



Office of Commissioner
Rohit Chopra

UNITED STATES OF AMERICA
Federal Trade Commission
WASHINGTON, D.C. 20580

October 16, 2019

The Honorable Ben Carson
Secretary
U.S. Department of Housing and Urban Development
451 7th Street SW
Washington, DC 20410-0001

RE: Proposed Rule to Amend HUD's Interpretation of the Fair Housing Act's Discriminatory Effects Standard

Dear Secretary Carson:

I write to share a comment I submitted today that outlines concerns with HUD's proposed rule amending the Fair Housing Act's discriminatory effects standard. This proposal appears to fundamentally misunderstand how algorithms, big data, and machine learning work in practice. It would provide safe harbors to the same technologies at issue in HUD's own action against Facebook, a complaint which details the many ways that platforms can discriminate by design.

My comment outlines three arguments against HUD's proposed changes. First, algorithms are not neutral, and even valid inputs can produce discriminatory results. Second, it is inappropriate to create safe harbors around technologies that are proprietary, opaque, and rapidly evolving. Finally, outsourcing liability for algorithmic discrimination to third parties distorts incentives and could lead to a race to the bottom among vendors.

If you have any further questions, please do not hesitate to contact me. Thank you for considering this comment, and I look forward to monitoring this proceeding carefully.

Respectfully submitted,

A handwritten signature in blue ink that reads "Rohit Chopra".

Rohit Chopra

**Before the
DEPARTMENT OF HOUSING AND URBAN DEVELOPMENT
Washington, D.C. 20410**

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| Proposed Rule to Amend HUD's |) | |
| Interpretation of the Fair Housing Act's |) | Docket No. FR-6111-P-02 |
| Discriminatory Effects Standard |) | |
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**COMMENT OF
FTC COMMISSIONER ROHIT CHOPRA***

I write to outline concerns with the Department of Housing and Urban Development's (HUD) proposed rule amending the Fair Housing Act's discriminatory effects standard, sometimes referred to as the disparate impact rule.

By way of background, I serve as a Commissioner of the Federal Trade Commission (FTC), which has significant interest in the application of discriminatory effects standards, as well as policies related to algorithmic bias. First, the FTC is the primary federal enforcement agency on competition, privacy, and data security issues, which are cross-cutting concerns when considering the widespread adoption and use of predictive analytics powered by algorithms. Second, the FTC has the authority to enforce the Equal Credit Opportunity Act (ECOA) and Regulation B, and the agency has been a member of an Interagency Task Force on Fair Lending. The FTC has also published relevant research reports, such as those related to data brokers and facial recognition. More recently, the FTC convened a public hearing focused on how bias and discrimination could impact the use of algorithms, artificial intelligence, and predictive analytics in business decisions and conduct. Third, we have taken enforcement actions against companies for deploying algorithms in ways that resulted in legal violations. In one such case, the FTC charged RealPage, Inc., for violating the Fair Credit Reporting Act (FCRA) by using an algorithm that resulted in major accuracy issues with the tenant screening information provided to its clients.¹

* This comment represents my own views and does not necessarily reflect those of the Federal Trade Commission or any other Commissioner.

¹ Press Release, Fed. Trade Comm'n, Texas Company Will Pay \$3 million to Settle FTC Charges That it Failed to Meet Accuracy Requirements for its Tenant Screening Reports (Oct. 16, 2018), <https://www.ftc.gov/news-events/press-releases/2018/10/texas-company-will-pay-3-million-settle-ftc-charges-it-failed>.

I previously served as an assistant director at the Consumer Financial Protection Bureau, which also enforced ECOA and Regulation B. Prior to my government service, I gained experience by analyzing discriminatory effects of online peer-to-peer lending.

Discrimination is a silent pickpocket. It illegally and unfairly robs people of economic gains based solely on certain aspects of their private identity, often without their knowledge. Whether it is a hidden tax imposed by inflated rates and rents or an invisible wealth drain caused by lost economic opportunities, discrimination carries an enormous economic cost and requires vigorous policing.

Discrimination can be tough to detect and challenging to prove because it often occurs when practices, policies, or systems that seem neutral produce discriminatory results. The appearance of neutrality does not mean that the impact was unintended, nor does it absolve the disparate outcome. This is why courts have recognized that it is appropriate for law enforcement to focus on such effects.

This effects-based standard, also known as the disparate impact standard, has long been used to fight housing discrimination under the Fair Housing Act. The Act prohibits discrimination based on race, color, national origin, religion, sex, familial status, or disability when renting or buying a home, getting a mortgage, seeking housing assistance, or engaging in other housing-related activities.²

The disparate impact standard for fair housing was codified in 2013 when HUD finalized a rule conferring liability for practices that actually or predictably result in a disparate impact, even if the discrimination is unintended.³ Anti-discrimination laws in other areas, including those in employment and credit, have also relied on effects-based standards. To legally justify a practice with discriminatory effects, HUD's rule laid out a burden-shifting framework that requires defendants to provide substantial evidence that the practice is serving a legitimate business purpose. In addition, the framework imposes liability when a less discriminatory alternative is available.

HUD's latest proposed rule would gut these protections in ways that should be well understood by the agency. In the Fair Housing Act complaint that it filed against Facebook this past March, HUD convincingly identified the ways in which algorithms like the ones at issue in the proposed rule facilitate discrimination against protected groups.⁴ The safe harbors that it is proposing would make it too difficult for victims to bring claims and would give defendants multiple ways to justify using algorithms with a discriminatory effect to achieve "legitimate objectives."⁵

² *Housing Discrimination under the Fair Housing Act*, DEP'T. OF HOUSING AND URB. DEV., https://www.hud.gov/program_offices/fair_housing_equal_op/fair_housing_act_overview (last visited Oct. 11, 2019).

³ Implementation of the Fair Housing Act's Discriminatory Effects Standard, 78 Fed. Reg. 11460, 11482 (Feb. 15, 2013) (codified at 24 C.F.R. pt. 100), <https://www.hud.gov/sites/documents/DISCRIMINATORYEFFECTRULE.PDF>.

⁴ Charge of Discrimination, FHEO No. 01-18-0323-8.

⁵ HUD's Implementation of the Fair Housing Act's Disparate Impact Standard, 84 Fed. Reg. 42854, 42858 (proposed Aug. 19, 2019) (to be codified at 24 C.F.R. pt. 100), <https://www.govinfo.gov/content/pkg/FR-2019-08-19/pdf/2019-17542.pdf>.

First, alleged perpetrators could identify all the inputs used by the algorithm and show (a) how the inputs are not substitutes for any protected class and (b) how the model is predictive of risk or another “valid objective.” Second, they could show that a third party created or maintains the algorithmic model. Or third, they could show that a neutral third party has analyzed the model and found it to be empirically derived, with no proxy inputs, and predictive of risk or other valid objectives. Among the objectives HUD appears to consider valid is enabling “profit-related decisions.”⁶ If enacted, this proposal would give immunity to companies and individuals when they discriminate against tenants using algorithmic tools.

My comment outlines three arguments against HUD’s proposed changes to the interpretation of the discriminatory effects standard. First, algorithms are not neutral, and even valid inputs can produce discriminatory results. Second, it is inappropriate to create safe harbors around technologies that are proprietary, opaque, and rapidly evolving. Finally, outsourcing liability for algorithmic discrimination to third parties distorts incentives and could lead to a race to the bottom among vendors.

Neutral Inputs Are Not Neutral Outputs

HUD’s proposed rule appears to fundamentally misunderstand how algorithms, big data, and machine learning work in practice. The proposed safe harbors rest on the false assumption that it is possible for an algorithm to operate free from bias and that neutral inputs produce neutral outputs. Overwhelming empirical evidence and HUD’s own experience prove this is a fallacy.

The legal violations that HUD alleges in the complaint against Facebook provide an important window into the bias that is baked into algorithms. The complaint alleges that the design of Facebook’s online behavioral advertising platform leads to biased results that discriminate against people from protected classes. As the complaint notes, Facebook “collects millions of data points about its users, draws inferences about each user based on this data, and then charges advertisers for the ability to microtarget ads” based on those inferences.⁷ This is a system built to selectively target and exclude people based on predictions about their behavior, surmised by closely tracking the details of their daily life and those they interact with.

Algorithms make predictions based on the universe of available data points. These predictions are then used to make decisions like whom to advertise to, whom to provide credit to, whom to select as tenants, and what to charge. Companies cannot use protected class statuses such as race, gender, or religion as factors to predict risk or make business decisions. But keeping data about protected characteristics out of an algorithm is not enough to prevent it from producing discriminatory predictions. That’s because other attributes can serve as a substitute or proxy for protected class when used as algorithmic inputs.

⁶ 84 Fed. Reg. 42854, 42855.

⁷ Charge of Discrimination ¶ 7.

These inputs do not have to be intuitive stand-ins to result in discrimination.⁸ Seemingly “neutral” inputs, especially when analyzed in combination with other data points, can also be a substitute. Members of a protected class will likely have a wide range of other characteristics in common that can be detected with the increased collection of more and different types of information. Amassing a long list of personal details about each member of a large population makes it easier to calculate correlations, patterns, and dependencies among groups of people.⁹ With more data points and more volume, any input or combination of inputs can turn into a substitute or proxy for a protected class.

HUD’s Facebook complaint clearly outlines how “neutral” inputs can produce pernicious discrimination. According to HUD, Facebook uses “machine learning and other prediction techniques to classify and group users”¹⁰ based on “the data it has about that user, the data it has about other users whom it considers to resemble that user, and the data it has about ‘friends’ and other associates of that user.”¹¹ Facebook’s data about users includes “which pages a user visits, which apps a user has, where a user goes during the day, and the purchases a user makes on and offline.”¹²

In using this data to classify users, HUD notes that Facebook “inevitably recreates groupings defined by their protected class. For example, the top Facebook pages users ‘like’ vary sharply by their protected class.”¹³ These discriminatory classifications not only decide who will see ads. They also set the prices advertisers will pay to show the same ad to different users. Therefore, as HUD points out, “by grouping users who ‘like’ similar pages (unrelated to housing) and presuming a shared interest or disinterest in housing-related advertisements, [Facebook’s] mechanisms function just like an advertiser who intentionally targets or excludes users based on their protected class.”¹⁴ That is, “neutral” inputs such as “likes” on Facebook can serve as a proxy for a protected class, giving landlords a green light to discriminate.

The discrimination HUD alleges on Facebook’s platform is only likely to worsen. The rise of mass surveillance is turning each individual’s every movement, communication, connection, and creation into a data point inputted into algorithms. As HUD’s complaint points out, Facebook alone is collecting millions of data points about each user, most of them passively or unknowingly provided. The HUD complaint describes how “users may disclose some data about themselves when they set up their profiles, such as name and gender” but disclose most data

⁸ In a recent article on the risks posed by modern algorithms, Prince and Schwarcz call this phenomenon “proxy discrimination.” They explain how artificial intelligence (AI) is “inherently structured to engage in proxy discrimination whenever they are deprived of predictive data. Simply denying AIs access to the most intuitive proxies for predictive variables does nothing to alter this process; instead it simply causes AIs to locate less intuitive proxies.” See Anya Prince & Daniel Schwarcz, Preliminary Draft, *Proxy Discrimination in the Age of Artificial Intelligence and Big Data*, IOWA L. J. (forthcoming 2020), <https://www.globaltort.com/2019/03/burgeoning-ai-issues-schwarcz-daniel-b-and-prince-anya-proxy-discrimination-in-the-age-of-artificial-intelligence-and-big-data-march-6-2019/>.

⁹ Charge of Discrimination ¶¶ 16 – 20.

¹⁰ *Id.* ¶ 20.

¹¹ *Id.* ¶ 17.

¹² *Id.* ¶ 16.

¹³ *Id.* ¶ 20.

¹⁴ *Id.*

“unwittingly through the actions they, and those associated with them, take on and off of [Facebook’s] platforms.”¹⁵

The sheer volume of data harvested about each individual exponentially expands the number of potential new substitutes and proxies for protected classes in both obvious and opaque ways. For example, geo-location tracking can identify an individual’s residence – a well-established proxy – but also other potential location proxies such as school, employer, doctor, house of worship, daycare, and the like. HUD should understand this as it was key to its lawsuit against Facebook. The HUD complaint quotes Facebook’s promotional pitch, which explains how the company “use[s] location-related information-such as your current location, where you live, the places you like to go, and the businesses and people you’re near to provide, personalize and improve [their] Products, including ads, for you and others.”¹⁶

Unless or until the government steps in to curtail online surveillance, the number of data inputs will continue to rapidly expand as technology opens up new ways to track and record people’s private lives. It is operationally impractical to expect the courts to expend time and resources on the process of individually identifying and analyzing what is likely to be a massive and growing universe of inputs, particularly given the increasing likelihood that big data can turn almost any input into a proxy. As algorithms become more sophisticated and machine learning becomes smarter, the complexity of the calculations used to produce predictions will make it nearly impossible for even the developers to isolate the impact of any given input on discriminatory outcomes.

Safe Harbors Should Be Public Not Proprietary

A safe harbor is supposed to function as a proven pathway for following the law. Safe harbors can be a reasonable tool when they provide industry with specific, public guidelines for compliance. Key to the success of these interventions is that the rules of the road are clear and readily verifiable: a company that fails to comply can be easily exposed by consumers, counterparties, and regulators.

But safe harbors do not work if regulators have no visibility into the practice at issue. Algorithms are not only nonpublic, they are actually treated as proprietary trade secrets by many companies. Victims of discriminatory algorithms seldom if ever know they have been victimized. Even if they do and bring a lawsuit, creators of the algorithm are likely to fiercely resist public disclosure of their systems, reducing the lawsuit’s salutary effect on public awareness and corporate compliance.

To make matters worse, machine learning means that algorithms can evolve in real time with no paper trail on the data, inputs, or equations used to develop a prediction. Given the rapid pace of evolution, it is plausible that even the creators of the algorithms may be unaware of how inputs interact with each other or which inputs are determinative in shaping the outcomes. This will make it all but impossible for regulators and the public to have visibility into broader patterns or problems in housing discrimination.

¹⁵ *Id.* ¶ 12.

¹⁶ *Id.* ¶ 7.

It is useful to contrast this proposal with other safe harbors that HUD has implemented. In the 1990s, HUD issued detailed guidelines for accessibility requirements in multifamily housing. It created a safe harbor for builders that followed the guidelines, which included “detailed illustrations and sample room designs.”¹⁷ This framework allowed HUD and the public to readily assess whether the law was being followed: building codes, unlike algorithmic codes, are not trade secrets.

The opacity and complexity of algorithmic decision-making heavily weigh against the proposed rule to allow companies to outsource their liability for discriminatory outcomes to third-party algorithms. It also strongly counsels against creating a safe harbor for point-in-time certification by a third-party expert, given the rapid pace at which the model can change to make such certification immaterial. We should be scrutinizing machine learning with caution and concern instead of allowing it to become a blanket shield for housing discrimination.

Outsourcing Liability for Discrimination Creates a Race to the Bottom

Shielding firms that purchase algorithms from third-party vendors creates a major loophole in civil rights protections by encouraging both lenders and vendors to ignore discriminatory outcomes. If landlords are shielded from liability, they have little incentive to vet vendors carefully. The result of this dynamic is predictable: vendors will not compete on algorithmic fairness, leading to a race to the bottom.

Although the rule requires that vendors be “recognized,” this is not a defined term,¹⁸ and there does not exist any widely recognized “industry standards”¹⁹ by which to evaluate algorithmic fairness. The result is that most lenders will turn to other competitive features, especially price, in choosing vendors, which only encourages vendors to forgo investing the resources in preventing discriminatory outcomes. When noncompliance carries no consequences, companies will not have the incentive to comply.

Where there are discriminatory effects, companies and individuals would escape liability by pinning the blame on vendor algorithms, while vendors will claim that they were not the ones that made the final decision.

The proposed rule moves enforcement against discrimination backwards and should not be finalized.

¹⁷ *Accessibility Requirements for Buildings*, DEP’T OF HOUSING AND URB. DEV., https://www.hud.gov/program_offices/fair_housing_equal_opp/disabilities/accessibilityR (last visited Oct. 11, 2019).

¹⁸ Bogus certifications is a problem across markets that the FTC has sought to tackle. *See, e.g.*, Press Release, Fed. Trade Comm’n, FTC Sends Warning Letters about Green Certification Seals (Sept. 14, 2015), <https://www.ftc.gov/news-events/press-releases/2015/09/ftc-sends-warning-letters-about-green-certification-seals>.

¹⁹ 84 Fed. Reg. 42854, 42862.