NOTES

ALL DATA IS NOT CREDIT DATA: CLOSING THE GAP BETWEEN THE FAIR HOUSING ACT AND ALGORITHMIC DECISIONMAKING IN THE LENDING INDUSTRY

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In June 2015, the Supreme Court decided Texas Department of Housing and Community Affairs v. Inclusive Communities Project, Inc. *and held that disparate impact claims are cognizable under the Fair Housing Act. Four years later, in August 2019, the Department of Housing and Urban Development published a proposed rule purporting to align the agency's regulations with the Supreme Court's interpretation of the Fair Housing Act in* Inclusive Communities. *The proposed rule, however, is inconsistent with* Inclusive Communities *and, in practice, effectively allows lenders to circumvent liability for algorithm-based disparate impact. This Note argues that these consequences are the result of a gap in statutory accountability within the Fair Housing Act for algorithm-based discrimination. It then calls for more permanent solutions to this problem that would prevent HUD—or any other agency under any administration—from interpreting the Fair Housing Act in a manner that contravenes the statute's history and purpose.*

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INTRODUCTION

When Rachelle Faroul, a thirty-three-year-old Black woman, applied for a loan from Philadelphia Mortgage Advisers in April 2016, she didn't foresee any problems.[1] She was a Northwestern University graduate, had good credit and a decent amount of savings, and at the time was making approximately $60,000 a year as a computer programming instructor at Rutgers University.[2] But Philadelphia Mortgage Advisers denied her initial loan application, citing that her contract income was inconsistent.[3] Rachelle persisted and got a full-time job at the University of Pennsylvania and again applied for a loan, this time with Santander Bank.[4] Santander Bank also denied her application.[5] By that point, Rachelle had been trying to get a mortgage loan for over a year, and the several hard inquiries from the various lenders she had sought a loan from had lowered her credit score.[6] It wasn't until Rachelle's partner, who is half-white and half-Japanese and was then working part-time at a grocery store, agreed to sign

1. Aaron Glantz & Emmanuel Martinez, For People of Color, Banks Are Shutting the Door to Homeownership, Reveal (Feb. 15, 2018), https://www.revealnews.org/article/for-people-of-color-banks-are-shutting-the-door-to-homeownership [https://perma.cc/GTQ3-N8RY] [hereinafter Glantz & Martinez, Shutting the Door].

2. Id.

3. Id.

4. Id.

5. Id.

6. Id.

on to the loan application that Rachelle was finally approved for the loan.[7] While Rachelle spent over a year attempting to get her loan approved, Jonathan Jacobs—another loan applicant—was approved for his loan from TD Bank soon after filling out the paperwork, which took him all of about fifteen minutes.[8] He had almost no savings, a modest income, and a less-than-stellar credit report.[9] But Jonathan is white.[10]

Such stark racial disparities are not unique to Rachelle's and Jonathan's stories or to Philadelphia.[11] In 2018, *Reveal* from the Center for Investigative Reporting conducted a study of thirty-one million mortgage records covering nearly every time an American sought a conventional mortgage loan in 2015 and 2016.[12] The analysis revealed that, even after controlling for several economic and social factors, Black applicants were almost three times more likely than white applicants to be denied a conventional home purchase loan.[13] *Reveal* also reported that lenders acknowledged the disparate impact of lending industry practices on people of color, but that lenders also claimed that the racial disparity can be explained by factors the industry has kept hidden from the public, such as credit scores.[14]

Housing discrimination, however, is not a recent problem; in fact, it has a long, sordid history in the United States. Ongoing housing discrimination throughout the twentieth century ultimately prompted Congress to act by passing the Fair Housing Act of 1968 (FHA), which prohibits discrimination in the sale, rental, and financing of housing on the basis of race, color, religion, sex, national origin, disability status, and familial status.[15] But outlawing only overtly discriminatory practices would

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7. Id.

8. Aaron Glantz & Emmanuel Martinez, Gentrification Became Low-Income Lending Law's Unintended Consequence, Reveal (Feb. 16, 2018), https://www.revealnews.org/article/gentrification-became-low-income-lending-laws-unintended-consequence [https://perma.cc/BC93-GG5C].

9. Id.

10. Id.

11. Philadelphia, however, is notorious for having one of the widest lending disparities among the largest U.S. cities. See Emmanuel Martinez & Aaron Glantz, How *Reveal* Identified Lending Disparities in Federal Mortgage Data 2 (2018), https://s3-us-west-2.amazonaws.com/revealnews.org/uploads/lending_disparities_whitepaper_180214.pdf [https://perma.cc/PY5C-4E8H] [hereinafter Martinez & Glantz, How Reveal Identified Lending Disparities] (explaining that the authors chose to focus investigation on Philadelphia because "among the largest metro areas, it has one of the widest lending disparities").

12. Banks Continue to Deny Home Loans to People of Color, Equal Just. Initiative (Feb. 19, 2018), https://eji.org/news/banks-deny-home-loans-to-people-color [https://perma.cc/TK33-P6CT].

13. Martinez & Glantz, How *Reveal* Identified Lending Disparities, supra note 11, at 2.

14. Glantz & Martinez, Shutting the Door, supra note 1.

15. Title VIII of the Civil Rights Act of 1968, Pub. L. No. 90-284, 82 Stat. 81 (codified as amended at 42 U.S.C. § 3601); Fair Housing Act, History (Jan. 27, 2010),

not adequately address the country's long history of housing discrimination. Consequently, courts and government agencies began applying the disparate impact framework first developed in the employment context in *Griggs v. Duke Power Co.* to housing discrimination claims.[16]

While all eleven federal circuit courts to consider the question recognized disparate impact claims under the FHA,[17] it was not until 2015 that the Supreme Court of the United States formally held in *Texas Department of Housing and Community Affairs v. Inclusive Communities Project, Inc.* that disparate impact claims are cognizable under the FHA.[18] The holding was largely perceived as a win for fair housing activists because it acknowledged liability for unintentional or covert discrimination under the FHA.[19]

Recent technological advancements, however, have raised questions about the FHA's reach. Once thought only marginally possible to achieve, artificial intelligence is now ubiquitous. Among other things, artificial intelligence is used today to estimate a defendant's likelihood of committing a future crime,[20] predict what content you want to see on

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https://www.history.com/topics/black-history/fair-housing-act [https://perma.cc/7XDW-DAMY] (last updated Sept. 12, 2018).

16. See 401 U.S. 424, 431 (1971) ("The [Civil Rights] Act proscribes not only overt discrimination but also practices that are fair in form, but discriminatory in operation."); Michael G. Allen, Jamie L. Crook & John P. Relman, Assessing HUD's Disparate Impact Rule: A Practitioner's Perspective, 49 Harv. C.R.-C.L. L. Rev. 155, 156 (2014) ("Consistent with . . . legislative intent, courts across the country have applied the disparate impact standard in evaluating claims under the FHA, in recognition that '[e]ffect, not motivation, is the touchstone because a thoughtless housing practice can be as unfair to minority rights as a willful scheme.'" (quoting Smith v. Anchor Bldg. Corp., 536 F.2d 231, 233 (8th Cir. 1976))).

17. Allen et al., supra note 16, at 156 ("Every circuit to consider the question—eleven in all—has held that the FHA prohibits housing practices that have a disparate impact on a protected group, even in the absence of discriminatory intent.").

18. 135 S. Ct. 2507, 2525 (2015) ("The Court holds that disparate-impact claims are cognizable under the Fair Housing Act upon considering its results-oriented language, the Court's interpretation of similar language in Title VII [of the Civil Rights Act] and the [Age Discrimination Employment Act], Congress' ratification of disparate-impact claims in 1988 . . . [,] and the statutory purpose.").

19. See Maxwell Tani, The Supreme Court Just Granted a Huge Victory to Fair-Housing Advocates, Bus. Insider (June 25, 2015), https://www.businessinsider.com/supreme-court-opinion-in-fair-housing-case-2015-6 [https://perma.cc/YK35-ZL6X].

20. Andrea Nishi, Note, Privatizing Sentencing: A Delegation Framework for Recidivism Risk Assessment, 119 Colum. L. Rev. 1671, 1672 (2019) ("Artificial intelligence already plays a significant role in judicial decisionmaking through the widespread use of recidivism risk assessment algorithms in state criminal justice systems. Today, at least twenty states use risk assessment algorithms to predict recidivism in their bail, parole, and sentencing proceedings . . . ."); Derek Thompson, Should We Be Afraid of AI in the Criminal-Justice System?, Atlantic (June 20, 2019), https://www.theatlantic.com/ideas/archive/2019/06/should-we-be-afraid-of-ai-in-the-criminal-justice-system/592084 [https://perma.cc/R65T-RKPT] (describing the experience of a public defense attorney

Netflix and on your Facebook Feed,[21] perform robot-assisted surgery,[22] power the spam filter in your inbox,[23] deposit checks through your bank's smartphone app,[24] and even place students in schools.[25] The pervasiveness of artificial intelligence is also changing the development of the housing market. Fifty years ago, when the Fair Housing Act of 1968 was passed, Congress could not have imagined how technological advances would impact the housing market and the ability of certain groups of people to access it. Today, artificial intelligence technology and big data play an important role in housing access, as landlords and lenders increasingly rely on predictive analytics to evaluate applicants.[26] More specifically, the lending industry has increasingly relied on big data and algorithmic

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learning that her client "had been deemed a 'high risk' for criminal activity" due to a "criminal-sentencing [artificial intelligence]" model).

21. Anne Sraders, What Is Artificial Intelligence? Examples and News in 2019, TheStreet (Jan. 3, 2019), https://www.thestreet.com/technology/what-is-artificial-intelligence-14822076 [https://perma.cc/Z6F7-8DJS].

22. Robotic Surgery, Mayo Clinic (Feb. 4, 2020), https://www.mayoclinic.org/tests-procedures/robotic-surgery/about/pac-20394974 [https://perma.cc/XSG6-67UU].

23. Daniel Faggella, Everyday Examples of Artificial Intelligence and Machine Learning, Emerj, https://emerj.com/ai-sector-overviews/everyday-examples-of-ai [https://perma.cc/5NZG-VRQS] (last updated Apr. 11, 2020).

24. Id.

25. Dominique Harrison, Civil Rights Violations in the Face of Technological Change, Aspen Inst. (Apr. 22, 2019), https://www.aspeninstitute.org/blog-posts/civil-rights-violations-in-the-face-of-technological-change [https://perma.cc/7BYT-MQGA] (last updated Oct. 22, 2020).

26. See, e.g., Fannie Mae, How Will Artificial Intelligence Shape Mortgage Lending? 10 (2018), https://www.fanniemae.com/resources/file/research/mlss/pdf/mlss-artificial-intelligence-100418.pdf [https://perma.cc/9LWX-SWLX] ("[I]n two years almost three-fifths of lenders expect to have adopted some AI/ML applications."); Douglas Merrill, AI Is Coming to Take Your Mortgage Woes Away, Forbes (Apr. 4, 2019), https://www.forbes.com/sites/douglasmerrill/2019/04/04/ai-is-coming-to-take-your-mortgage-woes-away/#1e38737c7567 [https://perma.cc/L5CV-CMXJ] (highlighting survey results that showed mortgage lenders anticipated drastically increasing their use of artificial intelligence in their businesses over the next two years); Naborly, https://naborly.com [https://perma.cc/E2AX-2BSP] (last visited Aug. 27, 2020) ("Our Applied Artificial Intelligence system learns from and leverages the experience gained from screening thousands of rental applicants and their tenancy outcomes. This helps Naborly's analysts and customers see patterns of risk that could only . . . be detected by our AI."); Artificial Intelligence Screening, RealPage, https://www.realpage.com/apartment-marketing/ai-screening [https://perma.cc/39SY-HWHS] (last visited Aug. 27, 2020) ("Using this new leading-edge, AI-based screening algorithm along with behavioral data, RealPage AI Screening precisely analyzes your applicant pool from our proprietary rental history database of over 30M records."); see also Conn. Fair Hous. Ctr. v. CoreLogic Rental Prop. Sols., LLC, 369 F. Supp. 3d 362, 367, 371–75 (D. Conn. 2019) (reasoning that because consumer reporting agencies that utilize algorithms to screen tenants can be utilized by housing providers as "an intermediary to take discriminatory and prohibited actions," such agencies must comply with the FHA when providing tenant screening services to landlords). Here, CoreLogic's tenant screening product, CrimSAFE, disqualified a disabled man with no criminal convictions from moving in with his mother on the basis of "unspecified criminal records." Id. at 367–68.

decisionmaking to evaluate the creditworthiness of consumers.[27] While the use of such predictive techniques by lenders may mitigate consumer lending credit risk, it is not without its perils. The accuracy of an algorithm model is only as good as the data inputs used to train it,[28] and data inputs based on a programmer's implicit biases can create a discriminatory algorithm that results in unfair lending practices.

Federal housing laws in the United States, however, have failed to catch up to technology. The FHA makes no mention of technology generally or artificial intelligence specifically and does not address fair lending violations by way of predictive analytics, despite the widespread use of proprietary or third-party algorithmic models in many credit-scoring systems. A recently proposed rule (Proposed Rule) from HUD has exposed this gap in the law.[29] HUD purports that the Proposed Rule—the first federal regulation to directly address disparate impact and algorithms—is aimed at aligning HUD's regulations with the Court's interpretation of the FHA in *Inclusive Communities*.[30] In practice, however, the Proposed Rule will allow lenders to circumvent liability for algorithmic discrimination, in violation of the Fair Housing Act and fair lending laws, by substantially raising the burden of proof for parties claiming discrimination and creating seemingly insurmountable defenses for lenders accused of algorithmic disparate impact discrimination.

This Note focuses on the gap in statutory accountability within the FHA for disparate impact discrimination arising from algorithmic decisionmaking in the lending industry. Part I of this Note provides a historical overview of disparate impact in credit scoring, including the present use of nontraditional data and artificial intelligence by lenders, thus highlighting the importance of the disparate impact doctrine as a tool to combat housing discrimination. Part II offers a legal overview of the

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27. Mikella Hurley & Julius Adebayo, Credit Scoring in the Era of Big Data, 18 Yale J.L. & Tech. 148, 151 (2016) ("Since 2008, lenders have . . . intensified their use of big-data profiling techniques. With increased use of [technology], every consumer leaves behind a digital trail of data that . . . lenders and credit scorers . . . are eagerly scooping up and analyzing as a means to better predict consumer behavior.").

28. See What Is Training Data?, Appen (Apr. 14, 2020), https://appen.com/blog/training-data [https://perma.cc/7RAE-BDT7] ("[T]he quality and quantity of your training data has as much to do with the success of your data project as the algorithms themselves.").

29. See HUD's Implementation of the Fair Housing Act's Disparate Impact Standard, 84 Fed. Reg. 42,854, 42,854 (proposed Aug. 19, 2019) (to be codified at 24 C.F.R. pt. 100) ("This rule proposes to amend HUD's interpretation of the Fair Housing Act's disparate impact standard to better reflect the Supreme Court's 2015 ruling in *Texas Department of Housing and Community Affairs v. Inclusive Communities, Inc.* . . . .").

30. Press Release, HUD, HUD Proposes Revised 'Disparate Impact' Rule (Aug. 16, 2019), https://www.hud.gov/press/press_releases_media_advisories/HUD_No_19_122 [https://perma.cc/5S5J-AX28] ("[HUD] today published a proposed rule to amend the HUD interpretation of the Fair Housing Act's disparate impact standard. The proposed rule as amended would provide more appropriate guidance on what constitutes unlawful disparate impact to better reflect the Supreme Court's 2015 ruling in [*Inclusive Communities*].").

FHA pre- and post-*Inclusive Communities* and grounds the need for disparate impact theory as a recourse for algorithm-based discrimination within the broader context of disparate impact litigation generally. This Part then assesses how HUD's Proposed Rule contravenes this history of disparate impact litigation and frustrates the purpose of the FHA. Part III offers suggestions for closing the gap in the law in the FHA and addresses potential counterarguments to the proposed solutions.

I. DISPARATE IMPACT OF CREDIT SCORING ON COMMUNITIES OF COLOR

Most Americans cannot afford to make major purchases, such as a car or house, outright in cash; instead they turn to lenders for loans.[31] Banks and other lenders, in turn, assess a potential borrower's creditworthiness—that is, the extent to which an individual is suitable for a financial loan—based primarily on a host of factors used to determine whether the individual will be able to meet their financial obligations.[32] While credit scoring is seemingly objective, there is a long history of denying communities of color access to housing based on discriminatory credit-scoring systems.[33] Given the necessity of a favorable credit score for mortgage loan access, discriminatory credit-scoring systems have historically denied communities of color equal access to housing.[34] This

31. See, e.g., Ben Eisen & Adrienne Roberts, The Seven-Year Auto Loan: America's Middle Class Can't Afford Its Cars, Wall St. J. (Oct. 1, 2019), https://www.wsj.com/articles/the-seven-year-auto-loan-americas-middle-class-cant-afford-their-cars-11569941215 (on file with the *Columbia Law Review*); Sarah Min, Average Americans Can't Afford a Home in 70 Percent of the Country, CBS News (Mar. 28, 2019), https://www.cbsnews.com/news/housing-market-2019-americans-cant-afford-a-home-in-70-percent-of-the-country [https://perma.cc/3DW3-KEFP] ("Even with rising wages and falling mortgage rates, Americans can't afford a home in more than 70 percent of the country. Out of 473 U.S. counties analyzed in a report, 335 listed median home prices more than what average wage earners could afford . . . ."); Sarah O'Brien, That Shiny New Car Is Out of Reach for Many Americans, CNBC (July 3, 2017), https://www.cnbc.com/2017/06/28/that-shiny-new-car-is-out-of-reach-for-many-americans.html [https://perma.cc/MRC4-QA4E] ("The report by Bankrate.com shows that in all but one of the 25 largest U.S. metro areas, households with median incomes cannot afford the average price of a new car. In six of the surveyed areas, they can afford less than half the amount."); see also Hurley & Adebayo, supra note 27, at 154 ("Without a sufficiently favorable score from a major credit bureau, a consumer likely cannot 'buy a home, build a business, or send [her] children to college.'" (alteration in original)).

32. See generally Josh Lauer, Creditworthy (2017) (offering a comprehensive analysis of the evolution of the credit-scoring industry from its nineteenth-century origins to the current modern industry that relies on algorithms).

33. See, e.g., id. at 142 ("During the first half of the twentieth century, racial and ethnic prejudice was . . . codified as standard operating procedure. 'Negroes, East Indians, [and] foreigners' were at the bottom of the hierarchy of credit risks, above only 'men and women of questionable character' and 'gamblers' . . . .").

34. Tracy Jan, Redlining Was Banned 50 Years Ago. It's Still Hurting Minorities Today., Wash. Post (Mar. 28, 2018), https://www.washingtonpost.com/news/wonk/wp/2018/03/28/redlining-was-banned-50-years-ago-its-still-hurting-minorities-today (on file with the *Columbia Law Review*) ("Neighborhoods that were predominantly made up of African

Part provides an overview of this history of lending discrimination. Section I.A begins with the discriminatory risk-rating system of the Home Owners' Loan Corporation (HOLC) throughout the early twentieth century. Section I.B looks at the discriminatory origins of the modern credit score. Section I.C then focuses on the lending industry's increasing use of algorithms and alternative data in credit scoring.

A. *The Discriminatory Risk-Rating System of the Home Owners' Loan Corporation*

The history of discriminatory credit-scoring and mortgage-lending systems in the United States can be traced back to the early twentieth century. In the early 1930s, the HOLC and the Fair Housing Administration were established as part of President Roosevelt's New Deal programs meant to alleviate the effects of the Great Depression.[35] The HOLC's mission was "to assist homeowners who were in default on their mortgages and in foreclosure,"[36] and the Fair Housing Administration was primarily tasked with "insur[ing] home mortgage loans made by banks and other private lenders."[37] In order to determine which areas were suitable for "government-backed lending and what rate borrowers would pay," the HOLC created "residential security surveys and maps."[38] The HOLC's surveys and maps assigned security grades to neighborhoods based in part on the racial composition of the neighborhood: Grade A (best), Grade B (still desirable), Grade C (definitely declining), and Grade

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Americans, as well as Catholics, Jews and immigrants from Asia and southern Europe, were deemed undesirable . . . . Loans in these neighborhoods were unavailable or very expensive, making it more difficult for low-income minorities to buy homes.").

35. Bruce Mitchell & Juan Franco, HOLC "Redlining" Maps: The Persistent Structure of Segregation and Economic Inequality 6, https://ncrc.org/wp-content/uploads/dlm_uploads/2018/02/NCRC-Research-HOLC-10.pdf [https://perma.cc/LMB6-BV3N] (last visited Aug. 27, 2020) ("In 1933, the HOLC was established . . . [as] one of many 'New Deal' programs . . . leading the way in establishing the modern government-backed mortgage system. In the case of the HOLC, stabilization of the nation's mortgage lending system was the primary goal.").

36. Id.

37. Marie Justine Fritz, Federal Housing Administration (FHA), Britannica, https://www.britannica.com/topic/Federal-Housing-Administration (on file with the *Columbia Law Review*) (last visited Aug. 27, 2020).

38. Who's Keeping Score? Holding Credit Bureaus Accountable and Repairing a Broken System: Hearing Before the H. Comm. on Fin. Servs., 116th Cong. 3 (2019), [hereinafter Rice, Testimony] (statement of Lisa Rice, President, National Fair Housing Alliance); see also 1934–1968: FHA Mortgage Insurance Requirements Utilize Redlining, Fair Hous. Ctr. of Greater Bos., https://www.bostonfairhousing.org/timeline/1934-1968-FHA-Redlining.html [https://perma.cc/FJZ5-KHNE] (last visited Aug. 27, 2020) ("Redlining is the practice of denying or limiting financial services to certain neighborhoods based on racial . . . composition without regard to the residents' qualifications or creditworthiness . . . [,] [and] refers to the practice of using a red line on a map to delineate the area where financial institutions would not invest.").

D (hazardous).[39] Properties in predominantly African American neighborhoods often were given low grades and deemed high-risk.[40] As the HOLC's grading system continued to permeate the housing industry, "[p]rivate financial institutions incorporated the new rating system in their own appraisals, thereby beginning the widespread institutionalization of . . . 'red-lining.'"[41]

The Fair Housing Administration expanded the HOLC's racialized system of redlining communities of color into the lending industry, developing "race-based underwriting guidelines that . . . promoted residential segregation."[42] As a result of this discriminatory risk-rating system, the real estate appraisal industry "adopted the notion that race had a direct impact on property values,"[43] and that, specifically, properties in predominantly African American neighborhoods were of less value.[44] Consequently, mainstream lenders pulled out of these communities, leaving members of these communities to scramble for credit access by way of subprime lenders.[45] Seeing a growing market of communities of color who had long been ignored by banks, subprime lenders targeted borrowers of color for "unsustainable, higher cost, subprime mortgages."[46] Even though subprime lending is generally for people with poor or limited credit histories, the discriminatory policies of subprime lenders resulted in borrowers of color being much more likely to receive subprime mortgage loans, even when their credit scores qualified them for prime credit.[47]

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39. Rice, Testimony, supra note 38, at 3.

40. Lisa Rice & Deidre Swesnik, Discriminatory Effects of Credit Scoring on Communities of Color, 46 Suffolk U. L. Rev. 935, 940–41 (2013) (describing the HOLC risk-rating system, wherein "borrowers were favored if their neighborhood was deemed new, homogeneous, and in demand," but "[p]roperties would be . . . judged high-risk[] if they were . . . located near an African-American neighborhood." (internal quotation marks omitted)).

41. Id. at 941 (internal quotation marks omitted) (quoting William J. Collins & Robert A. Margo, Race and Home Ownership, 1900 to 1990, at 19–20 (Nat'l Bureau of Econ. Rsch., Working Paper No. 7277, 1999), https://www.nber.org/papers/w7277.pdf [https://perma.cc/Q35F-Y7MM]).

42. Rice, Testimony, supra note 38, at 4.

43. Rice & Swesnik, supra note 40, at 941.

44. See id. at 940–41.

45. See Rice, Testimony, supra note 38, at 5; see also Sarah Burd-Sharps & Rebecca Rasch, Impact of the US Housing Crisis on the Racial Wealth Gap Across Generations 9 (2015), https://www.aclu.org/sites/default/files/field_document/discrimlend_final.pdf [https://perma.cc/Y7DK-B66W] ("A subprime mortgage is a loan with a higher-than-average interest rate. Subprime mortgages were designed for individuals who do not qualify for a conventional mortgage.").

46. Rice & Swesnik, supra note 40, at 943.

47. Id. at 943–44 ("While banks and others continued to defend the use of credit scores as the great equalizer, many borrowers with high credit scores received subprime mortgages even when they qualified for prime credit.").

B. *The Advent of the Credit Score*

While credit scores are an integral part of our financial lives today, the modern credit score was formalized only thirty-one years ago.[48] In 1956, credit-scoring services company Fair, Isaac and Company was founded with the goal of standardizing the credit-scoring system.[49] Throughout the early twentieth century, "most lending decisions were entrusted to individual loan officers and specialists who evaluated applicants on an individual basis," which increased the chances of personal biases influencing the evaluations.[50] At the time, character was more important for determining someone's creditworthiness than financial stability—it was "less about whether one *can* pay and more [about] whether one *will* pay."[51] Because character cannot be measured quantitatively, lenders instead looked to an individual's behaviors and relationships to judge character and assess credit risk.[52] Recognizing that "people were often denied credit because there was no unbiased structure for evaluating them objectively," Fair, Isaac and Company, now known as FICO, introduced the FICO Score in 1989, purportedly "[taking] prejudice out of the equation" by "focus[ing] solely on factors related to a person's ability to repay a loan."[53] Today, FICO is the most prominent developer of credit-scoring models.[54]

FICO utilizes a number of factors, each assigned a different weight, to calculate a consumer's credit score and evaluate their creditworthiness—payment history (thirty-five percent), amounts owed (thirty percent), length of credit history (fifteen percent), new credit (ten percent), and credit mix (ten percent).[55] FICO weighs most heavily whether credit

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48. See Andrew Tavin, A Brief History of Credit Scores, OppLoans, https://www.opploans.com/blog/a-brief-history-of-credit-scores [https://perma.cc/Z99X-XYAA] (last updated Apr. 20, 2020) ("The current FICO score system debuted in 1989 and has become the industry standard.").

49. Id.

50. Hurley & Adebayo, supra note 27, at 155 ("Prior to the 1980s, most lending decisions were entrusted to individual loan officers and specialists who evaluated applicants on an individual basis. These underwriting processes were not only labor-intensive, but could be influenced by personal bias.").

51. Lauer, supra note 32, at 19.

52. Id. at 20 ("To judge character, creditors thus looked for clues in an individual's outward behaviors and relationships: physical appearance and personality; marital stability (or strife); the condition of one's home; drinking habits; predilections for gambling or philandering; and one's reputation among neighbors, employers, and business associates.").

53. Learn About the FICO Score and Its Long History, FICO, https://www.fico.com/25years [https://perma.cc/QN7J-7XYZ] (last visited Aug. 27, 2020).

54. FICO Scores Are Used in over 90% of Lending Decisions, FICO Score, https://ficoscore.com/about [https://perma.cc/Q8YS-SRXS] (last visited Sept. 19, 2020) (claiming that FICO Scores are used in over ninety percent of U.S. lending decisions and that ten billion FICO Scores are purchased annually and twenty-seven million are purchased daily).

55. What's in My FICO Scores?, FICO, https://www.myfico.com/credit-education/whats-in-your-credit-score [https://perma.cc/5T4P-JCGD] (last visited Aug. 27, 2020).

payments have been made on time—credit cards, retail accounts, installment loans, finance company accounts, and mortgage loan accounts are all account types considered for credit payment history.[56] FICO also weighs heavily a consumer's credit utilization ratio on all accounts—that is, the percentage of all available credit used—on the presumption that a person using a high percentage of available credit is close to maxing out and possibly defaulting on future loan payments.[57] FICO also accounts for length of credit history, under the assumption that most credit histories get better with time, while recognizing that it is possible for people who haven't had credit for a long time to still have a good credit history.[58] Lastly, mix of credit cards is not a key factor in determining FICO Scores, but opening multiple new accounts in a short period of time can have a detrimental effect.[59] Among the things not factored into a FICO Score are race, salary or occupation, and place of residence.[60]

While FICO's credit-scoring system is supposed to be unbiased and objective, some scholars have argued that the five factors have a disparate impact on consumers of color.[61] First, FICO does not make distinctions between different types of loans when evaluating timely payments, taking into account *all* loans, including subprime loans.[62] Subprime loans generally carry higher interest rates, and, therefore, higher default and delinquency rates than prime credit loans.[63] Because consumers of color are targeted for subprime loans,[64] "they will undoubtedly experience

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56. What Is Payment History?, FICO, https://www.myfico.com/credit-education/credit-scores/payment-history [https://perma.cc/YJD6-EAK4] (last visited Aug. 27, 2020).

57. What Is Amounts Owed?, FICO, https://www.myfico.com/credit-education/credit-scores/amount-of-debt [https://perma.cc/DJM9-VZPC] (last visited Aug. 27, 2020).

58. What Is the Length of Your Credit History?, FICO, https://www.myfico.com/credit-education/credit-scores/length-of-credit-history [https://perma.cc/6GYT-995E] (last visited Aug. 27, 2020) (stating that while "[a] longer credit history will always have a positive effect on FICO scores," "people who haven't had credit for a considerable length of time can still have a high FICO Score if the rest of their credit report looks good").

59. What Does Credit Mix Mean?, FICO, https://www.myfico.com/credit-education/credit-scores/credit-mix [https://perma.cc/X4BU-4YZ7] (last visited Aug. 27, 2020).

60. What's Not in My FICO Scores, FICO, https://www.myfico.com/credit-education/credit-scores/whats-not-in-your-credit-score [https://perma.cc/3RBM-JZ87] (last visited Aug. 27, 2020).

61. See Hurley & Adebayo, supra note 27, at 156 ("As a practical consequence, traditional credit-scoring tools may also perpetuate unfairness by denying certain groups favorable access to credit merely because they have been excluded from the credit market in the past."); Rice & Swesnik, supra note 40, at 952–57 (describing how each of the five FICO factors has a disparate impact on people of color).

62. See Rice & Swesnik, supra note 40, at 953.

63. Id.; see also supra note 45.

64. See, e.g., Emily Badger, The Dramatic Racial Bias of Subprime Lending During the Housing Boom, CityLab (Aug. 16, 2013), https://www.citylab.com/equity/2013/08/blacks-really-were-targeted-bogus-loans-during-housing-boom/6559 [https://perma.cc/EV4Q-VKEY] ("Relative to comparable white applicants, . . . blacks were 2.8 times more likely to be denied for a loan, and Latinos were two times more likely. When they *were* approved, blacks and Latinos were 2.4 times more likely to receive a subprime loan than white

higher rates of poor performance in payment history."[65] Similarly, FICO's calculation of amounts owed "takes into consideration the amount of credit available to a borrower for certain types of revolving and installment loan accounts."[66] Communities of color have historically had limited access to credit and mainstream lenders, which impacts their ability to obtain revolving lines of credit and, in turn, leads to a "lower credit score from a system that considers how much 'extra' credit they may have available."[67] In other words, if communities of color have limited credit to begin with, the percentage of available credit used is likely to be higher, favoring a lower credit score. This historical lack of access to credit impacts the other factors as well. Because communities of color are more likely to access credit from subprime lenders and outside of the financial mainstream, their length of credit and mix of types of credit used will also be limited.[68] Further, a 2015 report from the Consumer Financial Protection Bureau (CFPB) found that, as of 2010, approximately twenty-six million Americans were "credit invisible"[69] and some other nineteen million had such limited credit records that they could not be scored,[70] adding up to more than forty-five million Americans without a credit score. The study also found that African Americans and Latinos are more likely than whites to be credit invisible or have an unscored credit record.[71]

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applicants."); Manny Fernandez, Study Finds Disparities in Mortgages by Race, N.Y. Times (Oct. 15, 2007), https://www.nytimes.com/2007/10/15/nyregion/15subprime.html (on file with the *Columbia Law Review*) ("Home buyers in predominantly black and Hispanic neighborhoods in New York City were more likely to get their mortgages last year from a subprime lender than home buyers in white neighborhoods with similar income levels, according to . . . researchers at New York University."); Gillian B. White, Why Blacks and Hispanics Have Such Expensive Mortgages, Atlantic (Feb. 25, 2016), https://www.theatlantic.com/business/archive/2016/02/blacks-hispanics-mortgages/471024 (on file with the *Columbia Law Review*) (citing the collapse of the subprime mortgage industry in 2008, the authors explain that "home loans are consistently more expensive for black and Hispanic buyers" because "banks and other lenders direct these groups toward high-risk, high-priced products . . . [,] which can increase the chance of financial ruin and default").

65. Rice & Swesnik, supra note 40, at 953.

66. Id. at 954.

67. Id. at 955.

68. See id. at 956–57.

69. Individuals that are credit invisible have no credit record from any of the three nationwide credit reporting agencies. Kenneth P. Brevoort, Philipp Grimm & Michelle Kambara, Consumer Fin. Prot. Bureau, Data Point: Credit Invisibles 4–6 (2015), https://files.consumerfinance.gov/f/201505_cfpb_data-point-credit-invisibles.pdf [https://perma.cc/J47X-4V89].

70. Id. at 12.

71. Id. at 17–18.

C. *Credit Scoring and Mortgage Lending in the Era of Predictive Analytics*

While FICO's credit-scoring model has remained largely unchanged since its introduction in 1989,[72] the credit-scoring and mortgage-lending industries have entered a new frontier with the rise of artificial intelligence. In the past, credit scoring was based solely on subjective perceptions of character and on financial data, but as access to big data has increased and artificial intelligence has proliferated, the credit-scoring industry has witnessed a rapid shift to risk assessment algorithms.[73] Specifically, lenders use algorithmic systems programmed with alternative data to automate decisions regarding an individual's creditworthiness.[74] Section I.C.1 first provides a brief overview of how algorithms work and how they can potentially discriminate and then discusses the role of artificial intelligence in credit assessments generally. Section I.C.2 explains how algorithm-based credit-scoring systems factor alternative data—nonfinancial data—into assessments of an individual's creditworthiness. Lastly, section I.C.3 discusses the disparate impact of artificial intelligence on communities of color.

1. *Artificial Intelligence in Credit Scoring*. — An algorithm is "any well-defined computational procedure that takes some value, or set of values, as input and produces some value, or set of values, as an output"; put simply, an algorithm is a mathematical formula.[75] The input—sets of data—is fed into an algorithmic model to train the algorithm until it is programmed to function similarly with other sets of data:

> [First,] . . . algorithms are often given training sets of data to process. Once the algorithm trains on that data, it is then tested with a new set of data used for validation. The goal of tuning a[n] . . . algorithm is to ensure that the trained model will generalize, meaning that it has predictive power when given a test dataset (and ultimately live data).[76]

But what happens between input and output? Few really know why or how an algorithm comes to a certain decision, hence why they are often referred to as black boxes, "devices that can be viewed in terms of their

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72. Lauer, supra note 32, at 249 ("In 1989 Fair Isaac unveiled a new generic credit bureau model that would become the industry standard.").

73. See generally Hurley & Adebayo, supra note 27, at 153–59 (discussing traditional credit assessment tools and the emergence of big data credit-scoring tools, such as machine learning).

74. See generally id. at 151 ("The credit-scoring industry has experienced a recent explosion of start-ups that take an 'all data is credit data' approach that combines conventional credit information with thousands of data points mined from consumers' offline and online activities.").

75. Id. at 159 (internal quotation marks omitted) (quoting Thomas H. Cormen, Charles E. Leisersen, Ronald L. Rivest & Clifford Stein, Introduction to Algorithms 1 (3d ed. 2009) (emphasis omitted)).

76. Yavar Bathaee, The Artificial Intelligence Black Box and the Failure of Intent and Causation, 31 Harv. J.L. & Tech. 889, 900 (2018).

inputs and outputs, without any knowledge of their internal workings."[77] Algorithmic models are expected to be more objective, free of the cognitive biases inherent in human decisionmaking.[78] But the lending industry's push to use nontraditional data to evaluate the creditworthiness of consumers increases the chances that those data points, when programmed in concert, effectively serve as a proxy for race or other protected characteristics:[79]

> When it comes to discussions about algorithmic discrimination, the concern is not only that someone might use a well-known substitute for protected class, like ZIP code, as an input when they secretly want to use race. That is a standard concern for disparate impact . . . . Algorithms present a more complex problem: [They] rely on interaction *between* features to find unexpected patterns in the data, which can disproportionately harm people in disadvantaged groups . . . .[80]

For example, imagine a scenario in which the zip code of loan applicants is indicative of their race. The bank can use the zip code as a proxy for race to evaluate loan eligibility and, subsequently, both intentionally and unintentionally reject loan applicants from certain zip codes with greater frequency than others. Likewise, imagine a landlord who decides to determine who might be a difficult tenant by using music streaming data to predict the number of noise complaints against that tenant.[81] The landlord might discover a correlation between preferred musical genre and how difficult a tenant is.[82] But if "an algorithm . . . equates a preference for hip-hop with noise complaints," that algorithm is "probably picking up on race as a factor in frequency of noise complaints" as well, despite the fact that "musical preference is not a substitute or close proxy for race."[83]

Programmers can introduce bias (even unintentionally) into an algorithm in multiple ways. Bias can seep into an algorithmic system during the input stage, training stage, or programming stage of the

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77. Bennie Mols, In Black Box Algorithms We Trust (or Do We?), Commc'ns of the ACM (Mar. 16, 2017), https://cacm.acm.org/news/214618-in-black-box-algorithms-we-trust-or-do-we/fulltext [https://perma.cc/LA4T-4GZL].

78. See, e.g., Alex P. Miller, Want Less-Biased Decisions? Use Algorithms., Harv. Bus. Rev. (July 26, 2018), https://hbr.org/2018/07/want-less-biased-decisions-use-algorithms [https://perma.cc/9TCT-QDKK].

79. Andrew D. Selbst, A New HUD Rule Would Effectively Encourage Discrimination by Algorithm, Slate (Aug. 19, 2019), https://slate.com/technology/2019/08/hud-disparate-impact-discrimination-algorithm.html [https://perma.cc/L4UW-K9Y2].

80. Id.

81. Id.

82. Id.

83. Id.

algorithm formation process.[84] At the input stage, the data fed into the model can be biased, inaccurate, or incomplete; at the training stage, the categorization of the input data—that is, how the data is labeled—can be based on biases; lastly, if the algorithm is trained to have a discriminatory outcome, it will continue to replicate such biases with future data sets.[85] Put more simply,

> Each of these steps creates possibilities for a final result that has a disproportionately adverse impact on protected classes, whether by specifying the problem to be solved in ways that affect classes differently, failing to recognize or address statistical biases, reproducing past prejudice, or considering an insufficiently rich set of factors.[86]

Revisiting the example above, an algorithm programmed to equate a musical preference for hip-hop with a greater likelihood of noise complaints might have been developed by a developer who inaccurately believes that frequent listeners of hip-hop make for more difficult tenants. This algorithm, programmed with a biased assumption, will continue to perform similarly for other data inputs, such as other musical genres and sports.

Within the lending industry, lenders use artificial intelligence to assess a prospective borrower's creditworthiness; specifically, the algorithmic model is trained to use financial data to predict default risk.[87] But first, an individual's financial data is collected.[88] Consumer reporting agencies, such as the three national credit bureaus—TransUnion, Experian, and Equifax—obtain financial data on individual consumers from "credit-information 'furnishers,'" such as credit card companies and mortgage lenders, and compile these data into credit reports.[89] The credit reports are then used "to score individual consumers using proprietary scoring models."[90] These models "teach[] computers to parse data, learn

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84. Algorithms and Bias: What Lenders Need to Know, White & Case (Jan. 20, 2017), https://www.whitecase.com/publications/insight/algorithms-and-bias-what-lenders-need-know [https://perma.cc/MKT5-YV5X].

85. See id.

86. Solon Barocas & Andrew D. Selbst, Big Data's Disparate Impact, 104 Calif. L. Rev. 671, 675 (2016).

87. Dinesh Bacham & Janet Zhao, Machine Learning: Challenges, Lessons, and Opportunities in Credit Risk Modeling, Moody's Analytics (July 2017), https://www.moodysanalytics.com/risk-perspectives-magazine/managing-disruption/spotlight/machine-learning-challenges-lessons-and-opportunities-in-credit-risk-modeling [https://perma.cc/K4BB-GLV4].

88. See Hurley & Adebayo, supra note 27, at 153–57 (describing the process by which credit scores are created, which begins with consumer-reporting agencies obtaining financial data on consumers that eventually get compiled into credit reports that are used to score individuals).

89. Id. at 154.

90. Id. at 154–55.

from it, and then make a determination or prediction regarding new data."[91]

2. *"All Data Is Credit Data": Alternative Credit Scoring with Nontraditional Data.* — Increasingly, the lending industry has been taking advantage of easily accessible personal data online to utilize nontraditional data to evaluate prospective borrowers.[92] Traditional credit models, such as the one used to produce the FICO Scores, "rely on a limited universe of financial data held by credit bureaus."[93] While the CFPB refers to this data as "traditional data,"[94] it has also been referred to as "baseline credit data"—that is, data that is typically reported to the national credit bureaus and traditionally used by lenders to evaluate creditworthiness.[95] Baseline, or traditional, credit data includes basic identifying information, credit account data "furnished" by creditors to the bureaus (e.g., types of accounts, dates the accounts were opened, credit limits, and payment histories), payment-related public record data (e.g., bankruptcies and foreclosures), histories of collections activities, and inquiry records.[96]

But in today's data-rich environment, lenders are now inferring creditworthiness from variables that have no direct connection to an individual's financial history or ability to repay loans.[97] While data used by companies' proprietary algorithms is protected from disclosure by intellectual property law, disclosures in patent applications have revealed the kind of nontraditional data companies now rely on for assessments of prospective borrowers.[98] Increasingly, lenders and financial technology companies use social media activities and retail-spending histories as factors indicative of how responsible an individual is.[99] Some even consider "where one attended college" and "one's use of capitalization in an online

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91. Bacham & Zhao, supra note 87.

92. See Hurley & Adebayo, supra note 27, at 163.

93. Robinson + Yu, Knowing the Score: New Data, Underwriting, and Marketing in the Consumer Credit Marketplace 8 (Oct. 29, 2014), https://www.upturn.org/static/files/Knowing_the_Score_Oct_2014_v1_1.pdf [https://perma.cc/JZ2F-2DPV].

94. Request for Information Regarding Use of Alternative Data and Modeling Techniques in the Credit Process, 82 Fed. Reg. 11,183, 11,184 (Feb. 21, 2017).

95. See Robinson + Yu, supra note 93, at 8.

96. Id.

97. See Lauer, supra note 32, at 267.

98. See Hurley & Adebayo, supra note 27, at 158, 164 (providing ZestFinance as an example of an alternative credit-scoring company whose patent application reveals some information about the kind of data used by its proprietary algorithm). Companies working with big data or artificial intelligence technology can protect their algorithmic models against the unfair practices of market competitors by patenting their models under U.S. intellectual property laws. Seeking patent protection for these systems requires satisfying disclosure requirements by "disclos[ing] to the public enough information about the invention to enable one of ordinary skill in the art to practice what is claimed." Frank A. DeCosta III & Aliza George Carrano, Intellectual Property Protection for Artificial Intelligence, Westlaw J. Intell. Prop., Aug. 30, 2017, at *1–2, 2017 WL 3734225.

99. Hurley & Adebayo, supra note 27, at 163.

application (typing in all caps is a red flag)."[100] Other examples of nontraditional or alternative data that are factored into lending decisions include residential stability, criminal history, employment and address history, professional licensure, cell and landline utility bill information, balances in savings or retirement accounts, and LinkedIn profiles.[101] Zest AI,[102] a financial-services technology company claiming to "deliver[] better decisions for better lending,"[103] even considers innocuous factors such as "how quickly a loan applicant scrolls through an online terms-and-conditions disclosure."[104] In February 2017, Zest AI launched the Zest Automated Machine Learning Platform for credit underwriting to "enable[] lenders to analyze vast amounts of nontraditional credit data to increase approval rates and reduce the risk of credit decisions," particularly for people who are credit invisible or whose "thin-file" credit records make them impossible to be scored.[105] Zest AI currently "powers $500 billion in total lending by clients in every geography and credit category," including mortgages, scoring approximately 250,000 applicants monthly.[106] The company's reach is just one example of the prevalent use of artificial intelligence and alternative data in credit scoring. A 2018 Gartner study predicts that the business value of artificial intelligence will reach $3.9 trillion in 2022.[107] This potential for profitability has led others

100. Lauer, supra note 32, at 267.

101. Hurley & Adebayo, supra note 27, at 166 tbl.1.

102. Zest AI was formerly known as ZestFinance, until it rebranded in 2019. ZestFinance Announces Rebrand to Zest AI, Bus. Wire (Oct. 21, 2019), https://www.businesswire.com/news/home/20191021005123/en/ZestFinance-Announces-Rebrand-Zest-AI [https://perma.cc/3THA-BBCV].

103. Transform Your Underwriting with the Power of AI, Zest AI, https://www.zest.ai [https://perma.cc/MQL7-Z5SY] (last visited Aug. 27, 2020).

104. Hurley & Adebayo, supra note 27, at 164.

105. ZestFinance Introduces Machine Learning Platform to Underwrite Millennials and Other Consumers with Limited Credit History, Bus. Wire (Feb. 14, 2017), https://www.businesswire.com/news/home/20170214005357/en/ZestFinance-Introduces-Machine-Learning-Platform-Underwrite-Millennials [https://perma.cc/4YJT-US3S].

106. ZestFinance Is Now Zest AI. Here's Why., Zest AI, https://zest.ai/article/zestfinance-is-now-zest-ai.-heres-why [https://perma.cc/AMH7-TVRW] (last visited Sept. 20, 2020).

107. Press Release, Gartner, Gartner Says Global Artificial Intelligence Business Value to Reach $1.2 Trillion in 2018 (Apr. 25, 2018), https://www.gartner.com/en/newsroom/press-releases/2018-04-25-gartner-says-global-artificial-intelligence-business-value-to-reach-1-point-2-trillion-in-2018 [https://perma.cc/J43R-7HNU].

to also use artificial intelligence and alternative data in credit scoring,[108] including FICO.[109]

Despite the growing use of alternative data, whether it actually helps score consumers more accurately and consistently is still debated. The CFPB points out that consumers of color are more often affected by the issue of credit invisibility, and alternative data offers lenders other means by which to assess their creditworthiness.[110] For example, a credit assessment based solely on financial information might yield an unfavorable score, but a lender might nonetheless be willing to lend if they could determine that the person is not as likely to default by looking at other sources of data.[111] LexisNexis, for example, in partnership with FICO and Equifax, has developed FICO Score XD, a consumer-reporting agency that "leverages alternative data sources to assess creditworthiness among traditionally unscorable populations."[112] Additionally, algorithmic decisionmaking can in fact be fairer because it reduces human involvement in the decisionmaking process and therefore the risk that decisions may be influenced by biases—this is particularly true for a "well-built model that evaluates objective criteria."[113] On the other hand, the CFPB also recognizes that alternative data can be inaccurate or incomplete and therefore its use can have unintended consequences, such as "a greater risk of unlawful discrimination if new variables or factors are more closely related to a [protected characteristic] under the law."[114]

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108. See Aite, Alternative Data Across the Loan Life Cycle: How FinTech and Other Lenders Use It and Why 11 (2018), https://www.experian.com/assets/consumer-information/reports/Experian_Aite_AltDataReport_Final_120418.pdf?elqTrackId=7714eff9f5204e7ca8517e8966438157&elqaid=3910&elqat=2 [https://perma.cc/Z4JU-9FDH] ("Aite Group's 2018 survey of banks, credit unions, finance companies, and fintech lenders with significant credit portfolios finds that over 80% of these institutions incorporate the use of alternative data sources into at least some aspect of their lending.").

109. Why Alternative Data Matters, FICO, https://www.fico.com/independent/alternative-data [https://perma.cc/ND2X-VFEE] (last visited Aug. 27, 2020).

110. Brian Kreiswirth, Peter Schoenrock & Pavneet Singh, Using Alternative Data to Evaluate Creditworthiness, CFPB (Feb. 16, 2017), https://www.consumerfinance.gov/about-us/blog/using-alternative-data-evaluate-creditworthiness [https://perma.cc/S8GQ-UKB4].

111. Id.

112. FICO Score XD, Generate a FICO Score for Unscorable Credit Applicants., LexisNexis Risk Solutions, https://risk.lexisnexis.com/products/fico-score-xd [https://perma.cc/L3LV-4CDQ] (last visited Aug. 27, 2020); see also Joanne Gaskin, Leveraging Alternative Data to Extend Credit to More Borrowers, FICO (May 22, 2019), https://www.fico.com/blogs/leveraging-alternative-data-extend-credit-more-borrowers [https://perma.cc/D23A-BRSK] ("With FICO Score XD, which takes into account . . . information not available in traditional credit files, millions of U.S. consumers with sparse or no traditional credit files can now be scored reliably and have the opportunity to receive offers of credit.").

113. Nicholas Schmidt & Bryce Stephens, An Introduction to Artificial Intelligence and Solutions to the Problems of Algorithmic Discrimination, 73 Consumer Fin. L.Q. Rep. 130, 137 (2019).

114. Kreiswirth et al., supra note 110.

The problem of utilizing "personal information *irrelevant* to creditworthiness" was addressed in the 1970s by the Equal Credit Opportunity Act (ECOA) when it prohibited lenders from considering gender, marital status, race, nationality, religion, age, or receipt of public assistance to assess a prospective borrower's creditworthiness.[115] Lenders followed suit by removing these categories from their applications and scoring systems, but this did not eliminate credit discrimination altogether.[116] Access to big data has expanded, giving lenders access to a wider breadth of personal information—including data points that are not prohibited by the ECOA or FHA—and statistical scoring systems purported to be objective have emerged.[117]

3. *The Disparate Impact of Artificial Intelligence on Communities of Color.* — The scoring systems used by many lenders today were believed to have removed all biases, but in practice, the complexity of these scoring systems have made discrimination much harder to eliminate.[118] These algorithmic scoring models "d[o] not weigh individual variables in isolation"; instead, "they rel[y] on complex calculations in which multiple variables interact[] with and affect[] the predictive power of the others."[119] It is more complicated than merely excluding certain factors from the analysis—"variables associated with statistical credit risk [are] so deeply embedded in socioeconomic contexts that they [are] virtually impossible to disentangle" and can inadvertently serve as proxies to race or other protected characteristics.[120] For example, residence zip code is highly correlated with race.[121] The correlation between zip code and race alongside the positive correlation between, for example, race and credit risk, means that "predictive algorithms will assign a higher risk score to individuals from majority black zip codes compared to otherwise similar individuals from majority white zip codes, even when the zip code of residence has no direct effect on outcomes."[122] A similar proxy effect would result with other factors highly correlated with race, such as criminal

115. Lauer, supra note 32, at 235–36.

116. Id. at 236.

117. See id.

118. Id. at 237.

119. Id.

120. Id. at 237–38.

121. Crystal S. Yang & Will Dobbie, Equal Protection Under Algorithms: A New Statistical and Legal Framework 13 (Oct. 2019) (unpublished manuscript) (on file with the *Columbia Law Review*); see also Katie Nodjimbadem, The Racial Segregation of American Cities Was Anything but Accidental, Smithsonian Mag. (May 30, 2017), https://www.smithsonianmag.com/history/how-federal-government-intentionally-racially-segregated-american-cities-180963494 [https://perma.cc/KK9R-R7LG] ("[American] cities tend to be organized in their own particular racial pattern . . . . A narrative of racially discriminatory landlords and bankers—all independent actors—has long served as an explanation for the isolation of African-Americans in certain neighborhoods in large cities.").

122. Yang & Dobbie, supra note 121, at 13.

history,[123] level of education,[124] and employment status.[125] The use of alternative data, then, can have a disparate impact—that is, the algorithms are facially neutral and seemingly unbiased but have a disproportionately adverse impact on certain groups of people. Using factors that are highly correlated with race in predictive algorithms is "almost tantamount to using race."[126]

In addition to having a disparate impact on racial minorities, "black box" credit-scoring systems are also opaque.[127] Algorithmic opacity is "a condition where algorithms lack visibility of computational processes, and where humans are not able to inspect its inner workings to ascertain for themselves how the results and conclusions were computed."[128] Given the opacity of these algorithmic credit-scoring systems, credit scores "cannot be fully understood, challenged, or audited by the individuals scored,"[129] making the scoring system as a whole difficult to scrutinize.[130] According to the 2018 Consumer Response Annual Report, the CFPB received approximately 329,800 consumer complaints in 2018, with credit reports and mortgages among the top three most complained about consumer financial services or products.[131] For complaints on credit reports,

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123. See id. at 13–14 (discussing the correlation between race and criminal history).

124. Matt Barnum, Race, Not Just Poverty, Shapes Who Graduates in America—And Other Education Lessons from a Big New Study, Chalkbeat (Mar. 23, 2018), https://chalkbeat.org/posts/us/2018/03/23/race-not-just-poverty-shapes-who-graduates-in-america-and-other-education-lessons-from-a-big-new-study [https://perma.cc/VB97-7RW7] ("Black students are much less likely to graduate from high school and attend college than white students with the same family income.").

125. See Derek Thompson, The Workforce Is Even More Divided by Race than You Think, Atlantic (Nov. 6, 2013), https://www.theatlantic.com/business/archive/2013/11/the-workforce-is-even-more-divided-by-race-than-you-think/281175 [https://perma.cc/2KTE-BDEN]; Janelle Jones, Black Unemployment Is at Least Twice as High as White Unemployment at the National Level and in 12 States and D.C., Econ. Pol'y Inst. (Oct. 30, 2018), https://www.epi.org/publication/2018q3_unemployment_state_race_ethnicity [https://perma.cc/N86P-BS2Y].

126. Cathy O'Neil, The Ethical Data Scientist, Slate (Feb. 4, 2016), https://slate.com/technology/2016/02/how-to-bring-better-ethics-to-data-science.html [https://perma.cc/Y55B-Y9SV].

127. Danielle Keats Citron & Frank Pasquale, The Scored Society: Due Process for Automated Predictions, 89 Wash. L. Rev. 1, 10 (2014) ("There are three basic problems with credit scoring systems: their opacity, arbitrary results, and disparate impact on women and minorities.").

128. Pragya Paudyal & B.L. William Wong, Algorithmic Opacity: Making Algorithmic Processes Transparent Through Abstraction Hierarchy, 62 Proc. Hum. Factors & Ergonomics Soc'y Ann. Meeting 192, 193 (2018), https://journals.sagepub.com/doi/pdf/10.1177/1541931218621046 (on file with the *Columbia Law Review*).

129. Citron & Pasquale, supra note 127, at 10.

130. See id. at 10–11.

131. CFPB, 2018 Consumer Response Annual Report: January 1–December 31, 2018, at 9 (2019), https://files.consumerfinance.gov/f/documents/cfpb_consumer-response-annual-report_2018.pdf [https://perma.cc/F5V3-QECA].

incorrect information was the most common issue,[132] and for mortgage complaints, conventional home mortgages were the most complained about mortgage type.[133] While the overwhelming majority of these complaints—seventy-two percent of the credit report complaints and eighty-five percent of the mortgage complaints—were "closed with an explanation,"[134] credit bureaus also "routinely deny requests for details on their scoring systems," leaving consumers confused as to how and why their credit score changes or why they vary across bureaus.[135]

These sophisticated credit-scoring models programmed to analyze large sets of data don't appear from thin air—they are developed by humans. Programmers decide "what variables to use, how to define categories or thresholds for sorting information, and which datasets to use to build the algorithm," and as section I.C.1 discusses, programmers can unknowingly inject their biases into the algorithm.[136] In recent years, experimentation with applications of artificial intelligence has proliferated, extending algorithmic bias and disparate impact discrimination beyond the lending industry. In the criminal justice context, for example, "automated risk assessments used by U.S. judges to determine bail and sentencing limits can generate incorrect conclusions, resulting in large cumulative effects on certain groups, like longer prison sentences or higher bails imposed on people of color."[137] People of color are also less likely to have access to certain housing advertisements,[138] as evidenced by recent lawsuits against Facebook alleging discriminatory advertising practices for housing ads.[139] Research on facial recognition

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132. Id. at 19.

133. Id. at 32.

134. Id. at 14–15.

135. Citron & Pasquale, supra note 127, at 10–12.

136. A.R. Lange & Natasha Duarte, Understanding Bias in Algorithmic Design, Medium (Sept. 6, 2017), https://medium.com/impact-engineered/understanding-bias-in-algorithmic-design-db9847103b6e [https://perma.cc/7UJU-A6RU].

137. Nicol Turner Lee, Paul Resnick & Genie Barton, Algorithmic Bias Detection and Mitigation: Best Practices and Policies to Reduce Consumer Harms, Brookings Inst. (May 22, 2019), https://www.brookings.edu/research/algorithmic-bias-detection-and-mitigation-best-practices-and-policies-to-reduce-consumer-harms [https://perma.cc/HF9Z-RPCN]; see also Julia Angwin, Jeff Larson, Surya Mattu & Lauren Kirchner, Machine Bias, ProPublica (May 23, 2016), https://www.propublica.org/article/machine-bias-risk-assessments-in-criminal-sentencing [https://perma.cc/3QGY-VQS6] (highlighting racial bias in a computer program used by judges in some states during criminal sentencing that predicts the likelihood of someone committing a future crime).

138. See generally Kody Glazer, Note, Fair Housing Act at 50: Challenging the Disparate Impact of Predictive Analytics, 46 Fla. St. U. L. Rev. 457 (2019) (arguing that the disparate impact theory of liability under the FHA can be used to challenge predictive algorithms in cases of housing advertising discrimination).

139. Katie Paul & Akanksha Rana, U.S. Charges Facebook with Racial Discrimination in Targeted Housing Ads, Reuters (Mar. 28, 2019), https://www.reuters.com/article/us-facebook-advertisers/hud-charges-facebook-with-housing-discrimination-in-targeted-ads-on-its-platform-idUSKCN1R91E8 (on file with the *Columbia Law Review*).

technology, with which some lenders have begun to experiment to assess creditworthiness,[140] also reveals bias—dark-skinned people are misidentified by the technology with greater frequency than whites,[141] including by being categorized as primates.[142]

II. CIRCUMVENTING LIABILITY FOR DISPARATE IMPACT UNDER THE FHA WITH HUD'S PROPOSED RULE

Despite the continuing discrimination by lending institutions—in recent years, the DOJ has sued several banks for lending discrimination[143]—and their now well-known use of artificial intelligence

140. What Your Face May Tell Lenders About Whether You're Creditworthy, Wall St. J. (June 10, 2019), https://www.wsj.com/articles/what-your-face-may-tell-lenders-about-whether-youre-creditworthy-11560218700 (on file with the *Columbia Law Review*).

141. Steve Lohr, Facial Recognition Is Accurate, if You're a White Guy, N.Y. Times (Feb. 9, 2018), https://www.nytimes.com/2018/02/09/technology/facial-recognition-race-artificial-intelligence.html (on file with the *Columbia Law Review*).

142. Maggie Zhang, Google Photos Tags Two African-Americans as Gorillas Through Facial Recognition Software, Forbes (July 1, 2015), https://www.forbes.com/sites/mzhang/2015/07/01/google-photos-tags-two-african-americans-as-gorillas-through-facial-recognition-software/#6dad1a94713d [https://perma.cc/49LR-VUMX].

143. See, e.g., Press Release, DOJ, Justice Department Reaches $335 Million Settlement to Resolve Allegations of Lending Discrimination by Countrywide Financial Corporation (Dec. 21, 2011), https://www.justice.gov/opa/pr/justice-department-reaches-335-million-settlement-resolve-allegations-lending-discrimination [https://perma.cc/P3D4-B7DL] ("[T]he department's complaint . . . alleges that Countrywide discriminated by charging more than 200,000 African-American and Hispanic borrowers higher fees and interest rates than non-Hispanic white borrowers . . . because of their race or national origin, and not because of the borrowers' creditworthiness or other objective criteria related to borrower risk."); Press Release, DOJ, Justice Department Reaches Settlement with Minnesota Bank to Resolve Allegations of Lending Discrimination (May 8, 2018), https://www.justice.gov/opa/pr/justice-department-reaches-settlement-minnesota-bank-resolve-allegations-lending [https://perma.cc/T5GB-WE78] ("The Justice Department today settled its suit against KleinBank, resolving allegations that the bank engaged in lending discrimination by 'redlining' predominantly minority neighborhoods in and around the Twin Cities of Minneapolis-St. Paul, Minnesota . . . by intentionally avoiding providing lending services to residents [of those neighborhoods]."); Press Release, DOJ, Justice Department Reaches Settlement with Wells Fargo Resulting in More than $175 Million in Relief for Homeowners to Resolve Fair Lending Claims (July 12, 2012), https://www.justice.gov/opa/pr/justice-department-reaches-settlement-wells-fargo-resulting-more-175-million-relief [https://perma.cc/53H6-AETG] ("The Department . . . filed the second largest fair lending settlement in the department's history to resolve allegations that Wells Fargo . . . [discriminated] against qualified African-American and Hispanic borrowers in its mortgage lending from 2004 to 2009."); Press Release, DOJ, Justice Department Settles Suit Against Indiana Bank to Resolve Lending Discrimination Claims (June 13, 2019), https://www.justice.gov/opa/pr/justice-department-settles-suit-against-indiana-bank-resolve-lending-discrimination-claims [https://perma.cc/L8JB-Q74G] (describing how the DOJ and U.S. Attorney's Office reached a settlement agreement with First Merchant Bank, resolving allegations that the bank "engaged in lending discrimination by 'redlining' predominantly African-American neighborhoods within Indianapolis, Indiana[,] . . . because of the race of the people living in those neighborhoods"); Press Release, DOJ, Manhattan U.S. Attorney Settles Lending Discrimination Suit Against JPMorgan Chase for $53 Million (Jan. 20, 2017),

technology, U.S. federal housing laws have not caught up to the pervasiveness of artificial intelligence technology. The FHA makes no mention of technology generally or artificial intelligence specifically. Noting this gap in the law, in August 2019, HUD proposed a new rule purportedly "to better reflect the Supreme Court's 2015 ruling in *Texas Department of Housing and Community Affairs v. Inclusive Communities Project, Inc.*," which formally recognized disparate impact claims under the FHA.[144] In practice, however, HUD's Proposed Rule—and any other laws and regulations that attempt to take similar approaches to algorithms and disparate impact—would allow lenders to circumvent liability under the FHA by heightening the plaintiff's burden of proof for algorithmic disparate impact discrimination. Section II.A provides an overview of the legislative history of the FHA and disparate impact liability post-*Inclusive Communities*. Section II.B then compares pre- and post-*Inclusive Communities* disparate impact liability in lending discrimination litigation. Lastly, section II.C assesses how HUD's Proposed Rule contravenes this history of disparate impact litigation and frustrates the purpose of the FHA, thus highlighting the need for greater statutory accountability for algorithmic disparate impact.

A. *Legislative History of the Fair Housing Act and Disparate Impact Post-* Inclusive Communities

While the FHA does not directly address artificial intelligence, the legislative history and language of the Act suggest that disparate impact claims are at the heart of the FHA and, therefore, should extend to algorithm-based disparate impact claims. The FHA was enacted in response to worsening racial segregation in American cities, exacerbated by government policies that were "facially neutral in themselves but ha[d] profound racial effects."[145] Congress sought to combat these effects by "enact[ing] legislation 'declaring that we have had the last of segregation in the sale and rental of living quarters in our country.'"[146] Senator Walter Mondale of Minnesota proposed a bill—"the precursor to the FHA"—that "included a provision making it unlawful 'to refuse to sell or rent . . . , *or*

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https://www.justice.gov/usao-sdny/pr/manhattan-us-attorney-settles-lending-discrimination-suit-against-jpmorgan-chase-53 [https://perma.cc/RLY4-CJGE] ("The [government] projects that, from at least 2006 through late 2009, certain of the approximately 106,000 African-American and Hispanic borrowers who obtained loans through independent mortgage brokers participating in Chase's wholesale channel paid higher rates and fees . . . [than] similarly situated white borrowers . . . .").

144. HUD's Implementation of the Fair Housing Act's Disparate Impact Standard, 84 Fed. Reg. 42, 854, 42,854 (proposed Aug. 19, 2019) (to be codified at 24 C.F.R. pt. 100).

145. Brief of Current & Former Members of Congress as Amici Curiae in Support of Affirmance at 3, Tex. Dep't of Hous. & Cmty. Affs. v. Inclusive Cmtys. Project, Inc., 135 S. Ct. 2507 (2015) (No. 13-1371), 2014 WL 7405734 [hereinafter Members of Congress Brief] (alteration in original) (internal quotation marks omitted) (quoting 114 Cong. Rec. 2688 (1968) (statement of Sen. Brooke)).

146. Id. at 7 (quoting 114 Cong. Rec. 2279 (1968) (statement of Sen. Mondale)).

otherwise make unavailable or deny, a dwelling to any person because of race, color, religion, or national origin.'"[147] This language of the bill, which was ultimately included verbatim in the FHA, focused on discriminatory *impact*—making housing unavailable to someone on account of a protected characteristic—as opposed to discriminatory intent.[148] With the FHA, Congress intended "to prohibit *all* forms of discrimination in housing—including actions having the effect of disproportionately denying housing based on a protected characteristic."[149] Similarly, Congress's rejection of the Baker amendment further illustrates that Congress did not intend for the FHA to cover only intentional discrimination.[150] The Baker amendment "would have expanded an exemption for individuals selling property without a real estate agent to also cover those who hired an agent but could not be proven to have intentionally discriminated in their use of that agent."[151] The Senate rejected the proposed amendment because "'it would require proof that a single homeowner had specified racial preference,' which 'would be impossible to produce.'"[152]

When Congress amended the FHA in 1988, it intended for the FHA to continue authorizing disparate impact claims, as evidenced by Congress's repeated rejections of proposed intent requirements.[153] For example, in 1980, Congress rejected a proposed amendment that "would have exempted minimum lot-size requirements from disparate-impact liability."[154] One senator expressed that an intent requirement "'would make a radical change in the standard of proof' for cases brought under the Act" and referenced "judicial decisions recognizing disparate-impact claims under Title VII—a statute that he called 'the functional equivalent of the fair housing law.'"[155] Congress again rejected proposals to add an intent requirement to the Act in 1981, 1983, and 1985.[156] By the time the Act was amended in 1988, nine federal circuit courts had held that disparate impact claims are cognizable under the FHA, and both HUD and the DOJ had also interpreted the Act similarly.[157] In light of this consensus, Congress amended the Act to include additional prohibited

147. Id. at 8 (emphasis added) (quoting S. 1358, 90th Cong. § 4(a) (1967)).

148. Id.; see also 42 U.S.C. § 3604(a) (2018) ("[I]t shall be unlawful to refuse to sell or rent after the making of a bona fide offer . . . or otherwise make unavailable or deny, a dwelling to any person because of race, color, religion, sex, familial status, or national origin.").

149. Members of Congress Brief, supra note 145, at 1.

150. Id. at 10.

151. Id. at 10–11 (citing 114 Cong. Rec. 5220 (1968)).

152. Id. at 11 (quoting 114 Cong. Rec. 5216 (1968) (statement of Sen. Percy)).

153. Id. at 13–14.

154. Id. at 14 (citing H.R. Rep. No. 96-865, at 36 (1980)).

155. Id. at 15 (quoting 126 Cong. Rec. 31,164 (1980) (statement of Sen. Bayh)).

156. Id. (citing S. 139, 99th Cong. § 6(e) (1985); 129 Cong. Rec. 808 (1983); 127 Cong. Rec. 22,156 (1981)).

157. Id. at 16 (citing United States v. City of Black Jack, 508 F.2d 1179, 1186 (8th Cir. 1974); 126 Cong. Rec. 31,166–67 (1980) (statement of Sen. Mathias)).

discriminatory practices and add familial status to the list of protected groups, but it did not include an intent requirement.[158] Instead, Congress also added "or to otherwise make unavailable or deny" to § 804(f)(1), language courts had unanimously held covers disparate impact claims.[159] Congress also significantly expanded HUD's power to enforce and implement the Act with the 1988 amendments and "did so fully aware that HUD had interpreted the Act to permit disparate-impact liability, which HUD had told Congress was 'imperative' to the Act's successful enforcement."[160] In fact, "HUD has *never* (either before 1988 or after) taken the position that the Fair Housing Act prohibits only overt discrimination,"[161] and, in February 2013, it "formalized its longstanding interpretation [of the FHA] by promulgating a final rule" that recognized disparate impact under the statute.[162]

While HUD, the DOJ, and eleven federal circuit courts had recognized disparate impact claims under the FHA by 2015, it was not until then that the Supreme Court formally recognized this interpretation.[163] In June 2015, the Supreme Court held in *Inclusive Communities* that the FHA prohibits not only intentional discrimination but also housing decisions with discriminatory effects on protected classes.[164] In its holding, the Supreme Court did not expressly adopt the standards for disparate impact established in HUD's 2013 final rule;[165] instead, it adopted a burden-shifting scheme consisting of three parts that in some ways reflects the regulatory standards.[166] First, the plaintiff has the burden of proving that a policy or practice caused or predictably will cause a discriminatory effect.[167] If the plaintiff satisfies that burden of proof, the burden shifts to

158. Id. at 17 (citing H.R. Rep. No. 100-711, at 89 (1988)).

159. Id. at 18; see also 42 U.S.C. § 3604(f)(1) (2018) (Fair Housing Act statute).

160. Members of Congress Brief, supra note 145, at 19 (quoting 126 Cong. Rec. 31,166–67 (1980)).

161. Id.; see also 24 C.F.R. § 100 (2019).

162. Members of Congress Brief, supra note 145, at 20; see also 78 Fed. Reg. 11460 (Feb. 15, 2013) (codified at 24 C.F.R. § 100) ("Through this final rule, HUD formalizes its long-held recognition of discriminatory effects liability under the Act and, for purposes of providing consistency nationwide, formalizes a burden-shifting test for determining whether a given practice has an unjustified discriminatory effect, leading to liability under the Act.").

163. Members of Congress Brief, supra note 145, at 2.

164. See Tex. Dep't of Hous. & Cmty. Affs. v. Inclusive Cmtys. Project, Inc., 135 S. Ct. 2507, 2524–26 (2015); see also Cong. Rsch. Serv., RL 95-710, The Fair Housing Act (FHA): A Legal Overview 7 (2016), https://www.everycrsreport.com/files/20160202_95-710_63c9f0069b35b1d2b24ab2ac04a8ccce94fa2645.pdf [https://perma.cc/KG8V-KAWL].

165. Cong. Rsch. Serv., supra note 164, at 8; see also *Inclusive Cmtys.*, 135 S. Ct. at 2525–26; 24 C.F.R. § 100.

166. See *Inclusive Cmtys.*, 135 S. Ct. at 2523–24; see also Cong. Rsch. Serv., supra note 164, at 8 ("The Court adopted a three-step burden-shifting test that shares some similarities with these standards.").

167. *Inclusive Cmtys.*, 135 S. Ct. at 2523 ("[A] disparate impact claim that relies on a statistical disparity must fail if the plaintiff cannot point to a defendant's policy or policies causing that disparity.").

the defendant to prove that the challenged policy or practice is "necessary to achieve a valid interest."[168] If the defendant satisfies this burden, the burden shifts back to the plaintiff to prove that the defendant's valid interest could be served by an alternative policy or practice that has a "less discriminatory effect."[169] The Court also "outlined a number of limiting factors that lower courts and HUD should apply when assessing disparate impact claims."[170] For example, "[B]efore a plaintiff can establish a *prima facie* case of discriminatory effect based on a statistical disparity, courts should apply a 'robust causality requirement' that requires the plaintiff to prove that a policy or decision led to the disparity."[171] The Court reasoned that this requirement helps avoid the "inject[ion] [of] racial considerations into every housing decision" and "protect[s] potential defendants against abusive disparate-impact claims."[172] The Court's new robust causality standard was already considered a challenge for future plaintiffs because it shifted the causal inquiry to the pleading stage,[173] but HUD's Proposed Rule further raises the standard for plaintiffs by changing the current three-prong burden-shifting framework to a five-part pleading standard and creating defenses specifically for algorithm-based disparate impact claims.[174]

B. *Disparate Impact Litigation Challenging Discriminatory Lending*

Not long after *Inclusive Communities*, disparate impact litigation challenging discriminatory lending emerged, but these early attempts to hold banks accountable failed to satisfy the Supreme Court's vaguely defined "robust causality" requirement.[175] For example, in *Bank of America Corp. v. City of Miami* and *Wells Fargo & Co. v. City of Miami*—consolidated for Supreme Court review—plaintiffs alleged that the banks had engaged in a decade-long practice of discriminatory and predatory lending.[176] Specifically, the City of Miami claimed that the banks had violated the FHA by targeting minority borrowers for high-risk, costly loans.[177] The banks, in

168. Id. at 2522–23.

169. Id. at 2514–15.

170. Cong. Rsch. Serv., supra note 164, at 9.

171. Id. at 9 (quoting *Inclusive Cmtys.*, 135 S. Ct. at 2523).

172. *Inclusive Cmtys.*, 135 S. Ct. at 2524.

173. See, e.g., Claire Williams, *Inclusive Communities* and Robust Causality: The Constant Struggle to Balance Access to the Courts with Protection for Defendants, 102 Minn. L. Rev. 969, 985–1017 (2017) ("[R]obust causality shifts . . . the focus from the prima facie stage to the pleading stage.").

174. See infra section II.C.

175. 135 S. Ct. at 2523 ("A robust causality requirement ensures that '[r]acial imbalance . . . does not, without more, establish a prima facie case of disparate impact' and thus protects defendants from being held liable for racial disparities they did not create." (quoting Wards Cove Packing Co. v. Atonio, 490 U.S. 642, 653 (1989))).

176. Bank of Am. Corp. v. City of Miami, 137 S. Ct. 1296, 1296 (2017).

177. Id. at 1298 ("The City's complaints charge that the Banks intentionally targeted predatory practices at African-American and Latino neighborhoods and residents, lending

turn, claimed that the City of Miami was not an "aggrieved person" who had been "injured by a discriminatory housing practice" within the meaning of the FHA.[178] Although the Eleventh Circuit had held that the banks' actions were the proximate cause of the harm because the banks could have reasonably foreseen the harm as consequence of their actions, the Supreme Court disagreed.[179] The Court held that the City of Miami is an "aggrieved person" authorized to bring a suit under the FHA,[180] but that "foreseeability alone is not sufficient to establish proximate cause under the FHA."[181] The Court remanded the case back to the Eleventh Circuit so that it could define "the contours of proximate cause under the FHA."[182] On remand, the Eleventh Circuit again found proximate causation and held that there was "some direct relation" between the city's injuries and the banks' alleged violations of the FHA.[183]

Two 2017 decisions from the Ninth Circuit Court of Appeals also shed light on the Court's robust causality standard in the context of disparate impact claims under the FHA. In *City of Los Angeles v. Bank of America Corp.* and *City of Los Angeles v. Wells Fargo & Co.*, plaintiffs alleged that the banks had violated the FHA.[184] In both cases, the City of Los Angeles argued that (1) the banks' "compensation scheme provided incentives for their loan officers to issue higher-amount loans," (2) the "marketing targeted low-income borrowers," and (3) the banks "failed to adequately monitor their

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to minority borrowers on worse terms than equally creditworthy nonminority borrowers and inducing defaults by failing to extend refinancing and loan modifications to minority borrowers on fair terms.").

178. Id. at 1301–09.

179. Id. at 1305 ("The Eleventh Circuit concluded that the City adequately pleaded that the Banks' misconduct proximately caused these financial injuries. The court held that in the context of the FHA 'the proper standard' for proximate cause is 'based on foreseeability.'" (quoting City of Miami v. Bank of Am. Corp., 800 F.3d 1262, 1279, 1282 (11th Cir. 2015))).

180. Id. at 1301.

181. Id. at 1305.

182. Id. at 1306.

183. City of Miami v. Wells Fargo & Co., 923 F.3d 1260, 1264 (11th Cir. 2019) (quoting *Bank of Am. Corp.*, 137 S. Ct. at 1306), vacated, 140 S. Ct. 1259 (2020). In March 2020, the Supreme Court vacated as moot the Eleventh Circuit's judgment following the City of Miami's voluntary dismissal of their lawsuits. See 140 S. Ct. 1259.

184. See City of Los Angeles v. Bank of Am. Corp., 691 F. App'x 464, 464–65 (9th Cir. 2017) ("The City of Los Angeles . . . appeals the district court's summary judgment rulings in favor of the Bank of America . . . and Countrywide Financial Corporation and Countrywide Home Loans, Inc. (collectively, 'Countrywide') on its claims that BOA and Countrywide violated the Fair Housing Act ('FHA') and were unjustly enriched."); City of Los Angeles v. Wells Fargo & Co., 691 F. App'x 453, 454 (9th Cir. 2017) ("The City sued under § 3605(a) of the FHA, which makes it unlawful for financial institutions like Wells Fargo 'to discriminate against any person in making available such a transaction, or in the terms or conditions of such a transaction, because of race [or] color.'" (quoting 42 U.S.C. § 3605(a) (2012))).

loans for disparities."[185] In the Bank of America case, the Ninth Circuit concluded that, while the City of Los Angeles had established a "statistical racial disparity" in lending through the testimony of its expert, the city "fell short . . . in failing to show a 'robust' connection between this disparity and any [Bank of America] or Countrywide facially-neutral policy."[186] The Ninth Circuit held that the city "failed to demonstrate how the first two policies were causally connected in a 'robust' way to the racial disparity, as they would affect borrowers equally regardless of race, and the third is not a policy at all."[187] In the Wells Fargo case, the court did not address whether the City of Los Angeles had actually established a statistical disparity and held that the city had also failed to show robust causality for the same reasons as in the Bank of America case.[188]

While these circuit court cases highlight the difficulty of satisfying the Court's robust causality standard, plaintiffs had successfully relied on the disparate impact theory of liability to challenge lending discrimination long before *Inclusive Communities*. For example, in a 2007 Florida case, *Beaulialice v. Federal Home Loan Mortgage Corp.*, the plaintiff, a woman of color, alleged that "[d]efendant's automated underwriting and credit scoring system [was] inherently discriminatory in that it contain[ed] racially discriminatory assumptions that [we]re embedded in the statistical formulas utilized to derive the underwriting decision."[189] Specifically, the plaintiff claimed that, as a result of the defendant's underwriting system, she was denied an $85,000 mortgage loan and forced to accept a loan on less favorable lending terms than would have been extended to a white borrower.[190] The loan company moved for summary judgment on multiple grounds, including that neither the FHA nor ECOA authorized a disparate impact claim.[191] The court, however, held that, while the Supreme Court had yet to decide the issue, the Eleventh Circuit had already held that disparate impact claims were recognized under the FHA.[192]

A similar case appeared before the District Court for the Northern District of Illinois in 2008. In *Zamudio v. HSBC North America Holdings, Inc.*, the plaintiff, a Mexican American man, was denied a loan application even after his residence was appraised at a higher value than was needed to qualify for the loan.[193] The plaintiff blamed the loan application rejection

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185. City of Los Angeles v. Bank of Am. Corp., 691 F. App'x at 465; City of Los Angeles v. Wells Fargo & Co., 691 F. App'x at 454–55.

186. City of Los Angeles v. Bank of Am. Corp., 691 F. App'x at 465 (quoting Texas Dep't of Hous. & Cmty. Affs. v. Inclusive Cmtys. Project, Inc., 135 S. Ct. 2507, 2523 (2015)).

187. Id.

188. See City of Los Angeles v. Wells Fargo & Co., 691 F. App'x at 454–55.

189. No. 8:04-CV-2316-T-24-EA, 2007 WL 744646, at *3 (M.D. Fla. Mar. 6, 2007).

190. Id. at *1.

191. Id. at *4.

192. Id. at *4 (citing Jackson v. Okaloosa Cnty., 21 F.3d 1531, 1543 (11th Cir. 1994)).

193. No. 07 C 4315, 2008 WL 517138, at *1 (N.D. Ill. Feb. 20, 2008).

on HSBC's automated underwriting and credit-scoring system.[194] Specifically, the plaintiff claimed that "racially discriminatory assumptions are embedded in the statistical formulas used to analyze credit information and ultimately form underwriting decisions."[195] HSBC argued that the plaintiff had failed to identify a specific discriminatory practice or policy, but the district court held that the plaintiff had identified the specific discriminatory practice to be HSBC's "use of specific credit attributes in its self-designed system of automated underwriting and credit scoring" and this was enough to meet pleading requirements.[196]

C. *The Impact of HUD's Proposed Rule on Disparate Impact Claims*

In August 2019, HUD published a Proposed Rule to amend its interpretation of the FHA's disparate impact standard.[197] In its press release announcing the Proposed Rule, HUD claimed that "[t]he proposed rule as amended would provide more appropriate guidance on what constitutes unlawful disparate impact to better reflect the Supreme Court's 2015 ruling in *Texas Department of Housing and Community Affairs v. Inclusive Communities Project, Inc.*"[198] HUD specifically claimed that the Proposed Rule "provide[d] a framework for establishing legal liability for facially neutral practices that have unintended discriminatory effects on classes of persons protected under the Fair Housing Act."[199] Yet, instead of clarifying *Inclusive Communities'* robust causality standard, HUD seems to be carving out a path by which lenders can circumvent liability for algorithmic disparate impact altogether. With its Proposed Rule, HUD raises the burden of proof for plaintiffs by changing the three-step burden-shifting framework to a five-step pleading standard and providing lenders with three seemingly insurmountable defenses. Section II.C.1 explains how HUD's Proposed Rule heightens the burden of proof for plaintiffs at the pleading stage. Sections II.C.2 and II.C.3 discuss the Rule's proxy and third-party defenses, respectively, and how these defenses are difficult for plaintiffs to overcome, particularly in algorithm-based discrimination claims.

1. *HUD's Heightened Burden of Proof for Plaintiffs.* —The Proposed Rule heightens the burden of proof for plaintiffs by requiring that several new elements be fulfilled at the prima facie stage. The Proposed Rule first requires that a plaintiff identify "a specific, identifiable, policy or practice" that has a discriminatory effect.[200] HUD makes clear that it will be

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194. Id. at *1–2.
195. Id. at *2.
196. Id.
197. Press Release, HUD, supra note 30.
198. Id.
199. Id.
200. HUD's Implementation of the Fair Housing Act's Disparate Impact Standard, 84 Fed. Reg. 42,854, 42,858 (proposed Aug. 19, 2019) (to be codified at 24 C.F.R. pt. 100).

"insufficient to identify a program as a whole without explaining how the program itself causes the disparate impact as opposed to a particular element of the program."[201] Once a specific policy has been identified, the Proposed Rule requires that the plaintiff plead facts supporting five elements: The first element is that the challenged policy or practice be "*arbitrary, artificial, and unnecessary* to achieve a valid interest or legitimate objective."[202] The second element requires that the plaintiff "allege a *robust causal link* between the challenged policy or practice and a disparate impact on members of a protected class."[203] Further, this second element also requires that "[c]laims relying on statistical disparities . . . articulate how the statistical analysis used supports . . . that the policy is the actual cause of the disparity."[204] The third element requires that the plaintiff "allege that the challenged policy or practice has an adverse effect on *members of a protected class* . . . as a group," as opposed to just a single member of a protected class.[205] The fourth element requires the "plaintiff to allege that the disparity caused by the policy or practice is *significant*."[206] Lastly, the fifth element requires the "plaintiff to allege that the *complaining party's alleged injury* is directly caused by the challenge[d] policy or practice."[207] HUD claims that this last element attempts "to codify the proximate cause requirement under the Fair Housing Act that there be 'some direct relation between the injury asserted and the injurious conduct alleged.'"[208] Because all of these elements need to be fulfilled at the prima facie stage, plaintiffs who do not meet this new standard will have their claims dismissed without ever reaching the discovery stage.[209]

HUD's proximate causation requirement (the second element) should have no place in disparate impact claims because it makes it particularly difficult for plaintiffs to succeed. First, the requirement reflects a general lack of understanding of how algorithms work. Causation tests are typically used to "limit the scope of far-reaching causes of action."[210] But when artificial intelligence is a black box (as are credit-scoring algorithmic models), "causation doctrines, such as proximate cause, fail because the causation inquiry will focus on what is foreseeable to the creator or user of the [artificial intelligence]."[211] Because the black

201. Id.

202. Id.

203. Id.

204. Id.

205. Id.

206. Id.

207. Id. at 42,859.

208. Id. (quoting Bank of Am. Corp. v. City of Miami, 137 S. Ct. 1296, 1306 (2017)).

209. See id. at 42,858 ("The proposed new burden-shifting framework provides, in paragraph (b), that a plaintiff's allegations that a specific, identifiable, policy or practice has a discriminatory effect must plead facts supporting five elements.").

210. Bathaee, supra note 76, at 922.

211. Id.

box makes it difficult for a user or creator of an algorithm model to reasonably foresee the result of the model's conduct, a proximate causation requirement makes it easy for a defendant to get away with liability for algorithmic discrimination by merely claiming that the disparate impact of the algorithm's decisions was unforeseeable. Presumably, if the user of a model reasonably foresaw discrimination and went on to use the model anyway, then the user *intentionally* discriminated, but the doctrine of disparate impact exists precisely to redress claims of *unintentional* discrimination.

Second, the requirement demands plaintiffs to prove, at the pleading stage, that the algorithm proximately caused the injury, a seemingly insurmountable obstacle for plaintiffs who may not have all of the information on how the defendant's algorithm model functions. For example, in *Hunt v. Aimco Properties., L.P.*, a post-*Inclusive Communities* case in which plaintiffs alleged discrimination under the FHA, the Eleventh Circuit reasoned that "[i]n a discrimination case, '[b]efore discovery has unearthed relevant facts and evidence, it may be difficult to define the precise formulation of the required prima facie case in a particular case.'"[212] The court held that "[a] complaint 'should be judged by the statutory elements of an FHA claim rather than the structure of the prima facie case,'"[213] and, in this case, plaintiffs had adequately stated a claim for failure to make a reasonable accommodation.[214]

HUD further complicates the proximate causation requirement by requiring plaintiffs to identify a "specific policy or practice" that had a discriminatory effect.[215] As the Second Circuit has previously explained, "the distinction between a single isolated decision and a practice [is] 'analytically unmanageable—almost any repeated course of conduct can be traced back to a single decision.'"[216] This would be particularly true in the context of algorithmic discrimination, in which an unexplainable interaction of multiple input factors is often the reason behind the disparate impact.[217] Plaintiffs are unlikely to be able to pinpoint this interaction, let alone explain it as the cause of the discrimination during the pleading stage.[218] Even outside the context of algorithmic discrimination, mortgage lending generally is a complex multi-step

212. 814 F.3d 1213, 1221 (11th Cir. 2016) (quoting Swierkiewicz v. Sorema N.A., 534 U.S. 506, 512 (2002)).

213. Id. (quoting Gilligan v. Jamco Dev. Corp., 108 F.3d 246, 250 (9th Cir. 1997)).

214. Id. at 1227.

215. HUD's Implementation of the Fair Housing Act's Disparate Impact Standard, 84 Fed. Reg. 42,854, 42,862 (proposed Aug. 19, 2019) (to be codified at 24 C.F.R. pt. 100).

216. Mhany Mgmt., Inc. v. County of Nassau, 819 F.3d 581, 619 (2d Cir. 2016) (quoting Council 31, Am. Fed'n of State, Cnty. & Mun. Emps., AFL-CIO v. Ward, 978 F.2d 373, 377 (7th Cir. 1992) (holding that a single action by an employer could be employment practice actionable under Title VII under the disparate impact theory)).

217. See supra sections I.C.1, I.C.3.

218. See generally supra sections I.C.1, I.C.3.

process that includes "advertising and outreach; pre-application inquiries; loan approval or denial; terms and conditions; and loan administration."[219] Discretion by multiple decisionmakers at each of these steps makes it difficult to isolate the singular practice or policy that led to the disparate impact.[220]

HUD's proximate causation requirement also entails requirements on the use of statistical evidence.[221] Disparate impact claims typically rely on "statistical proof . . . rather than proof of differing treatment based on protected factors."[222] Requiring plaintiffs to plead about statistical evidence before they have access to relevant data can lead to the unjustifiable dismissal of meritorious claims. For example, if a plaintiff cannot have access to relevant data that would point to discrimination across racial lines simply because the defendant does not collect such data, the plaintiff's meritorious claims might be dismissed. HUD's policy, then, would encourage even *intentional* discrimination because lenders would know that they would be able to circumvent liability by simply proving that they do not collect the data a plaintiff would need to plead about statistical evidence.

2. *The Proxy Defense.* — HUD's Proposed Rule creates three algorithmic defenses that also reflect a lack of understanding of how algorithms work.[223] The first, the proxy defense, states that a defendant can defeat an allegation of algorithm-based disparate impact by proving that the "material factors" used as inputs in the algorithm are not "substitutes or close proxies" for protected classes under the FHA and that the algorithm accurately predicts risk.[224] This defense ignores the fact that

219. Robert G. Schwemm & Jeffrey L. Taren, Discretionary Pricing, Mortgage Discrimination, and the Fair Housing Act, 45 Harv. C.R.-C.L. L. Rev. 375, 389 (2010).

220. See id. at 395–98 (describing the multiple steps and decisionmakers involved in discretionary pricing, a practice in which lenders allow their loan officers and brokers to increase borrowers' costs above an objectively determined rate).

221. See HUD's Implementation of the Fair Housing Act's Disparate Impact Standard, 84 Fed. Reg. 42,854, 42,858 (proposed Aug. 19, 2019) (to be codified at 24 C.F.R. pt. 100) ("Claims relying on statistical disparities must articulate how the statistical analysis used supports a claim of disparate impact by providing an appropriate comparison that shows that the policy is the actual cause of the disparity.").

222. Selbst, supra note 79.

223. See Jamie Williams, Saira Hussain & Jeremy Gillula, EFF to HUD: Algorithms Are No Excuse for Discrimination, Elec. Frontier Found. (Sept. 26, 2019), https://www.eff.org/deeplinks/2019/09/dangerous-hud-proposal-would-effectively-insulate-parties-who-use-algorithms [https://perma.cc/Q2DU-PW7H] ("HUD's proposal is flawed, and suggests that the agency doesn't understand how machine learning and other algorithmic tools work in practice. Algorithmic tools are increasingly relied upon to make assessments of tenants' creditworthiness and risk, and HUD's proposed rules will make it all but impossible to enforce the [FHA].").

224. HUD's Implementation of the Fair Housing Act's Disparate Impact Standard, 84 Fed. Reg. at 42,862 (stating a defendant may respond by "[providing] the material factors that make up the inputs used in the challenged model and show[ing] that these factors do

it is possible for an algorithm to be trained with facially neutral input factors that, when taken together, are an indicator—or proxy—of race;[225] therefore, an algorithm with neutral input factors may nonetheless be discriminatory. As Andrew Selbst, a leading scholar on the intersection of artificial intelligence and civil rights, explains, different input factors can interact to yield discriminatory results: "Algorithms present a more complex problem" because "[m]achine learning models rely on interaction *between* features to find unexpected patterns in the data, which can disproportionately harm people in disadvantaged groups . . . ."[226] How facially neutral factors interact with each other depends on how the algorithm is trained and, as Part I explains, algorithm developers can unintentionally reflect their biases in the algorithm models they create.[227] But even if the algorithm is accurately "predictive of credit risk," the FHA and other fair lending laws prohibit lenders from assessing creditworthiness in a discriminatory manner.[228] Thus, this defense allows lenders to evade liability by simply claiming that the algorithm model they used accurately measures credit risk.

3. *The Third-Party Defenses.* — HUD's second and third defenses, the third-party defenses, allow defendants to circumvent liability by claiming reliance on industry standards that do not exist. Specifically, HUD's third-party defenses allow defendants to defeat a claim of algorithmic discrimination by showing that (1) the algorithmic model is "produced, maintained, or distributed by a recognized third party that determines industry standards" or that (2) the algorithmic model "has been validated by an objective and unbiased neutral third party."[229] These defenses are invalid because there is currently no "industry standard" that algorithm developers should follow or "recognized third party" that lenders can rely upon to vet their algorithm models for bias.[230] Precisely because there is a lack of accountability, "third-party developers are free to design and implement algorithmic tools with no requirements to test the data sets or the algorithms that are used, no regulation, no oversight, and no clear standards by which to test the models against."[231] Algorithms are

not rely . . . on factors that are substitutes or close proxies for protected classes . . . and that the model is predictive of credit risk").

225. See supra section I.C.1.

226. Selbst, supra note 79; see also supra section I.C.1.

227. See supra section I.C.1.

228. HUD's Implementation of the Fair Housing Act's Disparate Impact Standard, 84 Fed. Reg. at 42,862.

229. Id.

230. Id.; see also Letter from AI Now Inst. & Ctr. on Race, Ineq. & L., to Off. of the Gen. Couns., HUD 9–12 (Oct. 18, 2019), https://ainowinstitute.org/ainow-cril-october-2019-hud-comments.pdf [https://perma.cc/75US-4QTK] [hereinafter Letter from AI Now Institute] ("There is no criteria that determines industry standards for standard-setting boards to follow when regulating algorithmic models. Even within the research community, there are ongoing debates about what standards or metrics should govern such models.").

231. Letter from AI Now Institute, supra note 230, at 11.

subsequently developed within a "black box," leaving plaintiffs with little knowledge as to how a particular model arrived at its decisions.[232] These third-party defenses are particularly problematic because defendants can use them as early as the pleading stage.[233] It is unlikely that a plaintiff will have access to critical information about a defendant's algorithm unless the defendant had previously disclosed it, making it difficult for plaintiffs to refute any claims about the algorithm a defendant might make.[234]

Yet, while there are no recognized third parties or industry standards, there are companies that have undoubtedly established themselves as industry leaders within the lending industry,[235] and HUD seems to have created these algorithm defenses with the intention of protecting and exempting the entire industry. For example, the language of Proposed Rule § 100.500(c)(2)(ii) seems to conveniently fit the automated underwriting systems of well-known lending and financial services companies, such as Fannie Mae's Desktop Underwriter[236] and Moody's CreditLens.[237] HUD suggests that when the defense applies, "the proper party responsible for the challenged conduct is not the defendant, but the party who establishes the industry standard."[238] HUD reasons that "suing the party that is actually responsible for the creation and design of the model would remove disparate impact from the industry as a whole," whereas suing the user "would only remove the model from use by one

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232. See supra section I.C.1.

233. HUD's Implementation of the Fair Housing Act's Disparate Impact Standard, 84 Fed. Reg. at 42,862 (beginning the section with, "A defendant, or responding party, may establish that a plaintiff's allegations do not support a *prima facie* case of discriminatory effect under paragraph (b) of this section, if: . . ." (emphasis added)).

234. For example, in *DeHoyos v. Allstate Corp.*, in approving a class-action settlement where plaintiffs claimed Allstate's credit-scoring algorithm was discriminatory, the court stated, "Allstate had never voluntarily disclosed its credit scoring algorithms prior to this settlement. Thus, there was presumably no avenue for independent observers to verify that Allstate was using the same scoring algorithm for its business as the credit scoring algorithm it disclosed in select states pursuant to state law." 240 F.R.D. 269, 305 (W.D. Tex. 2007).

235. See, e.g., FICO Score, supra note 54 (claiming that FICO Scores are used in over ninety percent of U.S. lending decisions and that ten billion FICO Scores are purchased annually and twenty-seven million are purchased daily).

236. Selling Guide, Fannie Mae (Aug. 7, 2018), https://www.fanniemae.com/content/guide/selling/b3/2/01.html [https://perma.cc/43GL-7X2C] ("Fannie Mae's automated underwriting system, Desktop Underwriter (DU), evaluates mortgage delinquency risk and arrives at an underwriting recommendation by relying on a comprehensive examination of the primary and contributory risk factors in a mortgage application.").

237. The CreditLens Solution, Moody's Analytics, https://www.moodysanalytics.com/microsites/the-creditlens-solution [https://perma.cc/8NPR-Z9ME] (last visited Sept. 2, 2020) ("The CreditLens platform is built on the latest technology with artificial intelligence . . . and machine-learning capabilities that help the solution learn as you use it. By digitizing and automating actions within the credit process, [CreditLens] speeds up the time it takes to process loan applications.").

238. HUD's Implementation of the Fair Housing Act's Disparate Impact Standard, 84 Fed. Reg. at 42,859.

party."[239] While a seemingly thoughtful rationale, this reasoning ignores that the FHA's fair lending provision covers only parties "engag[ed] in . . . [t]he making or purchasing of loans or providing other financial assistance" and so liability might not extend to those other "actually responsible" parties.[240] Under the FHA, it seems unlikely that the algorithm developer would be found liable if they did not directly engage in any real estate-related transaction, meaning that, in practice, Proposed Rule § 100.500(c)(2)(ii) makes it possible that nobody can be held liable.

The third-party defenses of the Proposed Rule also have broader implications. Affording a complete defense to lenders who claim that they used an algorithm developed by a third party will encourage lenders to continue outsourcing these services and discourage them from developing their own, perhaps improved, algorithmic models.[241] If lenders don't develop their own models and third-party developers go unchallenged, the general public's knowledge of these credit-scoring models will remain limited, and greater knowledge of how these models function and what makes them faulty is needed to improve their use within the lending industry.

Instead of furthering fair housing, these algorithmic defenses are contrary to the FHA because the text of the FHA does not indicate or even suggest that there should be a higher standard of proof when lending discrimination results from the use of an algorithm; in fact, the FHA makes no distinction between algorithm-based and nonalgorithmic discrimination. The Proposed Rule's proxy defense and third-party defenses are an obstruction to fair housing access.

III. CLOSING THE GAP

HUD's Proposed Rule makes it highly unlikely that future plaintiffs will succeed in their algorithm-based disparate impact claims. Thousands have recognized the harmful effect of the Proposed Rule on plaintiffs raising disparate impact claims under the FHA—the Proposed Rule drew 45,758 public comments,[242] many of them expressing concerns with the

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239. Id.

240. 42 U.S.C. § 3605 (2018).

241. See Kriston Capps, How HUD Could Dismantle a Pillar of Civil Rights Law, CityLab (Aug. 16, 2019), https://www.citylab.com/equity/2019/08/fair-housing-act-hud-disparate-impact-discrimination-lenders/595972 [https://perma.cc/T5ST-EUH8] ("If a bank isn't liable for [algorithmic discrimination], then it doesn't have any incentive to shop for a company that will guarantee that its algorithms won't discriminate. [Similarly], vendors who make automated decision-making systems don't have an incentive to . . . [ensure] that their products are safe from a liability perspective.").

242. FR-6111-P-02 HUD's Implementation of the Fair Housing Act's Disparate Impact Standard, Regulations.gov, https://www.regulations.gov/docket?D=HUD-2019-0067 [https://perma.cc/6BNY-XDA8] (last visited Aug. 27, 2020).

Proposed Rule and requesting that it does not pass.[243] Even if the Proposed Rule does not pass, however, HUD can continue to propose regulations with similar propositions, which is why the FHA's gap in the law—its failure to address algorithmic discrimination—requires more permanent solutions. As Part III argues, the FHA needs to be amended and there needs to be greater regulatory oversight of artificial intelligence.

A. *Amending the Fair Housing Act*

The FHA should be amended because regulatory responses have not adequately closed the gap in statutory accountability. While the FHA currently bars discrimination in the sale or rental of housing, its failure to acknowledge that algorithms can unintentionally cause this discrimination has left the door open for governmental agencies such as HUD to interpret *Inclusive Communities* as it wishes and to set the standard for raising algorithm-based disparate impact claims. It is precisely because the FHA does not address algorithmic discrimination that HUD has published this Proposed Rule addressing disparate impact and algorithms directly and purporting to align its interpretation of disparate impact under the FHA with *Inclusive Communities*.[244] HUD's Proposed Rule, however, hinders rather than aids plaintiffs' use of the disparate impact doctrine by heightening the plaintiffs' burden of proof and carving out bright-line defenses for lenders who use algorithm models to assess creditworthiness.[245] Because agency regulations, such as HUD's Proposed Rule, have been inadequate, the FHA should be amended to include a subsection addressing algorithm-based disparate impact specifically and causality standards more generally.

The FHA, which has not been amended since 1988,[246] should be amended to address the use of algorithms in the sale or rental of housing. Specifically, the FHA should outright bar algorithmic discrimination, whether intentional or unintentional, in the sale or rental of housing and in all real estate-related transactions. For example, subsection 804(a) of the FHA should include yet another subsection with language to the effect of "for the purposes of this subsection, the provision 'to refuse to sell or rent or to otherwise make unavailable' covers (1) facially neutral lending

243. Businesses, Policymakers, Advocates, Experts Submit Thousands of Comments Opposing HUD's Attack on Core Civil Rights Tool, Nat'l Fair Hous. All. (Oct. 23, 2019), https://nationalfairhousing.org/2019/10/23/businesses-policymakers-advocates-experts-submit-thousands-of-comments-opposing-huds-attack-on-core-civil-rights-tool [https://perma.cc/F4W8-7545].

244. See generally HUD's Implementation of the Fair Housing Act's Disparate Impact Standard, 84 Fed. Reg. at 42,854 ("This rule proposes to amend HUD's interpretation of the Fair Housing Act's disparate impact standard to better reflect the Supreme Court's 2015 ruling in [*Inclusive Communities*].").

245. See id. at 42,858–60.

246. Nat'l Fair Hous. All., The History of Fair Housing, Fair Hous. Act at 50, http://fhact50.org/history [https://perma.cc/G36G-TNS9] (last visited Aug. 27, 2020).

policies that have a disparate impact on members of a protected class and (2) algorithm-based lending policies or decisions that have a disparate impact on members of a protected class."

The FHA should also be amended to address causality standards more generally for algorithm-based disparate impact claims. Both *Inclusive Communities* and HUD's Proposed Rule impose a causality requirement—*Inclusive Communities*' robust causality requirement is meant to "protect potential defendants against abusive disparate-impact claims,"[247] and the Proposed Rule's "robust causal link" requirement purports to align HUD's disparate impact standard to that of *Inclusive Communities*.[248] But neither the Supreme Court nor HUD has clearly defined an adequate proximate causation standard for disparate impact claims, leaving the lower courts to define the contours of proximate causation.[249] Given, however, that algorithmic models by their nature involve a lack of transparency on what training data is being used and how input factors may be interacting to serve as proxies for protected characteristics,[250] proximate causation should have no place in algorithm-based disparate impact litigation. Plaintiffs should not bear the burden of proving that a specific policy or practice proximately caused the discriminatory effect. Instead, lenders and algorithm developers—who have greater knowledge of the algorithm's inner workings[251]—should bear the burden of proving that the algorithm model is unbiased. It is difficult to identify or challenge discrimination when it is unintentional and motivated by unconscious bias. Disparate impact is the strongest tool plaintiffs have to combat algorithmic discrimination, and if it is severely limited with burdensome pleading standards, there will be little accountability for users and developers of discriminatory credit-scoring systems.[252]

Amending the FHA to include clear statutory language stating that the FHA covers algorithm-based disparate impact in the lending industry will prohibit agencies like HUD from interpreting the FHA in a way that contravenes the statute's history and purpose. Some might argue that eliminating the causality standard for algorithm-based disparate impact claims will open the door to the very concern the Supreme Court

247. Tex. Dep't of Hous. & Cmty. Affs. v. Inclusive Cmtys. Project, Inc., 135 S. Ct. 2507, 2524 (2015).

248. HUD's Implementation of the Fair Housing Act's Disparate Impact Standard, 84 Fed. Reg. at 42,857–58 ("These amendments are intended to bring HUD's disparate impact rule into closer alignment with the analysis and guidance provided in *Inclusive Communities* as understood by HUD . . . .").

249. See, e.g., Williams, supra note 173, at 989–99 (arguing that the robust causality requirement in disparate impact litigation is flawed because it lacks guidance for lower courts).

250. See supra section I.C.1.

251. See supra section I.C.2.

252. See, e.g., supra section II.B (discussing four cases from the Ninth and Eleventh Circuits in which plaintiffs' claims failed to meet the robust causality standard set forth in *Inclusive Communities*).

expressed in *Inclusive Communities*—namely, that without the robust causality requirement, defendants might more easily be held liable for racial disparities they did not create.[253] This seems like an unlikely consequence, however, as plaintiffs would still have to meet basic pleading requirements and there would at least have to be a statistically demonstrable disparity on the basis of a protected class.[254]

B. *Regulatory Oversight of Artificial Intelligence*

The credit-scoring and mortgage-lending industries have been revolutionized by the rise of artificial intelligence and the expanded access to big data. Today, lenders are increasingly using algorithmic systems programmed with alternative nonfinancial data to evaluate the creditworthiness of prospective borrowers. While credit risk assessments used to be based solely on financial data, lenders are now inferring creditworthiness from data points that have little to no direct connection to an individual's financial history or ability to repay loans.[255]

These data-rich algorithms go largely unchecked because data privacy and artificial intelligence are woefully underregulated in the United States. Currently, there is no federal regulation of artificial intelligence in the United States, although there has been a strong push for it recently. In April 2019, lawmakers introduced the Algorithmic Accountability Act, sponsored by Senators Cory Booker and Ron Wyden.[256] The Act, aimed at regulating major companies with access to big data, calls for the Federal Trade Commission to develop regulations for evaluating "highly sensitive automated systems."[257] But the bill has stalled in Congress after being introduced in the House.[258] More recently, on January 13, 2020, the U.S. government published draft rules for the regulation of artificial intelligence.[259] The draft, which received only eighty-one public

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253. Tex. Dep't of Hous. & Cmty. Affs. v. Inclusive Cmtys. Project, Inc., 135 S. Ct. 2507, 2523 (2015) ("A robust causality requirement ensures that '[r]acial imbalance . . . does not, without more, establish a prima facie case of disparate impact' and thus protects defendants from being held liable for racial disparities they did not create." (quoting Wards Cove Packing Co. v. Atonio, 490 U.S. 649, 653 (1989), superseded by statute, Civil Rights Act of 1991, Pub. L. No. 102-166, 105 Stat. 1074)).

254. Id. ("A plaintiff who fails to allege facts at the pleading stage or produce statistical evidence demonstrating a causal connection cannot make out a prima facie case of disparate impact.").

255. See supra section I.C.

256. Adi Robertson, A New Bill Would Force Companies to Check Their Algorithms for Bias, Verge (April 10, 2019), https://www.theverge.com/2019/4/10/18304960/congress-algorithmic-accountability-act-wyden-clarke-booker-bill-introduced-house-senate (on file with the *Columbia Law Review*).

257. Id.

258. See Algorithmic Accountability Act of 2019, H.R. 2231, 116th Cong. (2019).

259. Joel Nantais, Federal Government Regulation of AI, Towards Data Sci. (Jan. 20, 2020), https://towardsdatascience.com/federal-government-regulation-of-ai-4fa08b7bd99a [https://perma.cc/FJN4-AB9M].

comments,[260] attempts to codify how government agencies, such as HUD, will regulate the use of artificial intelligence in the private sector, including banks and lending companies.[261] The draft memorandum sets out policy considerations for the application of artificial intelligence, including that applications of artificial intelligence "leverage scientific and technical information and processes," employ "consistent application of risk assessment and risk management," and serve in "already-regulated industries" with "appropriate disclosure and transparency" and consideration of the "impacts that [artificial intelligence] applications may have on discrimination."[262] The policies are general in nature and seem merely to offer guidance for the regulation of applications of artificial intelligence outside of the federal government without suggesting a more robust regulatory framework.[263] A good regulatory framework can provide broad guidance—that includes the goals articulated in the draft memo—while allowing for tailored implementation in different sectors. For example, the ECOA mandates that borrowers have a right to know the basis for credit denials,[264] but given the increasing use of algorithmic systems and alternative data to evaluate creditworthiness, this right isn't as helpful if it isn't accompanied by a right to know how credit outcomes are generally generated in the first place. Lenders who rely on algorithmic systems to evaluate creditworthiness should be required to provide information about the input data used to evaluate the individual and the general characteristics of the algorithmic system that generate the outcome, even if an explanation for the *specific* outcome cannot be made.

Regulation of artificial intelligence is a contested issue because both the technology and the law surrounding it are novel and evolving. Some critics of artificial intelligence regulation argue that too much regulation might stifle innovation in this developing area of technology;[265] others suggest that regulation of artificial intelligence may not be possible at all because "we don't have the code of ethics, laws, government accountability, corporate transparency and capability of monitoring . . .

260. FR-2020-00261 Draft Memorandum to the Heads of Executive Departments and Agencies, Guidance for Regulation of Artificial Intelligence Applications, Regulations.gov, https://www.regulations.gov/document?D=OMB-2020-0003-0001 [https://perma.cc/NEW8-CWPU] (last updated Jan. 13, 2020).

261. See Nantais, supra note 259.

262. Memorandum from Russell T. Vought, Acting Dir., OMB, to Heads of Exec. Dep'ts & Agencies 1–7, https://www.whitehouse.gov/wp-content/uploads/2020/01/Draft-OMB-Memo-on-Regulation-of-AI-1-7-19.pdf [https://perma.cc/E3D5-9FKP].

263. See id.

264. FICO, Know Your Rights, myFICO, https://www.myfico.com/credit-education/know-your-rights [https://perma.cc/2Y2X-7HYJ] (last visited Aug. 27, 2020).

265. See Andrea O'Sullivan, Don't Let Regulators Ruin AI, MIT Tech. Rev. (Oct. 24, 2017), https://www.technologyreview.com/s/609132/dont-let-regulators-ruin-ai (on file with the *Columbia Law Review*).

[this] space."[266] But artificial intelligence regulation is particularly important in the context of risk assessment because there are no industry standards for what constitutes a fair and unbiased algorithm.[267] Precisely because there are no such standards, the lending industry should be encouraged to ensure data quality and address algorithmic bias. Regulatory oversight of artificial intelligence can help ensure that model developers are at least taking precautions to mitigate any discriminatory effect.[268] In the meantime, organizations such as the Institute of Electrical and Electronics Engineers (IEEE)[269] and the Partnership on AI,[270] as well as company services such as Google's What-If Tool[271] and IBM's AI OpenScale,[272] have emerged to address issues of transparency and bias in artificial intelligence.

CONCLUSION

The United States has a long history of housing discrimination. But what used to be overt and intentional discrimination has now morphed

266. Michael Spencer, Artificial Intelligence Regulation May Be Impossible, Forbes (Mar. 2, 2019), https://www.forbes.com/sites/cognitiveworld/2019/03/02/artificial-intelligence-regulation-will-be-impossible/#100d3cf911ed [https://perma.cc/YEZ8-3835].

267. Selbst, supra note 79 (discussing the lack of industry standards for algorithms).

268. See Ricardo Vinuesa, Hossein Azizpour, Iolanda Leite, Madeline Balaam, Virginia Dignum, Sami Domisch, Anna Felländer, Simone Daniela Langhans, Max Tegmark & Francesco Fuso Nerini, The Role of Artificial Intelligence in Achieving the Sustainable Development Goals, 11 Nature Commc'ns 1, 1, 6 (2020), https://www.nature.com/articles/s41467-019-14108-y.pdf [https://perma.cc/2Z9P-DG67] ("The fast development of AI needs to be supported by the necessary regulatory insight and oversight for AI-based technologies to enable sustainable development. Failure to do so could result in gaps in transparency, safety, and ethical standards.").

269. The IEEE Global Initiative on Ethics of Autonomous and Intelligent Systems, IEEE Standards Assoc., https://standards.ieee.org/industry-connections/ec/autonomous-systems.html [https://perma.cc/Y74Y-AAER] (last visited Aug. 27, 2020) ("The IEEE Global Initiative's mission is, 'To ensure every stakeholder involved in the design and development of autonomous and intelligent systems is educated, trained, and empowered to prioritize ethical considerations so that these technologies are advanced for the benefit of humanity.'").

270. About Us, P'ship on AI, https://www.partnershiponai.org/about [https://perma.cc/GGF8-ABL6] (last visited Aug. 27, 2020) ("[We seek to] [a]ddress such areas as fairness and inclusivity, explanation and transparency, security and privacy, values and ethics, collaboration between people and AI systems, interoperability of systems, and of the trustworthiness, reliability, containment, safety, and robustness of the technology.").

271. What-If Tool, Google, https://pair-code.github.io/what-if-tool [https://perma.cc/93EL-XU75] (last visited Aug. 27, 2020) (providing an interactive visual interface by which developers and programmers of machine learning models "can test performance [of the models] in hypothetical situations, analyze the importance of data features, and visualize model behavior across multiple models and subsets of input data, and for different [machine learning] fairness metrics").

272. Janakiram MSV, IBM Wants to Make Artificial Intelligence Fair and Transparent with AI OpenScale, Forbes (Oct. 21, 2018), https://www.forbes.com/sites/janakirammsv/2018/10/21/ibm-wants-to-make-artificial-intelligence-fair-and-transparent-with-ai-openscale/#2869f8861251 [https://perma.cc/6U9H-T7J9].

into covert and unintentional disparate impact facilitated by the advent of artificial intelligence. The pervasiveness of artificial intelligence has changed the development of the housing market, as landlords and lenders increasingly rely on predictive analytics to evaluate loan applicants. These predictive tools, in the form of algorithmic models, are often unintentionally discriminatory. The increase in access to big data has resulted in algorithms that have been trained with massive amounts of data points that, when taken together, sometimes serve as proxies or close substitutes for protected classes.

While disparate impact claims under the FHA have historically been recognized by HUD and most federal circuit courts, the FHA makes no mention of algorithms or artificial intelligence. This results in a gap of statutory accountability within the FHA for disparate impact arising from algorithmic decisionmaking in the lending industry. The FHA's failure to directly address algorithmic disparate impact makes it possible for HUD, the very agency charged with enforcing the FHA, to interpret the statute's applicability to algorithmic decisionmaking in the lending industry as it sees fit. Instead of clarifying the Supreme Court's robust causality requirement in *Inclusive Communities*, HUD's Proposed Rule heightens the standard for plaintiffs raising disparate impact claims and creates defenses by which the lending industry can circumvent disparate impact liability. Even if the Proposed Rule does not pass, the Rule is an example of what can happen when the law does not catch up to technology, highlighting the need for a more permanent solution. Federal regulation of artificial intelligence can limit the amount of nonfinancial personal data lenders use to assess creditworthiness. More importantly, however, amending the FHA so that it explicitly extends disparate impact liability to algorithmic discrimination will prevent algorithm users and developers from circumventing liability merely because causation is difficult to establish and the algorithm discriminated unintentionally.