October 18, 2019

Submitted via regulations.gov

Office of General Counsel
Rules Docket Clerk
Department of Housing and Urban Development
451 7th Street SW, Room 10276
Washington, DC 20410-0001

Re: HUD's Implementation of the Fair Housing Act's Disparate Impact Standard, FR-6111-P-02, RIN 2529-AA98, Document Number 2019-17542

Dear Secretary Carson:

The Center for Responsible Lending, Self-Help Credit Union, and Self-Help Federal Credit Union[1] submit this comment to express strong opposition to the U.S. Department of Housing and Urban Development's proposed disparate impact rule and urge HUD to uphold the existing rule. While the proposed rule states that it is an effort to make HUD's 2013 rule consistent with the U.S. Supreme Court's decision in *Texas Department of Housing and Community Affairs v. Inclusive Communities Project* (2015), the Supreme Court decision did nothing to undermine the existing rule. Moreover, HUD has vastly exceeded its authority in issuing the proposed rule. The proposed rule decimates the existing burden-shifting framework – a framework supported by over 40 years of case law – and places all the burdens on the victims of housing discrimination. The proposed rule makes it virtually impossible for a potential complainant to make it past the pleading stage when bringing a claim under disparate impact theory. At the same time, in contradiction of the Fair Housing Act's broad remedial purpose, the proposed rule provides new safe harbors for industry. The proposed rule is opposite to HUD's mission, decades of legal precedent, and the Supreme Court's decision in *Inclusive Communities.*

The proposed rule will have a toxic effect on the mortgage lending industry. The Fair Housing Act's disparate impact doctrine has played a critical role in making fair housing available to all, while at the same time making the lending industry better at evaluating creditworthiness. A ban on unjustified disparate impact has encouraged the lending industry to systematically scrutinize its procedures and requirements to ensure that lenders more precisely measure creditworthiness and lending practices do not have unnecessary discriminatory impact. Thus, financial products are more widely available to people and communities historically denied them. At the same time, the lending industry has been able to identify a larger number of credit-worthy borrowers, continue to evaluate risk in a less discriminatory manner, and increase its profits. Backtracking on disparate impact theory will hurt borrowers' access to safe and affordable mortgage credit as well as hurt lenders' bottom line. Moreover, it will perpetuate

[1] The Center for Responsible Lending (CRL) is a nonprofit, non-partisan research and policy organization dedicated to protecting homeownership and family wealth by working to eliminate abusive financial practices. CRL is an affiliate of Self-Help Credit Union (SHCU) and Self-Help Federal Credit Union (SHFCU). SHCU is a North Carolina-chartered, federally-insured credit union with 77,000 members served out of 29 branches in North Carolina, South Carolina and Florida with $1 billion in assets. SHFCU is a federally-chartered and insured credit union with more than 76,000 members served out of 27 branches in California, Illinois, and Wisconsin with $1.1 billion in assets.

racial homeownership rate gaps and wealth gaps, especially today's low Black homeownership rate that stands at 40.6 percent, which is lower than when the Fair Housing Act became law in 1968.[2]

HUD's proposal ignores the reality that Congress passed the Fair Housing Act just seven days after the assassination of Dr. Martin Luther King, Jr.[3] At the bill's signing, President Johnson and Congress solemnly reflected on Dr. King's life work of attempting to defeat Jim Crow laws to ensure that African-Americans could live unencumbered by the nation's legacy of slavery as full citizens free of the burdens of discrimination. The fact that HUD's disparate impact proposal is made in the 400th year after the first enslaved Africans arrived in what would become modern day America[4] does not go unnoticed. Some of our nation's first mortgage loans and securities were created based on the speculation of the bodies of enslaved Africans[5] and the cotton that they were forced to pick against their will for which they earned no profit. African-Americans and other people of color continue to be stymied by our nation's past. In fact, the entire nation wrestles with this brutal legacy, and each year 4 million cases of ongoing housing discrimination occur, with most unreported.[6] Instead of creating barriers for claimants, HUD should honor its mission and work to ensure that African-American, Latino, and other communities harmed by housing and lending discrimination have every tool to stop it so that all Americans have an opportunity to thrive.

The proposed rule also introduces a new defense for those who design and use algorithmic models. Algorithms are "black boxes," which makes it extremely difficult to detect and address bias in the algorithmic system. HUD's proposed rule carves out special treatment for these models, gifting a safe harbor to the entire lending and insurance industry. As discussed in section IV.A below, there is no authority for HUD to create a safe harbor under the Fair Housing Act. Additionally, this safe harbor falsely assumes that algorithms are objective and bias-free.

I. The Proposed Rule Will Perpetuate Racial Homeownership Gaps and the Racial Wealth Gap.

The proposed rule will further cement the inequities in our nation, while flouting the Fair Housing Act's mandate to provide for fair housing throughout the United States.[7] Discrimination in our nation's lending and housing markets has a long and sordid history, driven by the federal government, state and

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[2] U.S. Census Bureau, *Quarterly Residential Vacancies and Homeownership, Second Quarter 2019* (July 25, 2019), available at https://www.census.gov/housing/hvs/files/currenthvspress.pdf.
[3] NHFA Staff, The National Fair Housing Alliance Honors Dr. Martin Luther King Jr. As a Champion of Fair Housing, National Fair Housing Alliance, April 4, 2018, available at https://nationalfairhousing.org/2018/04/04/the-national-fair-housing-alliance-honors-dr-martin-luther-king-jr-as-a-champion-of-fair-housing/#targetText=The%20Fair%20Housing%20Act%20was,than%20they%20were%20in%201918.
[4] The 1619 Project, NY Times Magazine, August 14, 2019, available at https://www.nytimes.com/interactive/2019/08/14/magazine/1619-america-slavery.html.
[5] Matthew Desmond, In Order to Understand the Brutality of American Capitalism, You Have to Start On the Plantation, NY Times, August 14, 2019, available at https://www.nytimes.com/interactive/2019/08/14/magazine/slavery-capitalism.html.
[6] National Fair Housing Alliance, *Making Every Neighborhood A Place of Opportunity* (2018), available at https://nationalfairhousing.org/wp-content/uploads/2018/04/NFHA-2018-Fair-Housing-Trends-Report.pdf.
[7] 42 U.S.C. § 3601.

local governments, private industry, and individual actors.[8] While discrimination and its ill effects continue to the present day, much of it has become covert and harder to pinpoint. Disparate impact theory is intended to root out discriminatory policies and practices that are difficult (and sometimes impossible) to prove via a finding of intentional discrimination. As the Supreme Court stated in *Inclusive Communities*, the theory "permits plaintiffs to counteract unconscious prejudices and disguised animus that escape easy classification as disparate treatment."[9] Disparate impact theory also allows companies to identify and prevent facially neutral, but unjustified, policies that disproportionately harm particular communities.

Federal housing policies created in the twentieth century in response to the Great Depression explicitly discriminated against African-American, Latino, and other families of color by denying them access to federally-insured mortgage programs because of their race. These policies are a significant factor in why white families today have higher rates of homeownership and greater family wealth than families of color. These federal programs helped white families, mostly former immigrant families with European backgrounds, affordably enter homeownership and build a solid foundation to help establish the American middle class. Policies underlying these programs, such as redlining and the Federal Housing Administration's denial of insurance for borrowers buying in predominantly African-American neighborhoods, granted whites the ability to build wealth through homeownership while denying equal opportunities for families of color to build similar home equity over the same period.

As a result, whites have amassed an economic advantage over families of color that has been passed on to future generations through intergenerational wealth transfers. In 2016, the median white family had more than ten times the wealth of the median Black family.[10] In fact, the racial wealth gap between Black and white families grew from about $100,000 in 1992 to $154,000 in 2016.[11] The median white family gained significantly more wealth, with the median increasing by $54,000, while median wealth for Black families did not grow in real terms over the same time period.[12] The racial wealth gap contributes to the fact that in the 46 largest housing markets in the country, a median income Black household can only afford 25 percent of homes on the market last year in comparison to the 57 percent that a median-income white household could afford.[13] Today, disparities in homeownership are a key contributor to the ongoing racial wealth gap and home equity still plays a central role in shaping family wealth for the middle class.

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[8] Richard Rothstein, *The Color of Law: A Forgotten History of How Our Government Segregated America.* New York: Liveright Publishing Corporation (2017).

[9] *Texas Dept. of Housing and Community Affairs v. Inclusive Communities Project Inc.*, 135 S. Ct. 2507, 2522 (2015).

[10] Nick Noel, Duwain Pinder, Shelley Stewart III, and Jason Wright, *The Economic Impact of Closing the Racial Wealth Gap*, McKinsey & Company (Aug. 2019), Exhibit 1 at p. 5, available at https://www.mckinsey.com/~/media/McKinsey/Industries/Public%20Sector/Our%20Insights/The%20economic%20impact%20of%20closing%20the%20racial%20wealth%20gap/The-economic-impact-of-closing-the-racial-wealth-gap-final.ashx.

[11] *Id.*

[12] *Id.*

[13] Paul Davidson, Black Households Can Afford Just 25% of Homes For Sale, October 15, 2019, USA Today, available at https://www.usatoday.com/story/money/2019/10/15/homes-sale-black-households-can-afford-just-25-percent-houses-market/3976383002/.

Furthermore, in lower-income communities and communities of color across the nation, homeownership has not recovered from the far-reaching damage of the Great Recession. In fact, the Great Recession wiped out 30 years of homeownership gains for African-Americans and Latinos. It exacerbated the already large racial homeownership gap, with Black homeownership rates falling to levels that predate the passage of the Fair Housing Act more than 50 years ago.[14] The current homeownership rate for Black families is only 40.6 percent, as compared to 73.1 percent for white families.[15] According to a report by Demos, if homeownership rates were the same for whites and people of color, we would see a decrease in the racial wealth gap by 31 percent for African-Americans and 28 percent for Latinos.[16]

Many business models and governmental policies unnecessarily tighten access to mortgage credit and make it more difficult for communities of color to achieve homeownership.[17] The conventional market does not well-serve borrowers of color. This is reflected in the low levels of conventional loans and high denial rates of mortgage applications for borrowers of color.[18] Excessive risk-based pricing by the GSEs and FHFA prevents many borrowers from accessing the conventional market, as the cost of credit is prohibitive. Overly restrictive credit practices persist despite the fact that credit risk is low and financial institutions are making record profits.[19]

In addition to the harms to individuals and communities, unjustified policies cause harm to the national economy. For example, research by the UC Berkeley's Haas School of Business found that both financial technology companies and brick-and-mortar lenders habitually charged borrowers of color higher interest rates than white borrowers with similar credit profiles – costing African-American and Latino customers an additional *$765 million* annually.[20] Rather than paying unjustified and discriminatory

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[14] Troy McMullen and Jason Henry, The 'Heartbreaking' Decrease in Black Homeownership, Washington Post, February 28, 2019, available at https://www.washingtonpost.com/news/business/wp/2019/02/28/feature/the-heartbreaking-decrease-in-black-homeownership/.

[15] Dana Olsen, Race Gaps in Homeownership Rates and Home Equity Have Widened During the Decade-Long Economic Expansion, Redfin, July 31, 2019, available at https://www.redfin.com/blog/black-americans-homeownership-rate/.

[16] Tanvi Misra, Why America's Racial Wealth Gap is Really a Homeownership Gap, Demos, March 12, 2015, available at http://www.demos.org/news/why-americas-racial-wealth-gap-really-homeownership-gap.

[17] Laurie Goodman, Jun Zhu, and Taz George, Tight Credit Has Hurt Minority Borrowers the Most, Urban Wire (blog), Urban Institute, April 7, 2019, available at https://www.urban.org/urban-wire/tight-credit-has-hurt-minorityborrowers-most.

[18] Center for Responsible Lending, New HMDA Data Show Despite Growing Market, African-Americans and Latinos Remain Underserved (Sept. 2017), available at https://www.responsiblelending.org/research-publication/new-hmda-data-show-despite-growing-market-african-americans-and-latinos-remain; Emmanuel Martinez and Aaron Glantz, How Reveal Identified Lending Disparities in Federal Mortgage Data, Center for Investigative Reporting, February 2018, available at https://s3-us-west-2.amazonaws.com/revealnews.org/uploads/lending_disparities_whitepaper_180214.pdf.

[19] Laurie Goodman, Jun Zhu, and Bing Bai, Overly Tight Credit Killed 1.1 Million Mortgage in 2015, Urban Wire (blog), Urban Institute, November 20, 2016, available at https://www.urban.org/urban-wire/overly-tight-credit-killed-11-million-mortgages-2015; Housing Credit Availability Index, Q1 2019, Urban Institute, Housing Finance Policy Center, available at https://www.urban.org/policy-centers/housing-finance-policy-center/projects/housing-credit-availability-index.

[20] Robert Bartlett, Adair Morse, Richard Stanton, and Nancy Wallace, *Consumer-Lending Discrimination in the FinTech Era*, Haas School of Business UC Berkeley (May 2019) at p.1, available at http://faculty.haas.berkeley.edu/morse/research/papers/discrim.pdf.

interest rates, consumers could use the funds to enrich their own lives, including purchasing consumer goods and other economic needs. McKinsey & Company estimates that addressing historic and ongoing discrimination for Black Americans could add up to $1.5 trillion to the economy of the United States and increase the GDP between 4 and 6 percent.[21] Additionally, studies show that lending discrimination causes intergenerational poverty, which threatens economic stability. "Like segregation, poverty becomes a generational condition. As a result, economic stability becomes hard to maintain."[22]

The federal government must address its role in fostering racial discrimination in the mortgage market and the resulting racial wealth gap. A straightforward and legally required method is to vigorously enforce existing fair lending laws and work to eradicate inequitable and unjustified policies. As the Court in *Inclusive Communities* stated: "The FHA must play an important part in avoiding the Kerner Commission's grim prophecy that '[o]ur Nation is moving toward two societies, one black, one white – separate and unequal.' The Court acknowledges the Fair Housing Act's continuing role in moving the Nation toward a more integrated society."[23] HUD's proposed rule is a complete abdication of that responsibility. By gutting the disparate impact standard under the Fair Housing Act, HUD's proposed rule ignores our nation's history and thwarts us from reaching a more integrated and equitable future.

II. HUD's Proposed Rule is Inconsistent with the Supreme Court's Decision in *Inclusive Communities*.

As a threshold matter, the disparate impact standard does not need to be revised. The Supreme Court's holding in *Inclusive Communities* is entirely consistent with HUD's 2013 disparate impact rule and rewriting the rule is wholly unnecessary. Rather, HUD's proposed rule would make it virtually impossible to bring a fair housing case under this theory. HUD's 2013 rule simply reaffirmed HUD's longstanding interpretation that the Fair Housing Act authorizes disparate impact claims. The rule did not change decades-old substantive law but rather "formalizes a clear, consistent, nationwide standard for litigating discriminatory effects cases under the Fair Housing Act."[24] In short, the rule did not go beyond the contours of existing disparate impact law. As HUD itself stated in a 2017 motion in *Property Casualty Insurers Association of America v. Carson*, "the Supreme Court's holding in *Inclusive Communities* is entirely consistent with the Rule's reaffirmation of HUD's longstanding interpretation that the FHA authorizes disparate impact claims."[25] HUD further stated: "[N]othing in *Inclusive Communities* casts any doubt on the validity of the Rule."[26] Additionally, HUD's disparate impact rule was implicitly adopted in

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[21] Nick Noel, Duwain Pinder, Shelley Stewart III, and Jason Wright, *The Economic Impact of Closing the Racial Wealth Gap,* McKinsey & Company (August 2019) available at https://www.mckinsey.com/industries/public-sector/our-insights/the-economic-impact-of-closing-the-racial-wealth-gap.

[22] Aleatra P. Williams, Lending Discrimination, the Foreclosure Crisis and the Perpetuation of Racial and Ethnic Disparities in Homeownership in the U.S., 6 Wm. & Mary Bus. L. Rev. 601 (2015), at 639, available at http://scholarship.law.wm.edu/cgi/viewcontent.cgi?article=1095&context=wmblr.

[23] 135 S.Ct. 2525-26. Kerner Commission Report (1968), available at http://www.eisenhowerfoundation.org/docs/kerner.pdf.

[24] Implementation of the Fair Housing Act's Discriminatory Effects Standard, 78 Fed. Reg. 11,460 (Feb. 15, 2013).

[25] HUD's Opposition to Plaintiff's Motion for Leave to Amend Complaint, No. 1:13-cv-08564 (N.D. Ill. 2017).

[26] *Id*.

the *Inclusive Communities* decision; the Supreme Court cited HUD's rule multiple times to support its analysis.[27]

Moreover, the *Inclusive Communities* decision did not change existing disparate impact law. In fact, the Supreme Court granted certiorari *solely* to address whether disparate impact claims are cognizable under the Fair Housing Act.[28] The Court explicitly declined to grant certiorari on the question of what standards and burdens of proof should apply, even though petitioner sought review of those questions.[29] Thus, while HUD's proposed rule destroys the longstanding burden shifting framework used to analyze disparate impact cases, the *Inclusive Communities* decision did not require any change to the burden-shifting test. The case simply reaffirmed that disparate impact claims are cognizable under the Fair Housing Act. The Court further acknowledged that disparate impact theory already properly limits liability: "[D]isparate-impact liability has always been properly limited in key respects."[30] For example, a statistical disparity has never been enough to establish disparate impact liability. Likewise, HUD's existing rule does not provide for the finding of disparate impact liability based solely on statistical evidence.

HUD's efforts to rewrite the rule would make it harder to bring these cases and could consequentially open up avenues to eradicate disparate impact theory in education, employment, and other sectors.

III. Disparate Impact Theory and HUD's Existing Disparate Impact Rule Have Driven the Lending Industry to Root Out Discriminatory Practices While Identifying More Accurate Means of Assessing Creditworthiness.

Under the existing disparate impact rule and before it under decades of case law, industry has had strong incentive to root out discriminatory practices while identifying more fair and accurate means of assessing creditworthiness, pricing mortgage products, and underwriting homeowners' insurance. The proposal jettisons that sound framework by imposing an unsustainable burden of proof on plaintiffs and shielding virtually any algorithmic model from challenge. The proposal also codifies a broad reading of the McCarren-Ferguson Act (which HUD lacks authority to interpret) to create additional hurdles for disparate impact claims related to homeowner's insurance. The result of these proposed changes would be to significantly limit the viability of disparate impact challenges and lessen the incentive for industry to develop better, often *more profitable*, means of avoiding discrimination.

Industry for decades has been adopting more reliable, accurate credit underwriting standards because the Fair Housing Act requires industry not turn a blind eye to the discriminatory impact of criteria. For example, following explosive reports based on HMDA data that showed discriminatory underwriting and disparities that could not be explained by economic factors,[31] the GSEs introduced automated underwriting systems that permitted any lender to evaluate prospective loans using objective criteria

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[27] 135 S.Ct. at 2514-15, 2522.
[28] *Id*. at 2515.
[29] *Id*. at 2525.
[30] *Id*. at 2512.
[31] See Margery Austin Turner & Felicity Skidmore, *Introduction, Summary, and Recommendations in Mortgage Lending Discrimination: A View Of Existing Evidence,* Urban Institute, at 1, 10 (1999) (describing "explosive effect" of Boston Fed study on industry and the "extensive soul searching" that followed), available at http://webarchive.urban.org/publications/309090.html.

such as loan-to-value and debt-to-income ratios that were, at least in theory, based on sound statistical principles. Their use quickly proved to make lending decisions both more accurate and fair.[32] Since that time, industry has further developed lending standards that more accurately and reliably assess creditworthiness.

Contrary to the claims that disparate impact "litigation risks" might reduce the availability of credit, the result of these developments is that these credit markets, while far from completely fair, are now more open than ever before to those traditionally shut out of access to credit.

The proposal would stem this progress towards better identification of risk and less discrimination. Today, lending institutions often seek to identify the least discriminatory underwriting criteria that also are reliable indicators of risk. As more information is available on prospective borrowers, lenders assess the utility of new variables, and can then identify the handful of factors that, collectively, are sufficiently predictive of risk. The lender then tests that collection of variables for discriminatory impact. Because different factors often correlate, a lender can substitute a different criterion for one that through testing reveals a discriminatory impact and repeat the testing process. Through this process, lenders can isolate and eliminate those variables that cause unnecessary discriminatory impact, without compromising identification of credit risk.

The proposal short circuits this process, first by requiring that plaintiffs allege not only that a given policy results in disparate impact, but that it is "arbitrary, artificial, and unnecessary."[33] This requires a plaintiff to understand and allege the motives and reasoning of a defendant at the time of filing a complaint. Such a requirement goes far beyond avoiding risks that prevent industry "from achieving legitimate objectives"[34] to creating a virtually impossible pleading requirement that the plaintiff identify an illegitimate objective based on speculation. Moreover, this requirement ignores the well-established burden-shifting under disparate impact doctrine that allows for the defendant, who presumably is best positioned to do so, to allege a legitimate purpose for the policy.

This disparate impact process – developed as a direct result of the challenge the disparate impact doctrine posed to the lending industry – is now standard practice among major lenders and balances the very real problem of proving discrimination for private/individual borrowers with the compliance capacity of lenders. It has resulted in a fairer loan process for all borrowers and a more profitable one for banks. Some of those who historically have been denied loans at a disproportionate rate now have greater access. And not only have lenders fully retained their ability to identify and respond to risk, they have also expanded their customer base. This offers enormous potential to increase profit. In short, the industry is better off for the rationalization of its processes required by disparate impact doctrine.

A. Property Insurance

The evolution of property insurance driven by the availability of the disparate impact tool helps illustrate why the proposal's framework would hinder improvement of industry practices. Even after the Fair Housing Act banned overt refusal to insure homes in predominantly African-American communities, the

[32] See, e.g., Susan Wharton Gates, et al., Automated Underwriting in Mortgage Lending: *Good News For The Underserved?*, 13 Hous. Policy Debate 369, 383-85 (2002).
[33] 84 Fed. Reg. at 42862.
[34] 135 S.Ct. at 2523-24.

industry for many years adopted exclusionary policies—not backed by evidence—that produced the same discriminatory effect. For example, many insurers refused coverage based on highly subjective assessments of a homeowner's "pride of ownership" or "good housekeeping."[35] They would refuse to insure homes worth less than a certain amount, or homes of a certain age.[36] Or they would refuse to insure homes that were valued at less than the estimated cost to rebuild them, on the assumption (not supported by evidence) that the owners of such homes would burn them down.[37] In essence these practices were simply a re-packaging of the same crude and untrue stereotypes that were used in federal policies that supported redlining in the mortgage lending process.

When sued under a disparate impact theory, insurers could not demonstrate any actuarial basis for these policies. Nor could they justify their decision to exclude these properties from insurance coverage altogether rather than charging rates that reflected their supposedly higher risk. Rather, the insurers simply created categorical exclusions (as well as highly subjective grounds for exclusion) that tracked their prior overt discrimination. Only when faced with disparate impact liability did the insurance industry eliminate these and other discriminatory practices – and they did not face the dire consequences (such as a rash of burned-down homes) that they had feared.

This example shows how the proposed rule will actually slow progress that benefits the market. Once faced with disparate impact liability, the insurance industry, like the lending industry, significantly changed its culture. It began looking for ways to profitably offer insurance to more people, rather than looking for reasons to exclude people from coverage. That required it to develop more refined underwriting criteria that could distinguish between good and bad risk in traditionally underserved communities, sometimes in cooperation with fair housing advocates. For example, instead of categorically excluding older homes, property insurers began requiring more rigorous inspection of older heating, plumbing, and electrical systems. Any problems that turn up in such inspections often can be redressed, resulting in the improvement of older housing stock even as property insurers' legitimate concerns are met. Nationwide, the subject of one of the major consent decrees addressing these practices, now is considered an industry leader in terms of developing effective, non-discriminatory underwriting criteria.

The bottom line is that disparate impact liability has forced the property insurance industry to become fairer, and at the same time more dynamic, creative, and profitable. There remains much work to be done to make the property insurance industry truly non-discriminatory, but considerable progress has been made in a short period of time.

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[35] See Consent Decree in United States v. Nationwide Mut. Ins. Co., C2-97-291 (S.D. Ohio Mar. 10, 1997), available at https://www.justice.gov/crt/housing-and-civil-enforcement-cases-documents-367.

[36] See, e.g., Toledo Fair Hous. Ctr. v. Nationwide Mut. Ins. Co., 704 N.E.2d 667, 674 (Ct. C.P. Ohio 1997) (describing evidence showing that minimum-value requirement excluded 83 percent of homeowners in majority African-American neighborhoods, compared with 31 percent in white neighborhoods).

[37] See Gregory D. Squires, *Racial Profiling, Insurance Style: Insurance Redlining And The Uneven Development Of Metropolitan Areas*, 25 J. of Urban Aff. 391, 400 (2003); see, e.g., *Nat'l Fair Hous. Alliance v. Prudential Ins*., 208 F. Supp. 2d 46 (D.D.C. 2002).

B. Refusal to Make Home Loans for Row Houses

In the late 1990s, appraisal fraud to facilitate "flipping" of row houses in certain predominantly African-American urban locations left buyers stuck in uninhabitable dwellings they had purchased at inflated prices.[38] While industry generally responded with an effective crack down on the practice, causing appraisal fraud to plummet, some lenders took a more blunt, exclusionary approach – they simply stopped making loans secured by row homes. This policy, ostensibly for a legitimate purpose, disproportionately affected people and communities of color.

The same predominantly African-American communities victimized by the fraudulent appraisals now faced difficulty in buying or selling their homes. Years after implementation of less discriminatory alternatives by much of the industry and the resulting decrease in reports of appraisal fraud, certain lenders continued to simply refuse to adopt these reasonable changes.[39] Only when faced with litigation under a disparate impact theory did these lenders agree to drop their no-row-houses policies.[40]

The no-row-house policies demonstrates how many industry players, if not required to do otherwise, will continue to employ shortcuts instead of precise solutions, and, in the process, cause unwarranted discriminatory results. Had these lenders been able to simply point to their supposed "legitimate purpose" or never even had to justify the discriminatory effect because of the proposal's harsh burden on plaintiffs, such practices might well continue to this day. The lenders in question confronted a real problem that did correlate to rowhouses in certain underserved areas. But the problem was not the rowhouses. The lenders could instead have focused on the actual problem, which was that the combination of poor underwriting practices and unreliable appraisals left them too often with loans in default and collateral that turned out to be worthless. Once the appraisal concern was resolved, they could have improved their loan products and underwriting policies to reduce the risk of default.

IV. HUD Proposes a Safe Harbor for the Lending Industry That Would Encourage Algorithmic Bias to Run Rampant.

Today, most mortgage lending is done through automated underwriting – algorithmic risk assessment models that have been shown to produce discriminatory outcomes despite industry assurances that they are free of bias.[41] HUD's proposed rule carves out a special defense for these models, which will operate as a safe harbor for the entire lending and insurance industries under the proposal. A disparate impact claim challenging the use of an algorithmic model would never survive so long as the lender, insurer, or secondary purchaser relies on so-called industry standards and conventions.[42] On the

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[38] See, e.g., Predatory Lending: Joint Hearing Before a Subcommittee of the Committee on Appropriations, 107th Cong. (May 14, 2001), available at https://bulk.resource.org/gpo.gov/hearings/107s/85218.txt.

[39] See Kenneth R. Harney, Discriminating Lenders, Or Just Discrimination?, Washington Post, May 19, 2007, available at http://www.washingtonpost.com/wp-dyn/content/article/2007/05/18/AR2007051800742.html.

[40] See, e.g., News Release, HUD Announces $100,000 Settlement of Fair Lending Complaint Against First Indiana Bank, N.A., available at https://archives.hud.gov/news/2007/pr07-080.cfm.

[41] Robert Bartlett, Adair Morse, Richard Stanton, and Nancy Wallace, *Consumer-Lending Discrimination in the FinTech Era*, Haas School of Business UC Berkeley (May 2019) at p. 1, available at http://faculty.haas.berkeley.edu/morse/research/papers/discrim.pdf.

[42] Michelle Aronowitz and Edward Golding, HUD's Proposal to Revise the Disparate Impact Standard Will Impede Efforts to Close the Homeownership Gap, Urban Institute (Sept. 2019), available at

contrary, HUD should incentivize lenders to remain vigilant to ensure their models are nondiscriminatory. One of the best methods is for lenders to run rigorous fair lending analysis, including a disparate impact analysis, to ensure that risk assessment models do not drive discriminatory outcomes. If HUD provides these models a nearly carte-blanche safe harbor, many industry players will not conduct these rigorous tests and discrimination will go undetected and unresolved.

A. HUD Does Not Have the Authority to Create Safe Harbors Under the Fair Housing Act

As a preliminary matter, HUD does not have the authority to create a safe harbor for algorithmic models. Particularly considering the federal government's history of housing discrimination, Congress did not provide HUD the authority to create its own exemptions or safe harbors.[43] Fair Housing Act exemptions are statutory, not regulatory. Furthermore, as HUD stated in 2016, in response to a requested exemption for the insurance industry: "Categorical exemptions would undermine the Act's broad remedial purpose and contravene HUD's own statutory obligation to affirmatively further fair housing."[44]

B. HUD Fails to Define Terms, Giving the Safe Harbor Limitless Reach

The proposed rule introduces a broad safe harbor without legal authority, while also leaving key terms undefined. When HUD refers to models being standard in the industry, it is likely referring to automated underwriting models, such as the ones the GSEs use. Yet, algorithmic models are used in many aspects of the lending business – credit scoring, pricing, marketing, and automated underwriting systems. The proposed rule does not explain who or what determines what counts as an industry standard or who or what is deemed a "recognized third party" that may bless such models. For instance, even if a GSE automated underwriting model excluded all Black and Latino applicants, under the proposed rule, if the model is used as intended, lenders would be exempt from liability because it is a supposed industry standard and provided by a third party. However, the burden shifting framework, including alleging and demonstrating business necessity, has been at the heart of the disparate impact standard.[45] As proposed, the safe harbor eliminates the need to show business necessity and would provide lenders blanket protection from liability. It also does not provide the plaintiff the opportunity to show that there is a less discriminatory alternative.[46]

Additionally, with the advent of financial technology ("fintech") companies in the lending industry, it is unclear whether the safe harbor would encompass any new "standards" that emerge. The proposed rule does not define how a new underwriting, marketing, or credit-scoring methodology – encapsulated in an algorithm – may become an industry standard. It also does not provide for any guardrails to prevent discriminatory and ill-tested models from being deemed industry standards and thus immune

https://www.urban.org/research/publication/huds-proposal-revise-disparate-impact-standard-will-impede-efforts-close-homeownership-gap.

[43] *Id.*

[44] 81 Fed. Reg. 69012 (Oct. 5, 2016).

[45] Michelle Aronowitz and Edward Golding, HUD's Proposal to Revise the Disparate Impact Standard Will Impede Efforts to Close the Homeownership Gap, Urban Institute (Sept. 2019), available at https://www.urban.org/research/publication/huds-proposal-revise-disparate-impact-standard-will-impede-efforts-close-homeownership-gap.

[46] *Id.*

from suit. With the safe harbor in place, companies would be disincentivized from conducting rigorous fair lending analysis on new and innovative models.

C. Algorithms Are Not Immune from Discriminating or Creating Clearly Discriminatory Outcomes

Algorithms are not objective or free of potential bias.[47] They are only as good as the data that biased humans program into them. And even when the data itself is not biased, the interactions between the data may produce biased outcomes. Bias in the context of algorithmic analysis has been defined as "outcomes which are systematically less favorable to individuals within a particular group and where there is no relevant difference between groups that justifies such harms."[48] In 2018, the New York Times published a study finding artificial intelligence – in particular, facial recognition technology – was much less effective when the subject of the analysis was not a white male.[49] While the software was correct 99 percent of the time when the subject in the photo was a white man, when the subject was a darker skinned female, the software was wrong 35 percent of the time.[50] This is because the data set used in artificial intelligence is often reflective of those creating it, who are disproportionately white and male.[51] As Joy Buolamwini, MIT professor, stated "[y]ou can't have ethical A.I. that's not inclusive" and "[w]hoever is creating the technology is setting the standards."[52] This is a fundamental issue with algorithms.

Artificial intelligence and algorithms have been exposed as problematic in various sectors. In the employment discrimination context, new developments – such as automated hiring systems – have ushered in novel mechanisms for discrimination.[53] "The high bar of proof to demonstrate a disparate impact cause of action under Title VII of the Civil Rights coupled with the "black box" nature of many automated hiring systems, render the detection and redress of bias in such algorithmic systems difficult" and "the automation of hiring both facilitates and obfuscates employment discrimination."[54] Potential discrimination claims are shielded due to the black-box nature of algorithms plus the fact that companies claim the algorithm is a trade secret. This creates an insurmountable and unjust obstacle for disparate impact claimants. Federal Reserve Bank Governor Lael Brainard gives a disturbing example taken from a hiring firm's AI algorithm: "the AI developed a bias against female applicants, going so far as to exclude resumes of graduates from two women's colleges."[55] Brookings' Aaron Klein expanded on

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[47] Claire Cain Miller, Algorithms and Bias: Q. and A. With Cynthia Dwork, NY Times, Aug. 10, 2015, available at https://www.nytimes.com/2015/08/11/upshot/algorithms-and-bias-q-and-a-with-cynthia-dwork.html.

[48] Nicol Turner Lee, Paul Resnick, and Genie Barton, Algorithmic Bias Detection and Mitigation: Best Practices and Policies to Reduce Consumer Harms, Brookings Institute, May 22, 2019, available at https://www.brookings.edu/research/algorithmic-bias-detection-and-mitigation-best-practices-and-policies-to-reduce-consumer-harms/.

[49] Steve Lohr, Facial Recognition Is Accurate, if You're a White Guy, NY Times, February 9, 2018, available at https://www.nytimes.com/2018/02/09/technology/facial-recognition-race-artificial-intelligence.html.

[50] *Id*.

[51] *Id*.

[52] *Id*.

[53] Ifeoma Ajunwa, Automated Employment Discrimination (March 15, 2019), available at https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3437631.

[54] *Id*.

[55] Aaron Klein, Credit Denial in the Age of AI, Brookings Institute, April 11, 2019, available at https://www.brookings.edu/research/credit-denial-in-the-age-of-ai/.

this example by stating "[o]ne can imagine a lender being aghast at finding out their AI was making credit decisions on a similar basis, simply rejecting everyone from a woman's college or a historically black college or university."[56]

Algorithms can both build in bias and reinforce bias in a systemic way. In the criminal justice context, COMPAS is an algorithm widely used in the United States to guide sentencing by predicting the likelihood of a criminal reoffending.[57] This system was reported in May 2016 as racially biased. According to the analysis, the system predicts that black defendants pose a higher risk of recidivism than they do, and the reverse for white defendants.[58] Also, predictive policing algorithms have been shown to lead to unjustified over-policing in communities of color.[59] Predictive policing moves police to places where large amounts of crime occurred, which the algorithm views as places where large amounts of arrests occurred. Most of the arrests used by the algorithm are for nonviolent crimes because they are more widespread and predictable, and more nonviolent crime arrests are for black individuals. Thus, the algorithm causes over policing for black neighborhoods, not because there is more crime there than in areas with large white populations, but because those neighborhoods have more arrests, often for discriminatory reasons. As has been demonstrated time and time again, there is enormous racial disparity and bias in the criminal justice system.[60]

Moreover, algorithms have been at the center of Medicaid litigation. For example, *K.W. v. Armstrong* was a class action lawsuit representing approximately 4,000 Idahoans with development and intellectual disabilities who receive assistance from the state's Medicaid program.[61] The State of Idaho had used an in-house formula to determine the dollar value of the disability services available to qualifying individuals.[62] A significant number of peoples' "dollar-figure numbers" decreased dramatically.[63] When pressed, the state said that a formula had caused the numbers to drop, but the state considered the formula a trade secret.[64] In litigation the court ordered the state to disclose its formula.[65] The court found that the formula was unconstitutionally arbitrary and ordered the state to fix the formula so it

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[56] *Id*.
[57] Julia Angwin et. al., Machine Bias, Pro Publica, May 23, 2016, available at https://www.propublica.org/article/machine-bias-risk-assessments-in-criminal-sentencing.
[58] *Id*.
[59] Andrew Guthrie Ferguson, The Police Are Using Computer Algorithms to Tell If You're a Threat, TIME Magazine, October 3, 2017, https://time.com/4966125/police-departments-algorithms-chicago/.
[60] Report to the United Nations on Racial Disparities in the U.S. Criminal Justice System, Sentencing Project, April 19, 2018, available at https://www.sentencingproject.org/publications/un-report-on-racial-disparities/.
[61] Rashida Richardson, Jason M. Schultz, and Vincent M. Southerland, Litigating Algorithms 2019 US Report: New Challenges to Government use of Algorithmic Decision Systems, AI Now Institute, New York University, available at https://ainowinstitute.org/litigatingalgorithms-2019-us.pdf; Jay Stanley, Pitfalls of Artificial Intelligence Decisionmaking Highlighted in Idaho ACLU Case, ACLU, June 2, 2017, available at https://www.aclu.org/blog/privacy-technology/pitfalls-artificial-intelligence-decisionmaking-highlighted-idaho-aclu-case.
[62] *Id.*
[63] *Id.*
[64] *Id.*
[65] *Id.*

allocated funds fairly to recipients.[66] In addition, the court ordered the state to test the formula regularly.[67]

These examples provide stark warnings against introducing an algorithmic safe harbor in the lending and insurance industries. Rather than shield algorithms from scrutiny, a recent research article urges us to create an "auditing imperative" for algorithmic systems.[68] This may be seen as akin to fair lending testing in the lending sphere.

D. Algorithmic Models are Black Boxes

Devising a model's intent is challenging and often impossible. Demonstrating that a model is being used for the "intended purpose of the third party" is required by the section 100.500(c)(2)(ii) defense. But the complex interactions that AI engages in to form a decision can be so opaque that they prevent any party from being able to devise the intent of the machine's creator.[69] For this reason, AI models are referred to as black boxes. When AI programs are black boxes, they are able to form predictions and decisions in the same way as humans, but they are not able to communicate their reasons for making these conclusions.[70] This situation has been analogized to a human attempting to communicate with another highly intelligent species, with both species able to reason and understand but not able to communicate with each other.[71] Scholars have stated that this difficulty in communication "means that little can be inferred about the intent or conduct of the humans that created or deployed the AI, since even they may not be able to foresee what solutions the AI will reach or what decisions it will make."[72] The following are two examples of widely used artificial intelligence machines, which are both considered black boxes.

i. Black-Box AI Models: Neural Networks

Neural networks are among the most commonly used models, but these networks are considered black-boxes because of their complexity.[73] The structure of a neural network is made up of input nodes, hidden nodes, and output nodes.[74] The complexity arises with the interactions between hidden nodes, which process data from the input nodes to form the output nodes.[75] This is because no node is

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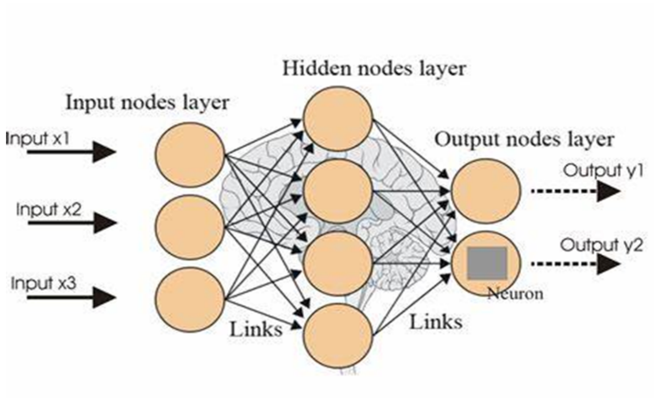
[66] *Id.*
[67] *Id.*
[68] Ifeoma Ajunwa, Automated Employment Discrimination (March 15, 2019), available at https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3437631.
[69] Yavar Bathaee, *The Artificial Intelligence Black Box and the Failure of Intent and Causation,* 31 Harv. J.L. & Tech. 890 (2018), at 892, 897, 907, available at https://jolt.law.harvard.edu/assets/articlePDFs/v31/The-Artificial-Intelligence-Black-Box-and-the-Failure-of-Intent-and-Causation-Yavar-Bathaee.pdf.
[70] *Id*. at 907.
[71] *Id*. at 893.
[72] *Id*. at 893.
[73] *Id*. at 901
[74] Neural Network Architecture, Stanford University, available at https://cs.stanford.edu/people/eroberts/courses/soco/projects/neural-networks/Architecture/feedforward.html.
[75] Yavar Bathaee, *The Artificial Intelligence Black Box and the Failure of Intent and Causation,* 31 Harv. J.L. & Tech. 890 (2018), at 901, available at https://jolt.law.harvard.edu/assets/articlePDFs/v31/The-Artificial-Intelligence-Black-Box-and-the-Failure-of-Intent-and-Causation-Yavar-Bathaee.pdf.

responsible for a distinct function; thousands of nodes overlap each other to form a decision.[76] Humans are able to extract and examine one of these groups of nodes.[77] But because of the different language of AI black-boxes, this will likely appear as visual noise to humans.[78] This means that neural networks are often highly unintelligible to humans, and therefore it is unlikely that one will be able to determine if the model was used in the way intended by the third party.

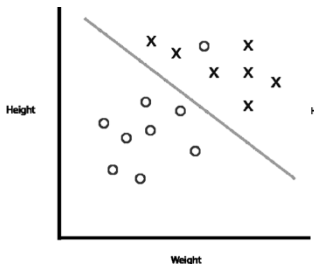


ii. Black-Box AI Models: Support Vector Models (SVMs)

Support Vector Models (SVMs) are also widely used and considered black-boxes. Unlike neural networks, which have a lack of transparency that arises from complexity, SVMs are black-boxes because they possess geometric relationships that humans cannot visualize.[79] The figures and the following example of SVMs is from *The Artificial Intelligence Black Box and the Failure of Intent and Causation*:

> SVM is tasked with taking height and weight and determining whether a person is male or female.[80] If we plotted each person's height and weight on a two-dimensional graph, Figure 1, we can then attempt to draw a dividing line through the data that we can use to make a prediction.[81] If a height/weight combination falls on one side of the line, the person is predicted to be female.[82] As Figure 2 shows, there are multiple ways one could draw the dividing line, but line b is clearly the best for making predictions.[83] Line b reflects the key insight upon which the SVM is based: the line that creates the largest distance or margin between one class and the other is probably the most predictive and one that generalizes the best.[84]

[76] *Id.* at 902.
[77] *Id.*
[78] *Id*. at 902.
[79] *Id*. at 903.
[80] *Id*.
[81] *Id*.
[82] *Id*.
[83] *Id*.
[84] *Id*.



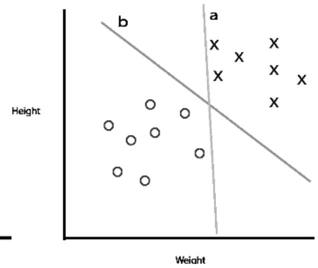


Figure 1 Figure 2

Figure 1: If we graph the men as Xs and the women as Os, we can see that the dividing line depicted above correctly classifies all the men and most of the women. Only 1 woman is misclassified out of a total of 9, meaning our model has an approximately 11% error rate.

Figure 2: The graph in figure two has two dividing lines, a and b. Both dividing lines have the same accuracy—that is, they classify all of the data correctly. The key insight exploited by an SVM is that line b is likely better suited for generalizing on new data than line a because line b maximizes the distance between the two classes and the dividing line (the margin).

What is important…. is to note that the dividing line is a line when there are only two features or variables given to the model.[85] When there are three variables, the dividing line will be a plane. If, however, we give the model with 17 variables or even 1000 variables, the human mind is unable to visualize what that dividing line looks like.[86]

Human brains simply cannot visually process high dimensionality. Moreover, not all SVMs use straight lines to divide the data—that is, a mathematical method used with SVMs allows for non-linear (i.e. curved) divisions.[87] Thus, when the number of variables or features given to an SVM becomes large, it becomes virtually impossible to visualize how the model is simultaneously drawing distinctions between the data based on those numerous features.[88] An AI that uses an SVM to process dozens or perhaps hundreds of variables would thus be a black box to humans because of the dimensionality of the model, despite being a shallow (i.e. less complex) model relative to deep neural networks.[89]

85 *Id*. at 905.
86 *Id*.
87 *Id*.
88 *Id*.
89 *Id*.

E. If AI is a Black box, Then Models Can Engage in Harmful Yet Undetected Actions

i. AI May Use Biased Data to Form Biased Conclusions and the Use of Non-Traditional Variables Places Algorithmic Models at Risk of Not Distinguishing Correlation from Causation.

Non-traditional variables increases the likelihood that conclusions will be biased as well as increase the likelihood that AI will draw a conclusion that there is causation where there is only correlation.[90] Non-traditional variables include data obtained from internet search histories, shopping patterns, social media activity, and various other consumer-related inputs.[91] This non-traditional information can be fed into machines, which can draw conclusions based on the patterns it observes in the dataset.[92] This is a major concern because financial technology companies are using nontraditional data more and more to make consumer credit decisions. As one article put it: "If there are data out there on you, there is probably a way to integrate it into a credit model. But just because there is a statistical relationship does not mean that it is predictive, or even that it is legally allowable to be incorporated into a credit decision."[93]

The following is an example of the use of non-traditional variables in a manner that causes bias from the article *Algorithmic Bias Detection and Mitigation: Best Practices and Policies to Reduce Consumer Harms*:

> Latanya Sweeney, Harvard researcher and former chief technology officer at the Federal Trade Commission (FTC), found that online search queries for African-American names were more likely to return ads to that person from a service that renders arrest records, as compared to the ad results for white names. Her research also found that the same differential treatment occurred in the micro-targeting of higher-interest credit cards and other financial products when the computer inferred that the subjects were African-Americans, despite having similar backgrounds to whites. During a public presentation at a FTC hearing on big data, Sweeney demonstrated how a web site, which marketed the centennial celebration of an all-black fraternity, received continuous ad suggestions for purchasing "arrest records" or accepting high-interest credit card offerings.[94]

The *National Fair Housing Alliance v. Facebook* lawsuit serves as an additional example of biased data used in an algorithm. The main allegation in the lawsuit was that Facebook's advertising platform contained pre-populated lists that allowed advertisers to place housing, employment, and credit ads that could exclude certain protected groups, such as African-Americans, Hispanics, and Asian

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[90] White & Case, Algorithms and Bias: What Lenders Need to Know, January 20, 2017, available at https://www.whitecase.com/publications/insight/algorithms-and-bias-what-lenders-need-know. See also Ian Ayres, *Testing for Discrimination and the Problem of Included Variable Bias* (2010) at p. 6, available at https://www.law.upenn.edu/live/files/1138-ayresincludedvariablebiaspdf.

[91] *Id*.

[92] *Id*.

[93] Aaron Klein, Credit Denial, Brookings Institute (April 11, 2019), available at https://www.brookings.edu/research/credit-denial-in-the-age-of-ai/.

[94] Nicol Turner Lee, Paul Resnick, and Genie Barton, Algorithmic Bias Detection and Mitigation: Best Practices and Policies to Reduce Consumer Harms, Brookings Institute, May 22, 2019, available at https://www.brookings.edu/research/algorithmic-bias-detection-and-mitigation-best-practices-and-policies-to-reduce-consumer-harms/.

Americans.[95] The plaintiffs also challenged that Facebook permitted advertisers to include or exclude Facebook users from receiving ads based on their sex or age, or based on demographics, behaviors and interests that were associated with protected classes.[96] Plaintiffs alleged that Facebook "extracts data from its users' online behavior, both on Facebook and off, and uses algorithms designed to sort that data, process it, and repackage it to group potential customers into new and salient categories for advertisers to choose from when targeting their ads."[97] Therefore, data sets were allegedly being crafted to increase the likelihood of particular outcomes with groups that were the equivalent of protected classes. Facebook's inclusion of certain groups and exclusion of others resulted in groups being disproportionately targeted by predatory lenders or excluded from reasonable and beneficial loans. This shows the risk of discrimination that can come with artificial intelligence, and that past bias (in this case, Facebook's selection of particular categories) can result in current bias (the discriminatory outcomes).

Furthermore, algorithms do not distinguish causation from correlation or know when it is necessary to gather additional data to form a sound conclusion. One notable example is social media. This is particularly relevant in the lending context, as some fintech lenders may use social media data as a predictor of default. But using this information might interfere with other more important and relevant indicators, "such as which connections are genuine and not superficial."[98]

Additionally, although consumers can check their credit reports for false information, "consumers cannot easily verify the myriad forms of nontraditional data that could be fed into a credit assessment algorithm. Consumers may not know whether an algorithm has denied them credit based on erroneous data from sources not even included in their credit reports."[99]

While some argue that the usage of non-traditional variables is beneficial in providing targeted information to different groups, it can lead to "unfair or discriminatory lending decisions if not appropriately implemented and monitored."[100] It can lead to decisions where patterns of discrimination are perpetuated from the initial entry of data to the conclusion. This is extremely dangerous territory for the civil rights of Americans and could enable the continuation of discrimination. It is also reason to be vigilant to fair lending considerations as new credit scoring and underwriting models are developed. While there is potential for more equitable access, there is also potential for abuse and discriminatory outcomes, driven by algorithmic bias.

ii. Close Proxies/Substitutes

Under the proposed rule, if the plaintiff identifies an offending policy or practice that relies on an algorithmic model, a defending party may defeat the claim under section 100.500(c)(2)(i) by identifying the inputs used in the model and showing that these inputs are not substitutes for a protected

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95 *National Fair Housing Alliance v. Facebook, Inc.*, No. 1:18-cv-02689 (S.D.N.Y), https://nationalfairhousing.org/facebook-settlement/.

96 *Id.*

97 First Amended Complaint, *National Fair Housing Alliance v. Facebook, Inc.*, No. 1:18-cv-02689, ¶ 52 (S.D.N.Y. June 25, 2018).

98 White & Case, Algorithms and Bias: What Lenders Need to Know, available at https://www.whitecase.com/publications/insight/algorithms-and-bias-what-lenders-need-know.

99 *Id*.

100 *Id*.

characteristic and that the model is predictive of risk or other valid objective.[101] The defendant may also use the defense in paragraph (c)(2)(iii) where the defendant shows that a neutral third party has analyzed the model in question and determined it was empirically derived, its inputs were not substitutes for a protected characteristic, the model was sufficiently predictive of risk or other valid objective, and is a demonstrably and statistically sound algorithm.[102]

As AI models are generally black boxes, a potential plaintiff will have no way to know what inputs were used.[103] Therefore, it will be virtually impossible for a potential plaintiff to overcome the safe harbor and prove that there was a substitute or close proxy for protected classes in a machine-learning algorithm. Furthermore, having a black box makes it challenging or impossible to devise intent, which in turn makes it unlikely that one could determine whether substitutes or close proxies have been used.[104] Indeed, a recent paper argues that artificial intelligence is inherently structured in a manner that makes "proxy discrimination" a likely possibility.[105]

F. Due to the Nature of Algorithmic Bias, a Potential Plaintiff Has No Way to Challenge an Algorithmic Lending Model Under the Proposed Rule.

Under the proposed rule, a potential plaintiff would have no way to successfully challenge any of the above-described issues with an algorithmic model. The plaintiff has no way of knowing what data is fed into the models, which factors the algorithm used in making the determination, whether there are proxies for protected classes, or whether the algorithm denied credit based on erroneous or biased data. Even if the plaintiff alleges the necessary elements, they will never get to discovery to learn what in the black box created the discriminatory outcome, as the defendant will cite the proposed rule's safe harbor. And even if miraculously the case makes it to discovery, the defendant will shield the algorithm from view by claiming it is a trade secret. Without the ability to challenge these models in court, there is no opportunity to unearth bias and discrimination built into models that can have a lasting impact.

While artificial intelligence holds great promise, we must not assume it is objective or bias-free. As demonstrated by the examples in section IV.C, it has been shown time and again that this is a false assumption. Rather than shield algorithms, we must find ways to test and audit algorithms to ensure they do not perpetuate bias or cause unjustified disparate outcomes.

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[101] 84 Fed. Reg. 42854, 42859.
[102] *Id.*
[103] Yavar Bathaee, *The Artificial Intelligence Black Box and the Failure of Intent and Causation,* 31 Harv. J.L. & Tech. 890 (2018), at 907, available at https://jolt.law.harvard.edu/assets/articlePDFs/v31/The-Artificial-Intelligence-Black-Box-and-the-Failure-of-Intent-and-Causation-Yavar-Bathaee.pdf.
[104] *Id*.
[105] Anya Prince and Daniel B. Schwarcz, *Proxy Discrimination in the Age of Artificial Intelligence and Big Data*, Iowa Law Review (August 5, 2019), available at https://ssrn.com/abstract=3347959.

V. Conclusion

For more than 45 years, disparate impact theory has been a crucial legal tool to fight discrimination and ensure equal housing opportunity. HUD's proposed rule would destroy this legal tool by weakening it beyond recognition, in contradiction of established legal precedent. HUD should withdraw the proposed rule immediately and maintain the existing rule.

Sincerely,

Center for Responsible Lending
Self-Help Credit Union
Self-Help Federal Credit Union