROI and  
 13 everything. But sometimes I feel that this can get  
 14 very complicated if your adversary is some state  
 15 actor.

16 So suppose you are being attacked by  
 17 somebody in some other country who might have very  
 18 nonmonetary incentives to actually -- so they want to  
 19 attack you because -- not because they want to steal  
 20 your data and make money off it. They just want to  
 21 have a -- cause a significant reputational damage to  
 22 you.

23 In this situation, it's a little -- it's  
 24 very challenging to think about the private investment  
 25 by a firm would be the right strategy to fight

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1 against, something that's happening. Then you kind of  
2 go into this, you know, is there a role for government  
3 here, is there a role for some public investment,  
4 whether it's diplomatically or whether any -- and it  
5 just opens a can of worms.

6 But it also means that the whole, you know,  
7 modeling gets very complicated because, you know, what  
8 are you modeling? You know, are you -- what exactly  
9 is your model of investing in security when, you know,  
10 you have some actors which are probably not driven by  
11 economics alone.

12 MR. NAGLE: And along those lines as well,  
13 these state-sponsored actors often will attack even  
14 small companies that have -- you know, they're not  
15 going after them at all, but they want some IP address  
16 in the U.S. to base their next attack against the  
17 bigger company or the better target or whoever. And,  
18 so, even if we think about the small places that have,  
19 you know, limited kind of juicy data or juicy whatever  
20 that they want to steal, they're still kind of getting  
21 caught up in these super-high, you know, priced kind  
22 of attacks, right? The super-expensive attack.

23 MR. ROMANOSKY: Yeah, and I'd -- I mean, I'd  
24 reiterate that it's still an outstanding question,  
25 right? It's one that's plagued the industry for

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1 decades of how much should firms invest and are they  
2 investing optimally and how would you even know. And,  
3 again, privacy and security advocates would argue  
4 that, no, firms are not investing because look at all  
5 these breaches that occur. And I would argue that  
6 that's not evident, that they're not investing  
7 optimally, at least for their own interest. Even if  
8 you take Target and Equifax and even if the cost is  
9 \$100 million, that's still not evidence that they're  
10 not investing optimally.

11 The other question that we still don't know  
12 is what kinds of security controls matter and by how  
13 much, right? We could all think of different kinds of  
14 technologies to implement that we would think would  
15 reduce risk of any given firm by a certain amount,  
16 but, I mean, even I can't tell you with all the  
17 experience that I have of by how much that should  
18 reduce a firm's or increase a firm's security posture.  
19 We just don't know.

20 The one place that I think we could answer  
21 that is with insurance. So any given firm, right, you  
22 would need to know this marginal benefit, the marginal  
23 cost in order to assess this. They don't really  
24 operate that way. Even a government agency doesn't  
25 really have that information. But insurance

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1 companies, right, through their claims data, they  
2 collected this body of data and observe these  
3 incidents. They have information about the firms  
4 ostensibly. They have information about the different  
5 kinds of security controls because of the applications  
6 that they provide to the applicant in order to sign up  
7 for the policy.

8 And, so, there is a potential there for --  
9 you know, I mean, it's not very complicated, it just  
10 runs through a regression to understand what the  
11 marginal effect is of different kinds of controls in  
12 preventing a claim and a breach and even therefore to  
13 understand the relative effects of one versus the  
14 other. And that's a dynamite thing to be able to do.  
15 I haven't encountered any firm, any carrier, that's  
16 doing anything like that, but it's possible to do it,  
17 and I look forward to the day when they start to do  
18 that.

19 MR. TELANG: It's the IT productivity  
20 question, for a long time we had no clue, then we  
21 started collecting good data. Maybe something good  
22 was going to happen. I'm not very optimistic because  
23 this was a question when I was doing doctorate  
24 dissertation. I'm glad I didn't attack it. But it's  
25 one of those things where we don't have good measures

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1 at all and, you know, both the technology,  
2 organization, management, they interact in ways that's  
3 really, really hard to predict good econometrics. You  
4 see case studies and anecdotes, but that's not -- I  
5 don't think that's very convincing.

6 MR. NAGLE: And, actually, to echo that, a  
7 few years after your dissertation I thought that was  
8 going to be my dissertation question as well, and it  
9 turned out there was no data and I couldn't do  
10 anything about it. Although I want to get back to the  
11 insurance angle is interesting because as we all know,  
12 insurance changes incentives and behavior as well,  
13 right? So are these companies -- if they know they  
14 get hosed by a bad guy that they -- the insurance  
15 company is going to clean up and take care of the  
16 loss? Does that mean -- lead them to underinvest in  
17 security? I'm not sure, but there might be data to  
18 chip away at that.

19 MR. ROMANOSKY: Yeah, I mean, there are all  
20 kinds -- I mean, this is why I've been studying it for  
21 a while. I've been trying to get at these questions  
22 of, you know, does the insurance even improve  
23 incentives, right? That's an outstanding question.  
24 We don't know. In theory, it's a testable one. I  
25 don't have data on the adoption time of any given

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1 company, but if we had it, it would be -- it would be  
2 answerable.

3 Yeah, does it lead -- I mean, the same, you  
4 know, information asymmetries that exist with any kind  
5 of insurance, you know, may still exist. If I'm a  
6 firm, I can buy insurance or I can invest. Why do I  
7 need to do both, right? Does that occur and to what  
8 extent?

9 Is it true or, you know, how much  
10 information do the carriers need in order to create  
11 the right incentives for firms to improve? Right, I  
12 think that gets back to they need to understand what  
13 kinds of security controls matter. So should they  
14 incentivize firewalls, two-factor authentication,  
15 better encryption, cloud services, et cetera? From  
16 what I've seen, they don't know that. They don't have  
17 the answers, right?

18 I've seen the price schedules. I've seen  
19 exactly the variables that they use to price the  
20 premiums and the effects on the premiums, like the --  
21 I mean, it's a linear product of a bunch of different  
22 variables, right, so I can see if some carriers feel  
23 that if accounting firms pose a lower risk so they  
24 have a multiplier of .85 versus government agencies  
25 are a higher risk and you multiply by 1.2, for

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1 example. But they still don't really have a good  
2 feeling for how to craft those and good justifications  
3 for any of those numbers. But I think that will just  
4 improve over time.

5 MR. SMITH: So, yeah, so that gets kind of  
6 into a product question about sort of what are some of  
7 the things that we still really need to figure out in  
8 this area. What are the big questions?

9 MR. WAGMAN: So from the perspective of  
10 privacy, I think there's been very little link in the  
11 literature between privacy and security, right?  
12 They've mostly been studied separately, and I'm  
13 partially guilty of the same thing. Having worked on  
14 a survey of the literature recently, I tried to tie  
15 them together, and I think there's a lot more that can  
16 be done there. So I think there's great opportunity  
17 for theoretical and empirical research to try to tie  
18 them together.

19 MR. SMITH: Can you talk a little bit like  
20 what that would look like, or --

21 MR. WAGMAN: Right. So I think I indicated  
22 earlier that privacy, at least economists have looked  
23 at it in IO is mostly revolved around price  
24 discrimination or search and seizure. And that's  
25 quite limited because there's this privacy in a bunch

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1 of other things as well. There's privacy in data  
2 storage and data transmission. Data that is stored in  
3 itself can be made more private by anonymizing it and  
4 so forth. And I think these considerations have  
5 largely been ignored, at least in the economics angle.  
6 Some computer scientists have looked at it, but not  
7 many economists. And I think there's a lot of  
8 opportunity there.

9 MR. TELANG: I think -- and, you know, many  
10 people have thought and commented on it, but when it  
11 comes to security particularly and privacy for sure as  
12 well is like, can we even say that there's a market  
13 failure? And what are the dimensions of those market  
14 failures? What are the things that are leading to  
15 these market failures?

16 Then we can ask the question, what is the  
17 good policy intervention. And then how effective  
18 those policy interventions are, right? I mean, the  
19 data breach notification law was passed, what, 10, 15  
20 years ago now? It's been around, and I don't think  
21 that even now we understand, you know, if you talk to  
22 the industry people, they'll come and say it's a lot  
23 of -- a bunch of checkmarks that I have to do, and I  
24 don't know what I get in return. Or they say it's so  
25 sometimes outdated that we actually do a whole lot

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1 better than what some of these laws are telling us to  
2 do.

3 So sometimes you hear from firms that it's  
4 very costly and onerous, but then you look at what the  
5 benefits are and then you're back to sort of square  
6 one. Some of it is just because the observation  
7 nature of data makes it so difficult to do any sort  
8 of, you know, sensible identification. You can't run  
9 a randomized experiment here. There's really no good  
10 exogenous shifter.

11 But those are the fundamentals, I think, you  
12 know, we don't know at some level where the market is  
13 failing. Or even if we know, we don't know what sort  
14 of policies would make sense and then come back in a  
15 while away, you know, is this the right policy? Can  
16 we tweak it? What way we should be tweaking it? So I  
17 think there are a lot of interesting questions both at  
18 the macro as well as at the micro level.

19 MR. NAGLE: And to kind of add on to  
20 something that's been underlying all of this is that,  
21 again, a lot of these things are difficult to price,  
22 right? What's the value of your Social Security  
23 number? And your Social Security number being safe,  
24 right? We don't know. And in the case of a lot of  
25 the firms that we used to do investigations of, a lot

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1 of it was related to intellectual property, right?

2 So a large multinational conglomerate got  
3 broken into; intellectual property was stolen for a  
4 widget; and that widget shows up on the black market  
5 for, you know, a third of the cost that it actually  
6 costs, you know, the company to make. And they end up  
7 shutting down this entire business unit, right? So  
8 they got breached, and they shut down the business  
9 unit and all the future profits that might stem from  
10 that.

11 And, so, how do you kind of value that as  
12 well in terms of it's just intellectual property,  
13 right? It's an idea. We know it has value, but how  
14 do you actually put a future number on that so you  
15 know how much to invest in protecting that idea?

16 MR. SMITH: Okay, so, I think it sounds like  
17 there's a lot of sort of sense that we don't really  
18 know what the market failures are or where there  
19 should be policy interventions. Are there any  
20 thoughts about sort of what government might do in the  
21 short term in terms of thinking about policy --  
22 towards privacy data and security?

23 MR. NAGLE: One thing I always think of just  
24 is a pure awareness, right? So educating the  
25 population, and this is one thing that is known to

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1 work fairly well in firm context. Presumably it would  
2 also work reasonably well in the broader populace, but  
3 everybody wants to invest their security dollars in  
4 the newest, latest, greatest technology to actually,  
5 you know, prevent the breach, right?

6 But how do most -- or a lot of breaches  
7 happen now is somebody clicks on an email that has a  
8 bad link and then bad things happen, right? So  
9 educating, you know, the employees, but also the  
10 general populace that this stuff is going on may be a  
11 cost-effective way to at least start approaching this.

12 MR. WAGMAN: I would add to that that the  
13 Government did step in in financial markets, for  
14 example, and made privacy disclosures very easy to  
15 read. It's basically a table that you can quickly go  
16 through. And, so, you know, it improves awareness, it  
17 improves understanding. I think there's very little  
18 of that in other markets, and that would go a long  
19 way.

20 MR. TELANG: So I feel like, sure, we cannot  
21 stop the data breaches, but I think we can do a whole  
22 lot more to control the cost that happens post data  
23 breach. So I think Equifax being a good example,  
24 right? Probably the breach itself was bad, but the  
25 response itself was so sort of incompetent that you

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1 would be, like, why would you do that. I mean, you  
2 know, you're -- we are in 2017, we should be expecting  
3 to be breached. And conditional on breach, we ought  
4 to have some sensible plan so that we make sure that  
5 the damage is contained.

6 So maybe there is some -- maybe there is  
7 some role for policymakers to say, okay, you know,  
8 sure, you know, you got breached, we give you benefit  
9 of doubt, but you really have no benefit of doubt on  
10 how you respond to the breach. I mean, there has to  
11 be some way. So containing the damage is something I  
12 think we should probably be focusing on, rather than  
13 saying how much dollars to spend and reduce the breach  
14 and that it should be zero probably. Probably that  
15 will never happen, but I think we can do a lot more in  
16 making sure.

17 In fact, how much consumer is harmed itself  
18 is not clear. Okay, there's a breach, hundred million  
19 records got breached, but so what? I mean, like, what  
20 does that mean, right? I mean...

21 MR. SMITH: So is there a sort of a  
22 practical set of things that firms should do when  
23 there's a breach? Is that, like, a pretty clear  
24 answer?

25 MR. NAGLE: There's, like, the industry

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1 standards of you have your team that -- your response  
2 team that includes not only the techies but also  
3 legal, also marketing and PR because you're going to  
4 have to, you know, publicize what you're doing and  
5 kind of, you know, you're supposed to have your strike  
6 team on speed dial, right? And, so, there are kind of  
7 standard sets of best practices pre-breach that help  
8 you know what to do so you're not running around in a  
9 panic. And I agree, Equifax's response was certainly  
10 not as good as it should have been.

11 MR. SMITH: So does this dovetail a little  
12 with Liad's point about, you know, how much data do  
13 you really need kind of issues? Is that sort of a  
14 similar feel in terms of we know things are going to  
15 happen, so let's minimize?

16 MR. WAGMAN: I think with the way the  
17 incentives are set up now firms want to collect as  
18 much as possible because the data itself often is the  
19 product or part of the product. And you don't know  
20 what you're going to need tomorrow. So the way the  
21 incentives are set up now, firms want to store more  
22 and more. So, you know, it's --

23 MR. NAGLE: Which, of course, makes it much  
24 worse when a breach inevitably happens, right?

25 MR. SMITH: But is that a market failure, or

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1 is it just that's --

2 MR. WAGMAN: I don't want to step on Rahul's  
3 toes here, but, you know, I think tastes for privacy  
4 have -- are constantly shifting, right? Things that  
5 used to be punishment, for example, you'd be put on  
6 some registry and public records, now people  
7 voluntarily want to be on some sort of public record,  
8 right, whether it's Facebook or other social media.  
9 So tastes are fluctuating, so it's hard to pinpoint  
10 the failure, but if firms are overstoring data, it can  
11 be showed in simple theoretical models that this is an  
12 inefficiency.

13 MR. TELANG: I don't know what government  
14 can say and tell firms what to store and what not to,  
15 so that is a -- that's really being -- you know, I  
16 don't think it will work at all. You can only think  
17 about the consequences that if you were to lose what  
18 are the consequences. And those carrots and sticks  
19 have to be in place to encourage them to do the right  
20 thing around what data they should have and what data  
21 they shouldn't have. I think that would be probably a  
22 more practical and implementable strategy versus kind  
23 of dictating or even saying anything that how much  
24 data you are to store.

25 MR. SMITH: So more time is outcomes in some

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1 sense.

2 MR. TELANG: I think so.

3 MR. SMITH: So we have a clock that's  
4 counting down. I don't totally know what it  
5 corresponds to. I think it corresponds to in 20  
6 seconds it's time to ask the audience questions -- or  
7 open up the -- for audience questions. So why don't  
8 we just move to that. So, yeah, any questions from  
9 the audience?

10 Nathan.

11 MR. WILSON: So there were multiple  
12 references to us not knowing the costs of breaches.  
13 Can't we at least establish some sort of lower bound  
14 by looking at how a breach correlates with the  
15 incidence of, you know, stolen identities and then  
16 there's -- I presume there must be some estimate  
17 of the -- you know, the hours spent dealing with  
18 that plus potentially some expenditures. Or is that  
19 data --

20 MR. ROMANOSKY: I don't know if we say we  
21 don't know the cost of breaches. So I actually have a  
22 paper on the cost of breaches, and it turns out to not  
23 be as high as we think it is. So the typical industry  
24 reports are in millions of dollars -- \$4, \$5, \$6  
25 million, and the reason they're high is because they

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1 report -- what they're trying to report is the  
2 typical, right? So they report the mean. But because  
3 loss distribution is so skewed, that's a pretty poor  
4 representation. We look at the median, which is much  
5 less, a couple hundred thousand dollars.

6 MR. SMITH: Sasha, are you talking about the  
7 cost to the firm, the cost to consumers, or --

8 MR. ROMANOSKY: Right, sorry, the cost to  
9 the firms, strictly to the firm.

10 MR. SMITH: Yeah, I think Nathan's question  
11 was maybe more about --

12 MR. WILSON: Right.

13 MR. SMITH: -- consumers, cost to consumers.

14 MR. WILSON: Does the cost to the firm --  
15 how does that compare to the inferred cost to the  
16 populace or the affected populace?

17 MR. ROMANOSKY: Oh, yeah, I'm sorry. Right,  
18 and so the reports -- right, the reports are  
19 scattered. Bureau of Justice Statistics has had some  
20 -- it's kind of sporadic over a few years. They've  
21 tried to collect those data, and, again, it's still  
22 very skewed. And the median might be close to zero,  
23 right? But for those people that did report losses,  
24 it was in the hundreds of dollars, right?

25 Now, it's -- right, this is always the

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1 problem with privacy, right? And between all of us  
2 here, it's one of the reasons why I avoid privacy  
3 research, it's just because it's so squishy and  
4 nebulous and difficult to figure out, right? So, you  
5 know, one measure of the harm, the privacy harm is  
6 looking at the dollars lost, but if it's true that the  
7 banks -- and a lot of these are due to financial fraud  
8 -- if the banks are always covering your costs, then  
9 really the harm is zero. But that's not really the  
10 extent of it because there are lots of emotional  
11 distress, and certainly, you know, very legitimate  
12 kinds of severe kinds of, like, forms of identity  
13 theft. And, so, I'm not to discount those, but  
14 relatively minor in terms of numbers.

15 And, so, how do you put all of that  
16 together? How do you mash it all together in some  
17 kind of metric that is sort of useful for us as  
18 researchers or for policymakers or for anyone to try  
19 and figure out. I don't have an answer for that.

20 MR. NAGLE: And along -- to go a little  
21 further, it also depends on what is stolen, right? So  
22 credit cards, absolutely, the bank makes you whole,  
23 not a big deal. Intellectual property, if you're a  
24 company, harder. Once it's out there, it's out there.  
25 So there are -- you know, you shut down a business

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1 line or have different responses.

2 And then somewhere in the middle is kind of  
3 the Equifax breach, right? So very easy to change a  
4 credit card number, very hard to change your birthday,  
5 right? That's pretty much there from when you're  
6 born. And, so, you can't change that once that's out  
7 in the open. And, so, what is the cost there? It's a  
8 little bit different depending on what data is stolen.

9 MR. TELANG: If you're willing to -- if  
10 you're willing to make an assumption that suppose  
11 after the breach, if you give me credit freeze and  
12 credit monitoring service, then I will not be harmed,  
13 then you can kind of look at that as saying, okay, you  
14 know, this is worth \$100, I have to service, you know  
15 \$100 million or 100 million consumers, maybe you can  
16 kind of get ballpark numbers, but as I said, how do I  
17 value the identity theft that happens two years after  
18 the breach happened?

19 MR. WAGMAN: So maybe you can do some  
20 different studies on increases in identity theft after  
21 breaches, and I would assume that a lot of people  
22 don't take advantage of credit monitoring or credit  
23 freezes when they're offered, especially when the  
24 source that offers them doesn't seem very reliable.

25 MR. NAGLE: And the source -- to get the

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1 free credit monitoring, you have to sign away your  
2 right to sue the source.

3 MR. WAGMAN: Right, exactly.

4 MR. NAGLE: Which skews my incentives.

5 MR. WILSON: Thanks.

6 MR. SMITH: I'll just make a quick note that  
7 on December 12th we're having a workshop on  
8 informational injuries, which part of the goal is to  
9 try to get some new thoughts on how to sort of think  
10 about measuring these kind of harms and even just  
11 conceptualizing them. So if anyone's interested, that  
12 will be happening, I guess, next month.

13 MS. JIN: Yeah, I really enjoyed the panel.  
14 So here is a question. I know variation in state  
15 regulation is great for research, but a lot of company  
16 names we heard today like Target, Home Depot, or  
17 Google or Facebook, they all operate in many, many  
18 states. So how relevant is local regulation in this?

19 MR. WAGMAN: In the case of financial  
20 markets, there's a national benchmark based on the  
21 Gramm-Leach-Bliley Act, and then local areas can put  
22 stricter regulations in place.

23 MR. NAGLE: And there's also -- and I think  
24 it's California, a lot of their regulations are  
25 written so that if you do business in California,

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1 which all these companies, you know, Facebook, Google,  
2 everybody does something, even if they're not located  
3 there, then for all of the customers, they have to  
4 kind of hit the bar, right? So for -- if California  
5 is moving the bar up, then everybody else benefits, at  
6 least in the U.S.

7 MR. TELANG: This is what I don't like about  
8 policymakers. They create policy but just make it so  
9 hard to do any identification. You're exactly right.  
10 I mean, you know, if they affect how independent your  
11 observations are, it's --

12 MR. ROMANOSKY: You might get struck by  
13 lightning as you leave the building. But there's lots  
14 of -- there are lots of different kinds of privacy  
15 laws, right? Local, DMV-related privacy laws, you  
16 know, nursing privacy laws, surveillance privacy laws,  
17 blood type privacy laws, which are all very localized  
18 to the state level. There's lots of variation there,  
19 and a couple of people have done -- written some  
20 compendiums of these state laws and put them together  
21 and tracked them over the years. And it's great  
22 stuff.

23 The trouble is finding the outcomes that are  
24 used mentioning -- that are useful to measure and to  
25 try to associate the two and come up with kind of a

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1 useful paper on that to try and answer a good  
2 question, but there are certainly lots of different  
3 kinds. And, yeah, the point about the breach laws is  
4 well taken, right? If you do business in that state,  
5 then, I mean, you know it well. But there's lots to  
6 go on, the trick is -- that I found is trying to find  
7 a useful outcome measure to study.

8 MR. WAGMAN: I think for those large firms,  
9 it's easier to cope with a patchwork of laws, but it  
10 might stifle innovation in the sense that a small  
11 company, you know, it would be really hard.

12 MR. SMITH: Okay, I think -- I want to thank  
13 everyone for their patience and thank the panelists  
14 for a really, really interesting conversation. And  
15 that's it for this panel. Thanks so much, guys.

16 (Applause.)

17 MR. ROSENBAUM: I just want to give a final  
18 thank-you to all of you for coming and to everyone who  
19 presented and helped to facilitate the conference. I  
20 hope to see you next year. Have a good weekend.

21 (Conference adjourned at 1:21 p.m.)  
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