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Fintech and Race-Based Inequality in the Home Mortgage and Auto Financing Markets

Winnie F. Taylor

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INTRODUCTION

The racial gap in wealth in the United States is astonishing. A 2019 survey found that the typical White family has eight times the wealth of the typical African American family and five times the wealth of the typical Hispanic family.[1] Unfortunately, discrimination in the home mortgage market and the lending industry has contributed greatly to the inequality of wealth gap by limiting wealth accumulation opportunities for racial minorities. The magnitude of economic loss that racial minorities experience from discrimination in mortgage lending is exemplified in a recent study by researchers at the University of California, Berkeley (the "Berkeley Study").[2] These researchers tested home loans for the presence of racial discrimination and estimated its levels in home mortgage

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* Professor of Law, Brooklyn Law School. This essay is based in part on ideas expressed in my previous scholarship on the Equal Credit Opportunity Act and racial discrimination in consumer credit. I thank Julia Cummings and Colleen Cummings for their excellent research assistance. I also thank the Brooklyn Law School faculty research fund for its support. I dedicate this essay to Dr. Joe Copes, my mentor and enduring inspiration.

[1] Neil Bhutta et al., *Disparities in Wealth by Race and Ethnicity in the 2019 Survey of Consumer Finances*, BD. GOVERNORS FED. RES. SYS., (last updated Sept. 28, 2020) https://www.federalreserve.gov/econres/notes/feds-notes/disparities-in-wealth-by-race-and-ethnicity-in-the-2019-survey-of-consumer-finances-20200928.htm.

[2] *See* Robert Bartlett et al., *Consumer-Lending Discrimination in the FinTech Era* (Nat'l Bureau of Econ. Research, Working Paper No. 25943, 2019).

credit, the largest consumer-lending market for lenders.[3] Their findings show that fintech and traditional lenders charged otherwise equal Latinx and African American borrowers higher interest rates than White borrowers for purchase and refinanced mortgages, costing the minority borrowers $765 million yearly, for the same product.[4]

Fintech describes a diverse group of nonbank companies that use digital technology to modernize and simplify both the provision of financial services and the customer experience in interfacing with financial services providers. Advances in electronic systems are eliminating time and space restrictions on the delivery of financial services, lowering the cost for some innovative products, and providing the incentive for newly emerging companies to offer financial products on a highly competitive basis. In short, as stated by one influential observer of financial market trends, the new digital technology unlocks new possibilities for fully frictionless transacting.[5] By making financial transactions infinitely faster, easier, and cheaper, fintech lenders also offer new opportunities for financial inclusion and expanded access to financial services.[6] While fintech tools have great potential to deliver a wide range of analytically grounded financial services and simplified choices that can benefit racial minorities, they also have the potential to deprive individuals and communities of color of significant wealth accumulation. Although the Berkeley Study shows that the fintech lenders discriminated forty percent less than traditional lenders in the pricing of home loans, it is important to point out that this level of racial discrimination is still intolerable.[7] By using algorithmic mechanisms and data analytics to make their lending decisions, fintech innovations are poised to amplify the racial wealth gap. The worry is that as fintech firms continue to grow and eventually overtake the financial services industry, the racial wealth gap will become even wider given that home ownership is the primary source of wealth for most Americans.[8] The additional

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[3] *Id.*

[4] *Id.*

[5] *See* Saule T. Omarova, *New Tech v. New Deal: Fintech as a Systemic Phenomenon*, 36 YALE J. ON REGUL. 735, 745 (2019).

[6] *Id.*

[7] *See* Bartlett, *supra* note 2.

[8] *See* ERIC BELSKY & JOEL PRAKKEN, HOUSING WEALTH EFFECTS: HOUSING'S IMPACT ON WEALTH ACCUMULATION, WEALTH DISTRIBUTION AND CONSUMER SPENDING, JOINT CTR. FOR HOUS. STUD. (2004), https://www.jchs.harvard.edu/sites/default/files/w04-13.pdf.

concern is that fintech credit assessment tools will make it more difficult for consumers to prove race-based lending discrimination claims in the home mortgage market and beyond. The automobile financing market is especially noteworthy because unabated discrimination in this market may also have a deleterious effect on wealth accumulation of racial minorities. It is thus imperative that policymakers acknowledge and prioritize racial discrimination in fintech firms as an urgent problem requiring prompt legislative and law enforcement attention.

The Berkeley Study findings show that although fintech lenders reduced biases by removing face-to-face interactions, their lending assessment tools nevertheless produced worrisome statistical discrimination that disproportionately impacted racial minorities.[9] To be sure, both human judgment bias and statistical discrimination impede opportunities for racial minorities to accumulate wealth and otherwise advance economically. But under current fair lending law, race-based, disparate impact discrimination claims in consumer lending are difficult to prove, if allowed to be litigated at all.[10] And yet given the proliferation of fintech firms with their ability to produce racially disparate outcomes, statistical discrimination will eventually become the dominant form of racial discrimination that exists in American society. Faced with this potentiality, policymakers should unequivocally endorse impact theory as a necessary methodology for proving lending discrimination claims and clarify how impact proof standards can be met.

The purpose of this essay is to stimulate and add to the discussion regarding the need for lawmakers to mitigate potential racial discrimination in fintech algorithmic consumer lending. It questions whether the vast array of data included in fintech algorithms will increase proof difficulties for plaintiffs who litigate race-based, disparate impact lending discrimination claims. Furthermore, it argues that proof difficulties present the ultimate challenge to achieving racial justice in consumer credit transactions because if this challenge is not met, price inequities will likely continue to economically devastate individuals and communities of color as they navigate the fintech marketplace. The essay is not intended to provide definitive answers to the racial discrimination questions fintech lending raises. Rather, its purpose is to shed light on why it is important that legislatures and fair lending

[9] *See* Bartlett, *supra* note 2.

[10] *See infra* Part VI.

enforcement officials consider in greater depth the problem of discriminatory algorithms and their effects on racial minorities. The home mortgage and automobile loan markets are highlighted to explore the concerns raised in this essay because houses and cars are likely to be the two most expensive assets consumers will own.

The essay proceeds as follows. Part I provides a brief historical overview of how the home mortgage policies and practices of the federal government and traditional banks contributed to the current racial wealth gap. Part II explains how traditional lenders make their credit decisions. This Part provides a backdrop for comparing traditional lender decision making with fintech credit assessment tools, which are discussed in Part III. Part III describes algorithmic scoring systems that fintech firms use to make their lending decisions and demonstrates why policymakers must scrutinize algorithmic data inputs and the structural design of algorithms to determine if they generate racial disparities. Part IV emphasizes why racial discrimination in fintech lending is an urgent problem that lawmakers should promptly address. This Part also analyzes how the problem of discriminatory algorithms exacerbates proof difficulties for plaintiffs who litigate racial discrimination claims based on lending disparities. Part V explores the problem of racial inequity in automobile financing and explains why lawmakers should address concerns about discriminatory lending practices in this market with greater nuance than has characterized their efforts to date. Part VI analyzes the problem of proving lending discrimination claims. As Part VII concludes, this essay underscores the need for policymakers to critically examine predictive analytics and machine learning decision making with the aim of eliminating their ability to further deplete the wealth of racial minorities. Also, at the federal level, the essay urges Congress to mandate the collection of race data in the automobile finance market so that plaintiffs with race-based discrimination claims against creditors that provide auto loans can have a realistic chance of proving their claims under federal fair lending law.

I. PART I: HISTORICAL RACE-BASED INEQUALITY IN MORTGAGE LENDING

Racial discrimination in mortgage lending has a long and varied history that is directly linked to the racial wealth gap. Notably, the federal government has played a key role in erecting racialized home mortgage barriers. For instance, the Federal Housing Administration (FHA), which President Franklin Roosevelt

and the U.S. Congress created to help stabilize the economy following the Great Depression, discriminated against racial minorities when it provided mortgage assistance to struggling Americans.[11] Specifically, beginning in the 1930s, the FHA implemented practices that helped White families obtain home ownership but failed to similarly help African Americans and other minorities.[12] Thus, by adopting policies that served only White families until 1968, the FHA racialized the housing market and systemically wrote people of color out of home ownership.[13] Racial exclusion of minorities from the home mortgage market at the federal level is also reflected in governmental conduct associated with the GI Bill, legislation Congress enacted in 1944 to help veterans prosper after World War II.[14] Although a major part of the GI Bill guaranteed low interest, home mortgage loans to veterans, White veterans were the primary beneficiaries of this governmental program.[15] In sum, for decades, the assistance of the federal government permitted White Americans to accumulate assets through the housing market. The exclusion of people of color from such home ownership opportunities has had a lasting effect on their wealth portfolios.

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[11] National Housing Act, Pub. L. No. 73-479, 48 Stat. 1246 (1934).

[12] *See* Brian Gilmore, *Home is Where the Hatred is: A Proposal for a Federal Housing Administration Truth and Reconciliation Commission*, 10 U. MD. L.J. RACE RELIG. GENDER & CLASS 249, 263–67 (2010) (giving examples of biased FHA policies, including the policy of giving neighborhoods grades based upon racial composition).

[13] *Id.*

[14] Servicemen's Readjustment Act of 1944, Pub. L. No. 78-34, 58 Stat. 284.

[15] Florence Wagman Roisman, *National Ingratitude: The Egregious Deficiencies of the United States' Housing Programs for Veterans and the "Public Scandal" of Veterans' Homelessness*, 38 IND. L. REV. 103, 149 (2005) ("Less than 2 per cent of the housing financed with federal mortgage assistance from 1946 to 1959 was available to [Black Americans]. Moreover, housing financed by the VA (and FHA) was strictly segregated on the basis of race, so that the few such homes that were available to non-whites were in non-white neighborhoods."); Lynnise E. Phillips Pantin, *The Wealth Gap and the Racial Disparities in the Startup Ecosystem*, 62 ST. LOUIS U. L.J. 419, 432 (2018) (noting that local administration of benefits allowed for discrimination); Juan F. Perea, *Doctrines of Delusion: How the History of the G.I. Bill and Other Inconvenient Truths Undermine the Supreme Court's Affirmative Action Jurisprudence*, 75 U. PITT. L. REV. 583, 596 (2014) (although the housing benefits under the GI Bill would've guaranteed "up to 50% of loans made by private banks and lending institutions to veterans," most banks would not loan to Black Americans, depriving Black veterans from reaping the benefits of the legislation).

Private financial institutions also used tactics that contributed to the race-based wealth gap. Like the FHA, some lenders practiced "redlining"—the refusal to grant mortgage loans in certain neighborhoods due to the race or ethnicity of the residents who live there."[16] Other lenders engaged in so called "reverse redlining" by deliberately seeking out minority borrowers for mortgage credit.[17] These lenders regularly targeted members of minority groups for the specific purpose of making toxic loans with grossly unfair terms and harmful effects.[18] During the 2008 financial crisis, many subprime lenders used this tactic to victimize racial minorities.[19] Their unscrupulous conduct resulted in massive foreclosures in minority communities.[20] According to Mehrsa Baradaran, a banking law scholar, the 2008 financial crisis disproportionally affected Black communities by wiping out fifty-three percent of total Black wealth.[21]

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[16] *See* Gene A. Marsh, *Lender Liability for Consumer Fraud Practices of Retail Dealers and Home Improvement Contractors,* 45 ALA. L. REV. 1, 15 (1993) (discussing the historical origin of the term "redlining"); *see also* United States v. Decatur Fed. Sav. and Loan Assn., No. 1 92-CV-2198-CAM, P-H: Fair Housing-Fair Lending Rptr.(N.D. Ga. 1992) (regarding consent decrees between governmental fair lending enforcement agencies and private lenders); United States v. Chevy Chase Fed. Sav. Bank, No. 9-1-1824 JG, P-H: Fair Housing-Fair Lending Rptr. (D.D.C. 1994); United States v. Albank FSB., C.A. No. 97-CV-1206, P-H Fair Housing-Fair Lending Rptr. 19,401 (N.D.N.Y. 1997); United States v. First Am. Bank, No. 1:04-cv-4585 (N.D. Ill. 2004); United States v. Centier Bank, No. 2:06-cv-344 (N.D. Ind. 2006); United States v. First Merch. Bank, No. 1:19-cv-02365-JPH-MPB, 2019 WL 3779768 (S.D. Ind. 2019).

[17] "Reverse redlining" is the practice of extending credit on unfair terms to specific geographic areas due to the income or ethnicity of its residents. *See* Linda Fisher, *Target Marketing of Subprime Loans: Racialized Consumer Fraud & Reverse Redlining,* 18 J.L. & POL'Y 121, 127 (2009) (explaining that the term "reverse redlining" refers to an inversion of the older practice of "redlining," which is the practice of excluding minority neighborhoods altogether from mortgage lending).

[18] *Id.*; *see also* Winnie F. Taylor, *Eliminating Racial Discrimination In The Subprime Mortgage Market: Proposals For Fair Lending Reform,* 18 J.L. & POL'Y 263, 274 (2009) (discussing Department of Justice reverse redlining lawsuit against Long Beach Mortgage Company).

[19] *See* Fisher, *supra* note 17.

[20] *See* DEBBIE BOCIAN ET AL., FORECLOSURES BY RACE AND ETHNICITY 6 (Center for Responsible Lending, 2010).

[21] MEHRSA BARADARAN, THE COLOR OF MONEY: BLACK BANKS AND THE RACIAL WEALTH GAP 249 (2017).

Whether discrimination in fintech algorithmic decision making will likewise cause tremendous economic harm to minority individuals and communities of color is the concern this essay raises. To effectively address this concern and ensure that new and innovative lenders do not fall into the same discriminatory lending patterns exhibited by traditional banks, policymakers must critically examine the fintech underwriting process. Parts II and III below briefly explore this component of fintech lending by comparing the fintech decision making process with that of conventional lenders. This comparison illuminates the potential economic harm that fintech loan underwriting systems pose to racial minorities.

II. PART II: JUDGMENTAL CREDITWORTHINESS EVALUATION AND CONVENTIONAL SCORING SYSTEMS

Judgmental and statistical scoring systems are the two types of evaluation systems lenders use to determine an applicant's creditworthiness, that is, whether an applicant is a suitable risk for credit extension.[22] Judgmental scoring involves a subjective process whereby a credit manager reviews information contained in an applicant's credit file and thereafter evaluates the applicant's ability and willingness to repay the loan. Typically, credit managers consider information such as home ownership, credit references, and payment history. After reviewing this information, they make professional judgments to grant or deny credit, relying in part on their past experiences as credit risk evaluators.[23] Explicit and implicit racial bias inevitably infects this type of human decision-making process, as the Berkeley Study confirms.[24]

Most lenders have probably abandoned the laborious task of judgmentally making loan decisions on a case-by-case basis. Instead, they automate decision making by using statistical scoring systems. Statistical scoring systems employ empirical techniques to predict the probability that a loan applicant will repay.[25] The FICO credit score is the archetypical automated underwriting

[22] *See* Winnie F. Taylor, *Meeting the Equal Credit Opportunity Act's Specificity Requirement: Judgmental and Statistical Scoring Systems*, 29 BUFF. L. REV. 73, 86 (1980).

[23] *Id.* at 86.

[24] Bartlett, *supra* note 2.

[25] Taylor, *supra* note 22, at 88.

predictor.[26] Certain credit-based data such as payment history, amounts owed, new credit, and types of credit are fed into computers to produce the FICO credit score.[27] Unsurprisingly, automated creditworthiness assessments based primarily on information associated with established credit histories disproportionately exclude minorities due to historical racial bias.[28]

III. PART III: CREDITWORTHINESS EVALUATION IN THE FINTECH ERA AND ALGORITHMIC DECISION MAKING

In the modern lending environment, algorithms and big data are key components of the underwriting process. In fact, these features distinguish fintech statistical scoring systems from conventional credit scoring models. Although "big data" does not have a uniform definition, it generally refers to the analysis of large, complex datasets that are collected from numerous sources.[29] Importantly, fintech firms do not rely exclusively on credit scores or credit history data to evaluate credit applicants. Instead, they employ algorithms that make creditworthiness predictions from massive combinations of big data acquired from traditional and nontraditional sources. Nontraditional data sources might include utility and cell phone bills, as well as rental payments, information that conventional lenders usually ignore. By drawing on a broader range of predictive variables than conventional statistical scoring systems, fintech firms have the potential to make mortgage and other forms of credit increasingly available to underserved individuals and communities. This is certainly good news for people of color. But accolades for greater inclusion and accessibility are greatly diminished by the reality that fintech firms nevertheless

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[26] The FICO credit score is a number that represents the creditworthiness of a person, that is, the likelihood that a person will repay her debts. *See generally,* Shweta Arya et al., *Anatomy of the Credit Score*, 95 J. ECON. BEHAV. & ORG. 175, 175 (2013).

[27] *Id.*

[28] MATT FELLOWS, CREDIT SCORES AND REPORTS: GETTING AHEAD IN AMERICA 9-10 (2006).

[29] *Big Data: What It Is and Why It Matters*, SAS INSTITUTE INC., https://www.sas.com/en_us/insights/big-data/what-is-big-data.html (last visited May 15, 2021) (defining "big data" as a term to describe the "large volume of data – both structured and unstructured – that inundates a business on a day-to-day basis").

discriminate in home loan pricing, thereby costing racial minorities millions, as the Berkeley researchers found. This reality check cautions against fully celebrating fintech lending inclusiveness before the pricing discrimination issue is squarely addressed.

Why algorithms produce racially disparate outcomes is an important question. Racialized input data may be the culprit. For instance, if lenders ask credit applicants for their racial classification and include this information in algorithms, this data would likely generate biased results. But even when the input data is not obviously racialized, algorithmic scoring models could produce biased outcomes. As one scholar points out, algorithmic input data could include proxies for race that might be found in relatively innocuous activities such as web-browsing behavior.[30] Accordingly, web searches for historically Black colleges and universities (HBCUs), Black female judges, or for a notorious Latinx food brand such as "Goya" might correlate with race and therefore embed racial bias into outcomes if such information is included in algorithmic datasets. Similarly, algorithms that include Facebook "likes" may contain input data that signal race or ethnicity. In one fascinating study using Facebook "likes" to determine racial identity, African Americans and White Americans were correctly classified in ninety-five percent of cases.[31] Zip code information can also be associated with race due to the nation's history of segregated housing patterns.[32] It is therefore important that algorithms exclude zip codes because they can be used as race proxies for Caucasian, African American, and other racial classifications.[33] This is not to say that fintech algorithmic credit assessments presently include zip codes or information obtained from tracking consumer technological devices. The point made here is that algorithms must be carefully scrutinized because they may contain facially neutral information that in fact reflects and replicates existing

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[30] Anupam Chander, *The Racist Algorithm?*, 115 MICH. L. REV. 1023, 1038 (2017).

[31] *Id.* (citing Michael Kosinski ET AL., *Private Traits and Attributes Are Predictable from Digital Records of Human Behavior,* 110 PROC. NAT'L ACAD. SCI. 5802, 5802 (2013).

[32] James A. Kushner, *The Fair Housing Amendments Act of 1988: The Second Generation of Fair Housing,* 42 VAND. L. REV. 1049, 1050-51 (1989); *see also,* Brian J. Connolly, *Promise Unfulfilled? Zoning, Disparate Impact, and Affirmatively Furthering Fair Housing,* 48 URB. L. 785, 789-96 (2016) (providing a historical account of past and present segregation in housing).

[33] Chander, *supra* note 30, at 1038.

discrimination generated from race proxy data.[34] Some scholars argue that no matter how diligent the effort, it is impossible for algorithms to exclude all information associated with past discrimination, such as credit history information which historically favors White Americans. They therefore conclude that algorithms are inherently racist.[35]

Independently of racialized data inputs, proxy or otherwise, the internal workings of the huge datasets that comprise algorithms may account for the racial disparities they generate. Scholars who hold this view argue that structural flaws in the way algorithms are designed cause biased results. They contend that the biased results emerge from data that may not in any way appear to be correlated with race or past discrimination when used alone but may be highly correlated with race when evaluated in conjunction with other information.[36] Proponents of this view emphasize that algorithms are designed to make lending decisions from the amalgamation of huge datasets and that it is this mixture that causes discriminatory outcomes, not credit analyses that are being skewed by racial input data.[37] The core of this argument appears to be that, due to design flaws, algorithms produce racial bias without any impermissible data inputs, which seems to make them insidious discriminators. According to artificial intelligence expert Frank Pasquale, algorithmic discrimination is indeed deeply troubling because the discrimination "is hidden behind subtle manipulations that are nearly impossible to discern for ordinary citizens not privy to the internal computer code."[38] Pasquale's reference to coding suggests that an examination of input data will not alone determine why algorithms produce racial disparities. That

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[34] Chander, *supra*, note 30, at 1036 (discussing what she calls the problem of viral discrimination—that algorithms simply compound the errors of the past).

[35] Deirdre K. Mulligan & Kenneth A. Bamberger, *Procurement as Policy: Administrative Process for Machine Learning,* 34 BERKELEY TECH. L.J. 773, 787 (2019); Matthew Adam Bruckner, *Fintech's Promises and Perils the Promise and Perils of Algorithmic Lenders' Use of Big Data,* 93 CHI. KENT L. REV. 3, 29 (2018).

[36] Jon Kleinberg ET AL., *Discrimination In The Age Of Algorithms,* 10 J. LEGAL ANALYSIS 1, 24 (2018).

[37] Bruckner, *supra* note 35, at 29; Ignacio N. Cofone, *Algorithmic Discrimination Is an Information Problem,* 70 HASTINGS L.J. 1389, 1404-05 (2019).

[38] FRANK PASQUALE, THE BLACK BOX SOCIETY: THE SECRET ALGORITHMS THAT CONTROL MONEY AND INFORMATION, 38 (2015).

determination can only be made by understanding the algorithmic coding apparatus, that is, understanding how algorithms are built.

Besides racialized data inputs and structural design flaws, there may be other ideas that explain why algorithms produce racial disparities. Lawmakers should fully explore this topic.

IV. PART IV: RACIAL DISCRIMINATION IN FINTECH LENDING: AN URGENT PROBLEM THAT NEEDS ADDRESSING

Whether algorithms perpetuate past credit bias or generate their own biased results, it is clear that they can produce racial disparities. The pricing discrimination the Berkeley Study revealed makes it difficult to ignore the economic risks that fintech firms pose to racial minorities, despite their potential to make mortgage credit more inclusive. The ultimate challenge for policymakers in combatting racial discrimination in fintech lending is to determine how to sever the harmful aspects and leave intact the beneficial services. To begin, financial regulators should regard algorithmic lending discrimination as a systemic problem and develop a holistic plan to address it. The plan should embrace the possibility that both input data and design flaws contribute to racially discriminatory outcomes in fintech risk assessments. To root out this discrimination, fintech algorithms must be vigilantly studied, monitored, and analyzed. Hopefully, this vigilance will reveal ways to adjust the input variables to eliminate any racial discrimination they generate and identify design flaws that can be corrected to achieve equitable results. Admittedly, trying to understand the inner workings of algorithms by opening up their black box structure is likely to present a formidable challenge to financial regulators. One potential barrier to obtaining greater transparency is the possibility that algorithmic input data and information about how algorithms function may be proprietary and subject to trade secret protection that exempts disclosure.[39] Legislative action may be required to make the data available to fair lending officials. Ultimately, greater transparency is needed to properly examine and monitor algorithms for racial discrimination, assuming they are not too complex to understand. The goal of the federal plan should be to discover ways to detect and eliminate the racially discriminatory effects of algorithmic credit assessments.

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[39] Robert Brauneis & Ellen P. Goodman, *Algorithmic Transparency for the Smart City*, 20 YALE J.L. & TECH. 103, 153-54 (2018).

With respect to detecting discrimination, some academic researchers believe that algorithms can be properly constructed to root out the sources that cause racially disparate outcomes. They argue that:

> [t]o understand how algorithms affect discrimination, we must understand how they affect detection of discrimination. With the appropriate requirements in place, algorithms create the potential for new forms of transparency and hence opportunities to detect discrimination that are otherwise unavailable——This implies algorithms are not only a threat to be regulated; with the right safeguards, they can be a potential positive for equity.[40]

Paradoxically, it may be that algorithms themselves hold the keys to addressing the racially discriminatory effects they produce. Fair lending enforcement officials should explore this possibility. In particular, they should examine and test the effectiveness of so-called "repair algorithms."[41] These innovative algorithmic models are specifically designed to detect racial discrimination in other algorithmic models.

If effective, repair algorithms and similar innovations should help regulators address the additional problem that fintech lending exacerbates, which is the problem of proving race-based lending discrimination claims. As discussed in Part III, fintech algorithms use big data variables to make their lending decisions.[42] These huge datasets will likely increase the difficulty of pinpointing the specific source of the racial discrimination that emanates from algorithms, unless innovative detection methods are employed. Fintech lending thus elevates concerns about how to prove racial discrimination claims.

V. PART V: *BRONX HONDA*, AUTO FINANCE DISCRIMINATION, AND MISSING RACE DATA

The extent to which fintech firms can hide illegal racial discrimination by using huge datasets in algorithmic risk assessment models should be a major concern of racial justice advocates. This concern should not be confined to home mortgage lending. It also

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[40] Kleinberg, *supra* note 36, at 1.

[41] *See generally,* Michael Feldman et al, *Certifying and Removing Disparate Impact* (2015), https://arxiv.org/pdf/1412.3756.pdf.

[42] *See id.,* Part III.

arises in the automobile financing industry. Claims of racial discrimination in auto financing merit heightened regulatory attention for several reasons. First, automobiles are the most expensive assets consumers own, second only to houses.[43] Second, over ninety-five percent of American households report having access to at least one automobile and most consumers finance their auto purchases.[44] Third, access to reliable transportation is a vehicle for higher wages and crucial to the livelihoods of most consumers.[45] Legal scholar Pamela Foohey describes the evolving fintech market for auto sales and argues that unless the government steps in to support consumers in the emerging new "car economy," new innovations will continue to be detrimental to consumers.[46]

Discriminatory pricing in the auto loan market is costly and therefore can cause significant economic harm to racial minorities. There is growing concern that in the fintech era, creditor reliance on big data, algorithms, and machine learning to make lending decisions will exacerbate this harm.[47] One way that fintech auto lending can harm consumers is by making it more difficult for plaintiffs to prove racial discrimination claims. Proving racial discrimination is especially challenging in litigation involving automobile financing because unlike home mortgage credit, race data is largely unavailable in nonmortgage credit transactions. The Home Mortgage Disclosure Act (HMDA) requires home mortgage lenders to collect race data from borrowers, however, there is no such collection requirement when consumers seek car loans.[48] In

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[43] *See* Pamela Foohey, Robert M. Lawless, & Deborah Thorne, *Driven to Bankruptcy*, 55 WAKE FOREST L. REV. 287, 289-90 (2020).

[44] *See* Adam Levitin, *The Fast and the Usurious: Putting the Brakes on Auto Lending Abuses,* 108 GEO. L. REV. 1257, 1259.

[45] Statement of FTC Commissioner Rohit Chopra (2020), https://www.ftc.gov/system/files/documents/public_statements/1576002/bronx_honda.

[46] Pamela Foohey, *Consumers' Declining Power in the Fintech Auto Loan Market*, 15 BROOK J. CORP. FIN. & COM. L. 2 (2020).

[47] *Id.* at 2.

[48] *See generally* Home Mortgage Disclosure Act of 1975, Pub. L. No. 94-200 89 Stat. 1125 (1975) (codified at 12 U.S.C. §§ 2801-10 (2006)). Congress enacted the HMDA in 1975 to address the issue of whether minority borrowers were denied mortgage loans more frequently than white borrowers and whether those disparities, if any, reflected discrimination in financial institutions' lending practices. Winnie F. Taylor, *Eliminating Racial Discrimination in the Subprime Mortgage Market: Proposals for Fair Lending Reform,* 18 J.L. & POL'Y 263 (2009). In 1989, Congress amended the HMDA to require lenders to collect and

fact, the federal Equal Credit Opportunity Act (ECOA) prohibits lenders from obtaining a credit applicant's race.[49] I argued in earlier work that Congress should amend the ECOA and thereby mandate the collection of race data in financed auto purchases because of the persistent claims of discrimination in this nonmortgage credit market, and because of the grave disadvantage ECOA plaintiffs experience when they attempt to prove race-based lending discrimination claims without this crucial data.[50] The inability to make accurate racial comparisons can be fatal to the plaintiffs' claims.

The structure of auto loans is an additional reason why financed auto sales are ripe for regulatory scrutiny in the fintech lending environment. This structure relates to the compensation arrangement between dealers and indirect lenders that finance auto purchases. A recent case highlights the potential economic harm that this arrangement poses to racial minorities. Last year, the Federal Trade Commission (FTC) filed a complaint against Liberty Chevrolet, a New York City automobile dealership doing business under the name "Bronx Honda."[51] The complaint contained numerous allegations of illegal conduct, including a claim of racial discrimination in violation of the ECOA. With respect to the racial discrimination claim, the complaint included the following allegation:

> Defendants have instructed sales personnel to charge African American and Hispanic consumers higher markup and additional fees, leading to higher prices for vehicles. Defendants have instructed personnel to perform these practices with African American and Hispanic consumers only, stating that these consumers have limited education. Defendants have told their employees not to attempt these practices with non-Hispanic white consumers. Defendants also have used derogatory terms to refer to African American and Hispanic consumers—

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report information about the race, sex, and income of applicants for home mortgage loans. *See* Home Mortgage Disclosure Act, 12 C.F.R. pt. 1003 (1989).

[49] Equal Credit Opportunity Act (ECOA), 15 U.S.C. § 1691(a) (2017).

[50] *See* Winnie F. Taylor, *Proving Racial Discrimination and Monitoring Fair Lending Compliance: The Missing Data Problem in Nonmortgage Credit*, 31 B.U. REV. BANKING & FIN. L. 199 (2011).

[51] Complaint, FTC v. Liberty Chevrolet, No. 20-CV-3945 (S.D.N.Y. May 21, 2020) https://www.ftc.gov/system/filrs/documrnts/cases/bronx_honda_complaint. (2020).

—African American consumers were charged about $163 more in interest than similarly situated non-Hispanic white consumers, while Hispanic consumers were charged about $211 more in interest.[52]

Pursuant to an agreement for Bronx Honda to pay $1.5 million to victims of the dealership's illegal conduct, the case ended with a settlement in May 2020.[53]

The compensation scheme in *Bronx Honda* is widely used in the auto financing industry. It involves conduct between auto dealers and auto finance companies whereby dealers make pricing-related discretionary decisions commonly known as dealer reserves.[54] This commission-driven pricing system allows auto dealers to mark up the risk-based "buy rate" set by finance companies that purchase retail installment contracts from dealers.[55] The buy rate is the lowest acceptable interest rate that a lender will charge for financing an automobile purchase. Lenders determine the buy rate by making assessments of customer credit risk. Dealers have the discretion to charge an interest rate above the lender's buy rate, ostensibly for their participation in the financing transaction.[56] Although the dealership's participation in the markup practice is legal, ECOA enforcement officials have alleged that dealers subjectively make their decisions in a racially discriminatory manner by charging African Americans and Latinx consumers higher interest rates than similarly situated nonminority purchasers.[57] Consumer rights advocates condemn the discretionary markup system

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[52] *See id.*

[53] *See* Press Release, Fed. Trade Comm'n Auto Dealership Bronx Honda, General Manager to Pay $1.5 Million to Settle FTC Charges They Discriminated Against African American, Hispanic Car Buyers (May 27, 2020) https://www.ftc.gov/system/files/documents/cases/bronx_honda_stipulated.

[54] *See generally* CONSUMER FIN. PROT. BUREAU, CFPB BULL. NO. 2013-92, INDIRECT AUTO LENDING AND COMPLIANCE WITH THE EQUAL CREDIT OPPORTUNITY ACT (2013), http://files.consumerfinance.gov/f/2013303_cfpb_march_Auto-Finance-Bulletin.pdf. [hereinafter CFPB BULL.].

[55] *See id.*

[56] *See id.*

[57] *See generally* Statement of FTC Commissioner Rebecca Kelly Slaughter, available at https://www.ftc.gov/system/files/documents.public_statements/1576006/bronx (2020); *see also,* CFPB BULL. *supra* note 54 at 2.

because they believe it provides perverse incentives for dealers to unfairly and deceptively charge higher interest rates to consumers.[58]

For more than two decades, private parties and ECOA enforcement officials have pursued discrimination claims against auto finance lenders in which they challenged discretionary markup systems for their discriminatory effects on racial minorities.[59] To compensate for missing race data, these litigants probably use race proxies such as surnames and zip codes to identify the minority victims of discrimination.[60] Notably, the *Bronx Honda* case is exceptional because the FTC filed its complaint against the auto dealership itself, instead of the financial institutions that granted the car loans to consumers.

Also, unlike in the *Bronx Honda* case, most ECOA plaintiffs who claim racial discrimination in the auto loan market will not have "smoking gun" evidence of illegal conduct to support their claims. Apparently, the FTC interviewed Bronx Honda personnel who were willing to testify that management directed them to charge African American and Latinx consumers higher interest rates than their White counterparts for car loans. Direct evidence that supports claims of intentional racial discrimination is rare. Indeed, in the fintech lending environment, most ECOA plaintiffs are likely to have even greater difficulty discovering direct evidence of discriminatory intent, either because it does not exist, or because it is too subtle to detect when algorithms make lending decisions by processing massive datasets.

Most lawsuits that challenge the compensation arrangement in auto financing as discriminatory will likely focus on the

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[58] *See* Center for Responsible Lending, Comments to the Federal Trade Commission Motor Vehicle Roundtables 6 (Mar. 30, 2012), https://www.ftc.gov/sites/default/files/documents/public_comments/public-roundtables-protecting-consumers-sale-and-leasing-motor-vehicles-project-no.p104811-00104/00104-82859.pdf.

[59] *See infra* Part VI.

[60] Formally, this is known as the Bayesian (BISG) statistical methodology for determining race and ethnicity and racial disparities. *See* CONSUMER FIN. PROT. BUREAU, USING PUBLICLY AVAILABLE INFORMATION TO PROXY FOR UNIDENTIFIED RACE AND ETHNICITY 5 (2014), https://files.consumerfinance.gov/f/201409_cfpb_report_proxy-methodology.pdf; *see also* Marc N. Elliot et al., *A New Method For Estimating Race/Ethnicity and Associated Disparities Where Administrative Records Lack Self-Reported Race/Ethnicity*, 43 HEATH SERV. RES. 1722 (2008) (explaining the use of the BISG method in the health services industry).

disparate effects of the loan lending structure on racial minorities. Discrimination, if it exists, is more difficult to prove in these cases because usually there is no direct evidence to support racially biased motives. But if litigation is going to be an effective enforcement tool to combat discrimination in auto financing, fair lending regulators will need sufficient tools to uncover hidden forms of illegal racial discrimination. These regulators must be able to deploy sophisticated means to proactively root out the discrimination that may be hidden in race proxies or the design structures of predictive technology. They must have alternatives to "smoking gun" evidence. Comparative race data can provide circumstantial and statistical evidence that can facilitate proof of racial discrimination claims. This evidence is particularly valuable at the initial stages of litigation because it can help establish a prima facie case and defeat summary judgment motions. As a result, more full-fledged hearings of race-based lending discrimination claims could be decided on their merits. Congress should mandate the collection of race data in financed auto purchases so that ECOA enforcement agencies can become better equipped to protect consumers from racial discrimination in the fintech lending environment. The next section discusses an additional legislative proposal.

VI. PART VI: FINTECH AND THE EQUAL CREDIT OPPORTUNITY ACT: PROVING DISPARATE IMPACT CLAIMS

The key federal law plaintiffs are likely to invoke to hold lenders liable for lending discrimination claims is the ECOA. Congress enacted this legislation in 1974 to eliminate unfair lending practices on the basis of race, national origin, sex, and other personal attributes. The goal of the ECOA is to ensure equality in the financial services industry by proscribing consideration of factors that are unrelated to an applicant's creditworthiness.[61] The law proscribes disparate treatment discrimination, which occurs when lenders treat borrowers differently on an ECOA prohibited basis such as race.[62] The other legal theory that plaintiffs use when litigating ECOA discrimination claims is disparate impact. Disparate impact discrimination occurs when a lender applies a racially neutral policy or practice equally to all credit applicants, but the policy or practice disproportionally excludes or burdens certain persons

[61] Equal Credit Opportunity Act (ECOA), 12 U.S.C. § 1691 (2017).

[62] *Id.* at § 1691 (a).

on an ECOA prohibited basis. However, if the policy or practice is justified by business necessity and there is no less discriminatory alternative available to financial institutions, then there is no violation of the ECOA.[63] Unlike the *Bronx Honda* case, most credit discrimination today is likely to be implicit and not brazenly intentional. For this reason, plaintiffs who sue fintech lenders will use the disparate impact theory of liability upon which to base their claims.

In recent years, some have questioned the use of impact theory in lending discrimination litigation. For instance, the question arose in the aftermath of lawsuits the Consumer Financial Protection Bureau (CFPB) filed against indirect auto lenders regarding auto loan race disparities.[64] All of these lawsuits ended with settlements.[65] But not only did several members of Congress oppose these settlements, a 2015 House Financial Services Committee report (Junk Science I) criticized the CFPB in part for invoking "a controversial theory of liability known as disparate impact" to support its claims against indirect lenders.[66] In a later 2016 House Financial Services Committee staff report (Junk Science II), the

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[63] *See* Griggs v. Duke Power Co., 401 U.S. 424, 431 (1971) ("The Act proscribes not only overt discrimination but also practices that are fair in form, but discriminatory in operation.") (discussing the disparate impact approach in the context of employment discrimination); *see also* Taylor, *supra* note 50 at 211-14.

[64] Although the conduct alleged against auto dealers actually involved the overcharging of minorities for auto loans, the CFPB could not sue the dealers because the Dodd-Frank Act exempted auto dealers from the regulatory supervision of the CFPB. *See generally* Dodd-Frank Wall Street Reform and Consumer Protection Act, 12 U.S.C. §§ 5301-5641 (2012). The term "indirect auto lenders" is the term used by the CFPB to refer to persons, such as banks and sales finance companies, that are engaged in the business of accepting assignments of automobile retail installment contracts from dealerships. *See* CFPB BULL., *supra* note 54, at 1-2.

[65] Consent Order at 12, Ally Financial Inc., (No. 2013-CFPB-0010), 2013 CFPB Admin. Proc. LEXIS 125 at *16; Consent Order, TMX Finance LLC (No. 2016-CFPB-0022), 2016 VFPB Admin. Proc. LEXIS 183; Consent Order http://files.cnsumerfinance.gov/f/201602cfpb consent-order-toyota-motor-credit-corporation.pdf; Consent Order, American Honda Finance Corp. (No. 2015-CFPB-0014), 2015 CFPB Admin. Proc. LEXIS 348 2015 CFPB Admin. Proc. LEXIS 401; Consent Order, Fifth Third Bank (No. 2015-CFPB-0024), 2015 CFPB Admin. Proc. LEXIS 2015 CFPB Admin. Proc. LEXIS 401.

[66] REPUBLICAN STAFF OF THE COMM. ON FIN. SERV., 114 CONG., UNSAFE AT ANY BUREAUCRACY, PART II: CFPB JUNK SCIENCE AND INDIRECT AUTO LENDING (Comm. Print 2015), https://financialservices.house.gov/uploaded-files/11-24-15_cfpb_indirect_auto_staff_report.pdf.

CFPB was again criticized. Specifically, the report claimed that "[i]n pursuing its ECOA enforcement agenda, the Bureau has pursued disparate impact cases without justifiable authority..."[67] These objections to the use of disparate impact theory in ECOA lending discrimination claims highlight the fundamental question of whether disparate impact liability is cognizable under the ECOA and is therefore an enforcement tool the law authorizes the CFPB and other plaintiffs to use. The ECOA does not specifically address this question, however, its implementing regulation, Regulation B, specifically proscribes discriminatory effects of lending on consumers with ECOA protected class status.[68] In earlier work, I argued that the ECOA does indeed proscribe disparate impact discrimination and I demonstrated how the pre-enactment and post-enactment histories of the ECOA persuasively reflect the intent of Congress to allow ECOA plaintiffs to use impact methodology to prove their claims.[69] Federal courts and regulators agree with this view.[70] On the other hand, some commentators disagree.[71] To date, the United States Supreme Court has not addressed this question.[72] Of course, there is no good reason to wait

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[67] *Id.*

[68] 12 C.F.R. § 1002.5(b) (2018).

[69] *See* Winnie F. Taylor, *The ECOA and Disparate Impact Theory: A Historical Perspective*, 26 J.L. & POL'Y 575 (2018).

[70] *See* Cherry v. Amoco Oil Co., 490 F. Supp. 1026, 1030 (N.D. Ga. 1980) (discussing the significance of utilization of the disparate impact theory to prove lending discrimination claims in light of the likelihood of unintentional discrimination by lenders); *see also,* Francesca Lina Procaccini, *Stemming the Rising Risk of Credit Inequality: The Fair and Faithful Reading of the Equal Credit Opportunity Act's Disparate Impact Prohibition,* 9 HARV. L. & POL'Y REV. 44, S44-45, S57 (2015); *CFPB to Hold Auto Lenders Accountable for Illegal Discriminatory Markup,* CONSUMER FIN. PROT. BUREAU (Mar. 21, 2013), https://www.consumerfinance.gov/about-us/newsroom/consumer-financial-protection-bureau-to-hold-auto-lenders-accountable-for-illegal-discriminatory-markup. (CFPB Bulletin providing guidance to assist lenders on how to comply with the ECOA and thus avoid liability for disparate impact discrimination).

[71] *See* Peter N. Cubita & Michelle Hartmann, *The ECOA Discrimination Proscription and Disparate Impact—Interpreting the Meaning of the Words That Actually Are There,* 61 BUS. L. 829, 830-33 (2006) (arguing that Congress did not intend for the disparate impact method of proving discrimination claims to apply in ECOA litigation because neither the ECOA's statutory discrimination proscription nor its legislative history supports a finding that the Act prohibits facially neutral practices that disparately affect protected class members).

[72] In Texas Department of Housing & Community Affairs v. Inclusive Communities Project, 135 S. Ct. 2507 (2015), the United States Supreme Court

for the Court to eliminate doubt some have regarding whether disparate impact liability is a valid lending discrimination proof method. Rather than waiting for a case to make its way to the Supreme Court, Congress should amend the ECOA to expressly state that disparate impact liability is a necessary antidiscrimination tool that is cognizable under this fair lending legislation.

VII. CONCLUSION

The problem of racial discrimination in a completely virtualized financial world has profound legal and social consequences for racial minorities. This is especially true when it comes to home and automobile purchases, the two most expensive and consequential decisions consumers make. Besides providing shelter, real property builds equity that can be used as collateral for loans for business, education, and other important purposes. Access to reliable transportation is crucial to getting to work, to the grocery store, to the doctor, to school, and to childcare.[73] Together, homeownership and reliable transportation also enhance the ability of American consumers to accumulate and transfer enormous wealth. In the coming years, fintech's impact on the home mortgage and auto loan markets will grow exponentially. This growth should not impede the goal of achieving economic equality for racial minorities. To prevent such a catastrophe, it is incumbent upon policymakers to promptly develop approaches to effectively examine, analyze, and monitor fintech algorithmic credit assessment tools. Legislation that mandates the collection of race data in financed auto sales and states unequivocally that disparate impact claims are cognizable under the ECOA are major steps toward eliminating racial discrimination in consumer credit. Unless and until the problem of racial discrimination in lending is sufficiently addressed, the pervasiveness of race-based inequality in wealth will continue to beset people of color.

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decided that disparate impact claims are cognizable under the Fair Housing Act, federal legislation enacted to combat housing discrimination. Whether the Court will decide similarly in ECOA cases is an open question.

[73] *See* Foohey, *supra* note 46.