Algorithmic Fairness in Consumer Credit Underwriting: Towards a Harm-Based Framework for AI Fair Lending

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ABSTRACT

Credit discrimination undermines consumer financial autonomy and distorts market pricing of lending risks. To ensure equal access to credit, existing federal fair lending laws—e.g., Equal Credit Opportunity Act, Fair Housing Act—prohibit lenders from considering race, sex, age, or national origin in their lending decisions. For decades, the fair lending laws have largely held the banking industry in check. However, as lenders increasingly delegate lending decisions to artificial intelligence (AI) through the service of fintech and data intermediaries, it is questionable whether existing laws can still adequately safeguard equal credit access.

This Article argues that the current fair lending regime can no longer protect consumers in the age of AI. This is because our regime does not account for harms traceable to automatic, unsupervised algorithmic processes. Unlike human actors, algorithms cannot desire to cause harm or intend to use suspect factors. Yet, courts and litigants are constrained by the language of the fair lending laws to hold AI accountable under an antiquated legal theory—treating discrimination as analogous to common law torts. Under this regime, victims of AI discrimination carry the burden of showing lender animus and causal explanations linking the victim's injury to the lender's specific acts or policies. Consequently, such victims are often barred from recovery due to insurmountable pleading and evidentiary hurdles.

Thus, any attempt to combat AI discrimination must consider two unique features of algorithmic harm. First, an algorithm's discriminatory decision may have no explicable connection—let alone causal relation—to the acts or policies of the lender due to the algorithm's self-learning capabilities. Second, whether an algorithm discriminates depends on a host of variables typically outside the lenders' control. The unpredictable nature of AI calls into question the effectiveness of regulating AI bias under the fair lending laws—a conduct-based

DOI: https://doi.org/10.15779/Z38CF9J785

* J.D., Harvard Law School, 2023; A.M., Harvard University Graduate School of Arts & Sciences, 2020. The author would like to thank Mr. David Silberman, the former Acting Director of the Consumer Financial Protection Bureau, and Professor Christopher Bavitz at Harvard Law School, for their invaluable guidance and support. All mistakes and omissions are the fault of the author.

liability regime that emphasizes causation, reasonable foreseeability, and ex-ante risk mitigation.

As a blueprint for reform, this Article proposes an alternative harm-based framework to address the root cause of AI discrimination: data opaqueness. To implement this framework, this Article recommends the CFPB to adopt a new rule prohibiting the use of "black box" algorithms in consumer lending, pursuant to the CFPB's authority to prohibit "unfair, deceptive, or abusive acts and practices" (UDAAPs) under the Dodd-Frank Act.

INTRODUCTION

The role of credit in American economic life cannot be exaggerated. Almost all transactions that underpin important life decisions, from the financing of home mortgages to education access, involve credit.[1] The legislative history of

1. *See* ADAM J. LEVITIN, CONSUMER FINANCE: MARKETS AND REGULATION 1-3, 9-13 (2d ed. 2018).

the Equal Credit Opportunity Act (ECOA)[2] reveals that Congress emphasized that "the availability of credit often determines an individual's effective range of social choice."[3]

Despite the importance of credit availability, regulators and consumers lack visibility into how credit is supplied and distributed. In 2018, the Consumer Financial Protection Bureau (CFPB) estimated that at least 26 million Americans lacked documented credit history (i.e., are credit invisible), and that 19 million had blank credit profiles (i.e., are credit unscorable).[4] About 27-28% of non-white populations are either credit invisible or credit unscorable.[5]

Credit invisibility impacts some groups more than others. New immigrants, young people, people of color, and people with lower levels of education are disproportionately impacted.[6] Credit invisible consumers often face hurdles in obtaining financial products and services because of risks associated with credit invisibility. Lenders often charge higher interest rates and include restrictive covenants in lending agreements to compensate for these risks.[7] Consequently, credit invisible consumers often fall prey to predatory loans and illicit, underground financing.

The advent of artificial intelligence (AI) has offered new possibilities to bridge the financing gap that credit invisible consumers face. Many in the banking industry see AI as an opportunity to reach credit invisible consumers who would otherwise be denied access to essential financial goods and services.[8] Their optimism is not unwarranted. Now that machine learning[9] algorithms[10] can process mass volumes of informal consumer data, lenders are able to gain insights into a borrower's credit risks even if the borrower is credit invisible or

2. 15 U.S.C. § 1691.

3 *See* H.R. REP. NO. 94-210, at 3 (1975).

4. *See* Patrice Alexander Ficklin & J. Frank Vespa-Papaleo, *A Report on the Bureau's Building a Bridge to Credit Visibility Symposium*, CONS. FIN. PROT. BUR., at 7-10 (Jul. 19, 2019), https://files.consumerfinance.gov/f/documents/cfpb_building-a-bridge-to-credit-visibility_report.pdf.

5. *See id.* at 7.

6. *See id.*

7. *See infra* Part I.A.2.

8. *See, e.g.*, Derek Hosford, *AI Can Provide a Solution to the Problem of Credit Invisibility*, THE AMERICAN CONSUMER INSTITUTE CENTER FOR CITIZEN RESEARCH (Jun. 10, 2021), https://theamericanconsumer.org/2021/06/ai-can-provide-a-solution-to-the-problem-of-credit-invisibility/; Arvind Nimbalker, *Enterprise Finance and AI: Bridging the Financing Gap and Reaching the Credit Invisibles*, NASDAQ (Feb. 4, 2022), https://nasdaq.com/articles/enterprise-finance-and-ai%3A-bridging-the-financing-gap-and-reaching-the0credit-invisbles/.

9. "*Machine learning* is a subset of artificial intelligence that sense new patterns in data and adapt to those changes. . . [T]his type of AI can learn from data and improve its accuracy over time without being programmed to do so." Janine S. Hiller, *Fairness in the Eyes of the Beholder: AI; Fairness; and Alternative Credit Scoring*, 123 W. VA. L. REV. 907, 910 (2021) (internal quotations omitted).

10. In data science terms, an "algorithm" is a sequence of statistical processing steps that consists of "precisely specified series of instructions for performing some concrete tasks." *See* MICHAEL KEARNS & AARON ROTH, THE ETHICAL ALGORITHM: THE SCIENCE OF SOCIALLY AWARE ALGORITHM DESIGN 12 (2019).

credit unscorable.[11] However, as lenders begin to use "black box" algorithms in pursuit of higher profits, AI's beneficial force for credit equality has come into question.[12]

More broadly, the introduction of AI solutions to consumer credit underwriting has generated new legal problems that could further exacerbate socioeconomic inequalities with respect to financing access.[13] This Article argues that the current statutory,[14] regulatory,[15] and doctrinal[16] fair lending frameworks fail to protect consumers from algorithmic discrimination because they do not capture the essential features of algorithmic decision-making. That is, existing fair lending frameworks do not account for harms that arise out of automatic, unsupervised algorithmic processes.

Existing fair lending laws are products of the 1970s civil rights discourse.[17] These laws originate from the congressional desire to ensure equal credit access by punishing reprehensible lender misconduct. Specifically, the fair lending laws target the disparate treatment of consumers based on their immutable racial or gender characteristics and the use of facially neutral policies that disparately impact members of a protected class.[18] Fair lending laws provide consumers with a private right of action to challenge and recover from a discriminatory credit decision if the harm arises from lender misconduct.[19] However, the fair lending laws cannot hold lenders accountable for instances of proxy discrimination—those that lack a direct causal link between the alleged harm and the lender's specific acts or practices.[20] Algorithmic processes that perpetuate preexisting inequalities often lack causal connections to lender conduct. As such, these discriminatory harms tend to escape the purview of the current fair lending laws.[21]

11. Mikella Hurley & Julius Adebayo, *Credit Scoring in the Era of Big Data*, 18 YALE J. L. & TECH. 148, 148 (2016).

12. *See infra* Part I.C.

13. *See infra* Part I.C.2.

14. Referring to the Equal Credit Opportunity Act ("ECOA") (codified at 15 U.S.C. § 1691), Title VIII of the Civil Rights Act of 1968, as amended ("Fair Housing Act") (codified at 42 U.S.C. § 3601), and the Dodd-Frank Wall Street Reform and Consumer Protection Act of 2010 ("Dodd-Frank Act") (codified at 12 U.S.C. §§ 5301-5641).

15. Referring to the CFPB's Regulation B (codified at 12 C.F.R. § 1002), which implements ECOA.

16. Referring to the disparate treatment liability and disparate impact liability doctrines.

17. *See* Abbye Atkinson, *Borrowing Equality*, 120 COLUM. L. REV. 1403, 1420 (2020).

18. *See* BD. OF GOV. OF THE FED. RESRV. SYS. (FRB), FAIR LENDING REGULATIONS AND STATUTES: OVERVIEW, CONSUMER COMPLIANCE HANDBOOK 1 (2017), https://www.federalreserve.gov/boarddocs/supmanual/cch/fair_lend_over.pdf.

19. *See infra* Part II.C.1.

20. *See infra* Part II.C.2.

21. *See id.*

Simply put, the existing fair lending laws are inadequate to combat AI bias—a new form of proxy discrimination.[22] Instead of recognizing discrimination as outcomes of intersectional inequalities (of race, class, gender, etc.), the fair lending laws treat discrimination as outcomes of discrete, individual actions that are divorced from social context. Thus, the fair lending laws largely do not account for harms that lie outside this narrow conduct-based conception of discrimination. This is a salient gap in the algorithmic domain. Most instances of AI discrimination are traceable to indirect, proxy discrimination stemming from the machine learning process. However, fair lending laws fail to recognize these evolving AI-based forms of discrimination.

Two emerging trends in the judicial interpretation of fair lending laws exacerbate the disjuncture between the fair lending laws and contemporary realities. First, courts have increasingly disavowed disparate impact as an actionable claim of discrimination by adhering to textualist modes of statutory interpretation.[23] Second, courts have treated fair lending laws as extensions of common-law torts[24] by insisting on proof of causation and implied discriminatory intent as prerequisites for remedy.[25] Unlike human actors, AI models do not exhibit neither cause nor intent. However, the emerging judicial interpretations of fair lending laws effectively require litigants to analogize artificial intelligence to aspects of natural intelligence.[26] Not only do judicial attempts to conform AI to human standards of conduct miss the mark, they but they also depart from Congress' broader purpose in establishing the fair lending laws: elimination of systemic barriers to credit equality.[27]

To fulfill the congressional promise of equal credit access protection, this Article urges lawmakers to consider two unique features of algorithmic harm when crafting new laws to combat credit discrimination.

Inexplicability: An algorithm's credit results may have no explicable connection—let alone causal relation—to the acts or policies of the lender that develops the algorithm.[28] Due to AI's self-learning capabilities, the algorithm may pick up patterns and carry out analyses that are neither anticipated nor captured by the lender's programming instructions. The algorithm's

22. *See* Aaron Klein, *Credit Denial in the Age of AI*, BROOKINGS INSTITUTION (Apr. 11, 2019), https://www.brookings.edu/articles/credit-denial-in-the-age-of-ai/ (arguing that regulators need to rethink the 1970s legal framework to incorporate new challenges of AI).

23. *See infra* Part II.B.3.

24. *See generally* Sandra F. Sperino, *Let's Pretend Discrimination Is a Tort*, 75 OHIO ST. L. J. 1107, 1107 (2014).

25. *See infra* Part II.C.

26. *See* Talia B. Gillis, *The Input Fallacy*, 106 MINN. L. REV. 1176, 1182 (2022).

27. *See* S. REP. NO. 94-589, at 4 (1976), *as reprinted in* 1976 U.S.C.C.A.N. 403, 406 (stating that Congress's goal is to "prevent the kinds of credit discrimination which have occurred in the past, and to anticipate and prevent discriminatory practices in the future.").

28. *See* Daniel Faggella, *AI Transparency in Finance—Understanding the Black Box*, EMERJ (Jan. 27, 2020), https://emerj.com/partner-content/ai-transparency-in-finance/.

unsupervised learning, which reflects, aggregates, and replicates decisions made by past actors unrelated to the lender, may result in discrimination.[29]

Unpredictability: Whether an algorithm discriminates depends on a host of variables typically outside of a lender's control.[30] An algorithm may be programmed simply to optimize credit risk and maximize lending profits without regard to race, sex, age, or national origin. But, depending on what data the algorithm is trained on and how the algorithm adjusts its weight assignment to reflect new data inputs, the algorithm may produce a discriminative result, even if the lender excludes proxies for race, sex, age, or national origin from the algorithm's learning process.[31] Moreover, the algorithm's decision logic may be opaque and unpredictable, even to its developer.[32]

These features present a Schrödinger's paradox:[33] it is nearly impossible for a lender to anticipate whether using a complex machine learning algorithm for credit underwriting will yield a discriminatory impact on consumers until the algorithm inflicts irreversible injury.[34] However, the fair lending laws condition the victims' recovery on their ability to prove that the lenders knew or reasonably foresaw the discriminatory consequences of their actions beforehand. This paradox calls into question the effectiveness of regulating AI bias under the fault-based liability regime established by the fair lending laws—a legal regime that emphasizes causation, reasonable foreseeability, and ex-ante risk mitigation.[35]

The rest of this Article proceeds as follows. Part I first provides an overview of the current practices of risk-based credit assessment by banks, fintech lenders, and other key players in the credit underwriting business. Part I then discusses how the advent of AI lending has created impediments to transparency, fairness, and accountability in consumer financial markets.

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29. *See infra* Part III.B.1.

30. *See id.*

31. *See id.*

32. *See, e.g.*, Laura Blattner, P-R Stark & Jann Spiess, *Machine Learning Explainability & Fairness: Insights from Consumer Lending*, FINREGLAB 1, 23-24 (2022), https://finreglab.org/wp-content/uploads/2022/04/FinRegLab_Stanford_ML-Explainability-and-Fairness_Insights-from-Consumer-Lending-April-2022.pdf; Florian Perteneder, *Understanding Black-Box ML Models with Explainable AI*, DYNATRACE ENGINEERING (Apr. 29, 2021), https://engineering.dynatrace.com/blog/understanding-black-box-ml-models-with-explainable-ai/; Alexey Surkov, Val Srinivas & Jill Gregorie, *Unleashing the Power of Machine Learning Models in Banking Through Explainable Artificial Intelligence (XAI)*, DELOITTE (May 17, 2022), https://www2.deloitte.com/us/en/insights/industry/financial-services/explainable-ai-in-banking.html.

33. *See generally* "Schrödinger's Cat," *in* JOHN DAINTITH, A DICTIONARY OF PHYSICS (Oxford University Press, 6th ed. 2009). Deriving from Physicist Erwin Schrödinger's famous thought experiment, the metaphor describes a problem in quantum mechanics in which we cannot know the state of two quantum particles until measured and both states are possible at the same time. In popular culture, the metaphor "Schrödinger's paradox" is used to describe situations where the result of an observed process cannot be known until the result has come about.

34. *See infra* Part II.C.2.

35. *See infra* Part II.C.1.

Part II examines the existing legal frameworks for fair lending protection and assesses the inadequacies of these frameworks in handling the nascent threat of algorithmic bias. Part II first lays out the current statutory scheme for fair lending protection. Part II then scrutinizes recent cases concerning this statutory scheme. Specifically, Part II examines cases determining the actionability of disparate impact claims under the fair lending statutes and those interpreting such statutes to carry common-law tort meanings. These cases substantially heighten the plaintiff's pleading and evidentiary burden for disparate impact claims and make it more difficult for them to recover for algorithmic discrimination.

Part III evaluates existing proposals for legal reform. It begins by critiquing proposals to enhance public scrutiny of algorithmic inputs[36] and broadening the scope of discrimination liability for problematic algorithmic outputs.[37] Although these proposals address a dimension of algorithmic harm, they do not fundamentally challenge the flawed judicial assumption that AI can be conformed to human standards of conduct.

Part IV urges regulators to move beyond the traditional conduct-based framework and consider a harm-based model to address the adverse impacts of AI bias. This Part also proposes a new policy design: leveraging the CFPB's power under the Dodd-Frank Act (DFA) to identify and prohibit "unfair, deceptive, abusive acts and practices" (UDAAPs).[38] Specifically, Part IV explores promulgating an "unfairness" rule to address algorithmic harm. It recommends prohibiting the market's use of "black box" algorithms and instead using transparent, explainable "white box" algorithms for consumer credit underwriting. Finally, Part IV addresses both market concerns and possible legal responses to the proposed rule.

Part V concludes the Article and asks how AI bias challenges what it means to provide equal credit access.

I. Contextualizing the Problem: The Current Landscape

AI is probably one of the most potent forces transforming the modern landscape of consumer lending. The turn towards AI has been driven by several factors, including "the accelerated maturation of [AI] algorithms," the competition for market share by financial service providers, the paradigm shifts in consumer preference for digital products, and the market's increasing reliance

36. "Inputs" refer to the types of data that is fed into the algorithm. An algorithm may receive two types of data: (i) market-level data, such as the average home prices in a geographic area or the default rate of a certain type of consumer; and (ii) individual-level data, such as an individual's shopping list, credit history, and online digital footprint.

37. "Outputs" refer to the types of decision that the algorithm is asked to make. For example, an algorithm may be asked to calculate the optimal risk-return trade-off of a loan based on the credit risk profile of a borrower and the risk tolerance of the lender.

38. *See* section 1031(a) of the Dodd-Frank Wall Street Reform and Consumer Protection Act ("Dodd-Frank Act") (codified at 12 U.S.C. § 5531).

on big data for information processing.[39] AI applications have clear potential to expand credit access for the credit invisible consumers. However, AI bias can perpetuate deep economic injustice, from racialized disparities in homeownership to disproportional accumulation of consumer debt in non-white households.[40] Scholars and regulators should pay special attention to the potential for AI applications to create biased outcomes for U.S. consumers.

While most scholarship has espoused one-sided views on the subject—either justifying or vilifying lenders' efforts to incorporate AI into consumer credit underwriting—this Part underscores the nuanced potential of AI. In particular, this Part explains the uniqueness of AI governance in the consumer financial protection space by probing into the practices, incentives, and values that undergird AI's growth in this area. This Part first investigates how lenders came to embrace AI technologies to improve the efficiency of risk-based loan pricing. It then looks at how AI became a dominant market trend. Subsequently, this Part examines how the adoption of AI technologies in credit underwriting has affected consumers, highlighting benefits and costs. Finally, this Part illustrates how AI bias differs from traditional forms of discrimination in fair lending and pinpoints potential opportunities for legal action and reform in credit underwriting.

A. Traditional Credit Underwriting Practices

1. Risk-Based Lending: How Lenders Determine Loan Prices and Terms

Depository lending institutions, such as banks, credit unions, and industrial loan companies (ILCs), typically base their decisions to extend or deny loans to a consumer on the probability of default (i.e., default risk), the opportunity cost of lending (i.e., expected return), and the success rate of loan recovery for the type of financial product under consideration.[41] If the lending institution accepts

39. *See* Makada Henry-Nickie, *How Artificial Intelligence Affects Financial Consumers*, BROOKINGS INSTITUTION (Jan. 31, 2019), https://www.brookings.edu/research/how-artificial-intelligence-affects-financial-consumers/.

40. An investigation by The Markup found that lenders using AI for home loan approvals are more likely to deny home loans to people of color than to white people with similar financial profiles. Specifically, 80% of African American applicants are more likely to be rejected, along with 40% of Latinx applicants, and 70% of Native American applicants. *See* Emmanuel Martinez & Lauren Kirchner, *The Secret Bias Hidden in Mortgage-Approval Algorithms*, THE MARKUP (Aug. 25, 2021), https://apnews.com/article/lifestyle-technology-business-race-and-ethnicity-mortgages-2d3d40d5751f933a88c1e17063657586; *see also* Kori Hale, *AI Bias Caused 80% of Black Mortgage Applicants to be Denied*, FORBES (Sep. 2, 2021), https://www.forbes.com/sites/korihale/2021/09/02/ai-bias-caused-80-of-black-mortgage-applicants-to-be-denied/?sh=15fdf3e336fe.

41. *See* Nat'l Credit Union Admin., Letter to Federally Insured Credit Unions on Risk-Based Lending, Letter No. 99-CU-05 (Jun. 1999), https://www.ncua.gov/regulation-supervision/letters-credit-unions-other-guidance/risk-based-lending. The NCUA 1999 Letter describes risk-based lending as "a means by which a credit union may be able to more effectively meet the credit needs of all its members." Most industry best practice guides refer to the NCUA 1999 Letter as establishing the standard for risk-

the consumer's application for a loan, it calculates an estimated price range for the risk-return tradeoff that would render the loan extension profitable.[42] Non-depository lenders (e.g., mortgage companies and payday lenders) engage in a similar process when deciding whether to extend a loan, albeit without the same level of standardization.[43]

At the most basic level, risk-based lending concerns how lenders account for each borrower's unique characteristics to determine the borrower's ability to perform their loan obligations.[44] After assessing these characteristics, lenders tailor the price (e.g., interest rates, annual percentage rates, upfront fees) and terms (e.g., coverage, grace-periods, security interests, repayment formalities, penalties, overdrafts) of the underlying loan agreement. The loan agreement allows the borrower to obtain capital to fund their consumption or investment activities and confers a right to the lender to claim the debt outstanding under specified circumstances.[45] This process is commonly referred to as credit underwriting.[46]

Traditionally, lending institutions rely on two methods to ensure the accuracy of risk-based pricing in the credit underwriting process: credit reports and credit scores. Credit reports are issued by third-party bureaus (e.g., Equifax, Experian, and TransUnion) and include a consumer's credit and payment history.[47] Credit scores are numerical scores computed by credit-rating agencies based on a statistical evaluation of a potential borrower's "apparent creditworthiness" and

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based lending. *See* Mark A. Condon, *Publisher's Note*, CREDIT UNION MAGAZINE 1, 2 (2006), http://ma.leagueinfosight.com/files/infosight/192/file/RBL%20Best%20Practices.pdf.

42. *See* Nat'l Credit Union Admin., *supra* note 42.

43. Depository lending institutions like banks, ILCs and credit unions are subject to prudential regulation—i.e., capital requirements—to ensure the "safety and soundness" of their operations. But non-depositories are not. Since lower debt recovery increases the risk of systemic financial risk (*i.e.*, bank runs), depository institutions need to ensure that the ratio of non-performing loans in their balance sheet complies with capital restrictions. *See generally* MICHAEL S. BARR, HOWELL E. JACKSON & MARGARET E. TAHYAR, FINANCIAL REGULATION: LAW AND POLICY 277-347, 617-80 (3d ed. 2021).

44. *See, e.g.*, Cons. Fin. Prot. Bur. (CFPB), *What Is Risk-Based Pricing?*, CFPB CONSUMER EDUCATION BLOG (Aug. 5, 2016), https://www.consumerfinance.gov/ask-cfpb/what-is-risk-based-pricing-en-767/; Ben Luthi, *What Is Risk-Based Pricing?,* EXPERIAN LOAN BASICS (Nov. 12, 2018), https://www.experian.com/blogs/ask-experian/what-is-risk-based-pricing/.

45. The rights conferred to the lender depends on the type of loan extended. Home equity lines of credit, mortgages and auto loans are typically structured as secured loans, which grants the lender (*i.e.*, secured creditor) a non-recourse right to repossess the collateral upon default. *See* U.C.C. §§ 9-609(a), 9-609(b)(2) (stating that the secured creditor may repossess collateral without causing a breach of the peace.). Most personal loans (e.g., credit cards, payday loans) are not secured by collateral, which means that the creditor only has a fixed claim on the debt outstanding.

46. Credit underwriting is the process by which the lender decides whether an applicant is creditworthy and should receive a loan. *See* FED. DEP. INS. CO. (FDIC), RISK MANAGEMENT EXAMINATION MANUAL FOR CREDIT CARD ACTIVITIES, FDIC - DIVISION OF SUPERVISION AND CONSUMER PROTECTION (Mar. 2007), https://www.fdic.gov/regulations/examinations/credit_card/pdf_version/ch7.pdf.

47. *See, e.g.,* Bev O'Shea & Amanda Barroso, *Credit Score vs. Credit Report: What's the Difference?,* NERDWALLET (last updated Nov. 7, 2023), https://www.nerdwallet.com/article/finance/credit-score-vs-credit-report-whats-difference. *See also* Michael Staten, *Risk-Based Pricing in Consumer Lending*, 11 J. L. ECON. & POL'Y 33 (2015).

potential to "default on a credit obligation."[48] Typically, a lender pays credit reporting or rating agencies a fee to obtain relevant information about a consumer in order to assess the consumer's risk profile for lending purposes.[49] In addition to using risk-based pricing, lenders hedge against risk by including restrictive covenants and higher interest rates in a loan transaction with borrowers they perceive to pose a higher risk of default.[50]

2. *Conventional Automated Solutions: Problem of Credit Invisibility*

Over the past three decades, automated credit underwriting systems have become the dominant method by which lenders assess applications for consumer and small business credit.[51] Relying mostly on linear and logistic regression, automated credit models identify a set of variables with the strongest correlation to a particular outcome (e.g., loan performance and delinquency) and assign a weight to each variable in the model.[52] These automated credit models predict a consumer's likelihood of default by computing a score using the preassigned weighted variables.

One of the most widely used automated models in the credit underwriting industry is the credit scoring process created by the Fair Isaac Corporation (FICO).[53] All FICO scoring models use a score range from 300 to 850, with higher scores indicating lower credit risk.[54] These credit score ranges are further subdivided into five risk categories. Scores above 800 are considered "super-prime" (i.e., excellent), scores between 740-799 are considered "prime" (i.e., good), scores between 670-739 are considered "near-prime" (i.e., average), scores between 580-699 are considered "subprime" (i.e., below average), and scores below 579 are considered "deep subprime" (i.e., poor).[55] FICO scores became widely adopted in the 1990s, when automated solutions became seen as better alternatives to case-by-case human evaluations because they could enhance efficiency while avoiding the most egregious forms of discrimination.[56]

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48. David Robinson & Harlan Yu, *Knowing the Score: New Data, Underwriting, and Marketing in the Consumer Credit Marketplace: A Guide for Financial Inclusion Stakeholders*, UPTURN.ORG 1, 7 (2014), https://www.upturn.org/static/files/Knowing_the_Score_Oct_2014_v1_1.pdf.

49. *See* R. RUSSELL BAILEY, FAIR LENDING IMPLICATIONS OF CREDIT SCORING SYSTEMS 23 (2005), https://www.fdic.gov/regulations/examinations/supervisory/insights/sisum05/sisummer05-article3.pdf.

50. *See id.*

51. *See* Blattner, Stark & Spiess, *supra* note 32, at 8.

52. *See id.* at 8-9.

53. *What Are Credit Scoring and Automated Underwriting?,* FED. RSEV. BANK OF ST. LOUIS, (Jan. 1, 1998), https://www.stlouisfed.org/publications/bridges/winter-1998/what-are-credit-scoring-and-automated-underwriting.

54. *See* CONSUMER FIN. PROT. BUREAU, THE CONSUMER CREDIT CARD MARKET 18-20 (2021), https://files.consumerfinance.gov/f/documents/cfpb_consumer-credit-card-market-report_2021.pdf.

55. *What Are the Different Ranges of Credit Scores?* EQUIFAX (accessed Sep. 26, 2022), https://www.equifax.com/personal/education/credit/score/credit-score-ranges/.

56. *See* Hurley & Adebayo, *supra* note 11, at 155.

However, traditional automated solutions like FICO scores are often criticized for unjustifiably disadvantaging consumers who are credit invisible or credit unscorable. People of color and new immigrants are disproportionately rated with lower creditworthiness. Data shows that 1 in 5 Black consumers and 1 in 9 Hispanic consumers have FICO scores below 620. Meanwhile, only 1 out of every 19 white consumers are in the sub-620 category.[57] The FICO score typically takes into account a consumer's payment history, outstanding debt, pursuit of new credit, types of credit used, and debt-to-credit ratio—categories of traditional credit that people of color often have less access to than white Americans.[58] Yet, the FICO score omits "factors such as employment history, salary, and other items that might suggest creditworthiness."[59] The FICO scoring method even penalizes people for past medical debt after it has been paid.[60]

The widespread usage of automatic credit scoring methods has directly resulted in erroneous loan rejection and pricing for a variety of consumer credit transactions. The Federal Trade Commission (FTC) found that, in 2012, "26% of consumers surveyed [out of 1,000 consumers] had errors in their credit reports," and these "mistakes were material for 13% of consumers, potentially resulting in denials, higher rates of interest[,] and other less-favorable terms."[61] The COVID-19 pandemic has exacerbated the inaccuracy of FICO scores. Specifically, FICO scores do not reflect forbearance or deferment, factors which the COVID-19 pandemic has made increasingly relevant to default risk.[62]

Scoring inaccuracies compound barriers that credit invisible consumers face in obtaining basic financial services. Traditional automated credit scoring schemes may subject a consumer in the "subprime" pool to excessive risk premiums based on the consumer's low, but inaccurate, credit score.[63] In fact, many such consumers may not be risky borrowers. Consumers placed in the "subprime" risk category due to scoring inaccuracies are discouraged from opening bank accounts or applying for loans due to higher transactional costs,

57. *See* Natalie Campisi, *From Inherent Racial Basis to Incorrect Data—The Problems with Current Scoring Models*, FORBES ADVISOR (Feb. 26, 2021), https://www.forbes.com/advisor/credit-cards/from-inherent-racial-bias-to-incorrect-data-the-problems-with-current-credit-scoring-models/.

58. *See* Hale, *supra* note 41.

59. Hurley & Adebayo, *supra* note 11, at 156.

60. *See* Hale, *supra* note 40.

61. *See* FED. TRADE COMM'N, REPORT TO CONGRESS UNDER SECTION 319 OF THE FAIR AND ACCURATE CREDIT TRANSACTIONS ACT OF 2003 i (2012), https://www.ftc.gov/system/files/documents/reports/section-319-fair-accurate-credit-transactions-act-2003-sixth-interim-final-report-federal-trade/150121factareport.pdf.

62. AnnaMaria Andriotis, *FICO Score's Hold on the Credit Market is Slipping*, THE WALL STREET JOURNAL (Aug. 2, 2021), https://www.wsj.com/articles/fico-scores-hold-on-the-credit-market-is-slipping-11627119003.

63. *See* Julapa A. Jagtiani & Catharine Lemieux, *The Roles of Alternative Data and Machine Learning in Fintech Lending: Evidence from the LendingClub Consumer Platform* 1, 18 (Fed. Rsrv. Bank of Phila. Working Paper, Paper No. 18-15, 2018, revised 2019), https://www.philadelphiafed.org/-/media/frbp/assets/working-papers/2018/wp18-15r.pdf.

such as higher credit card overdrafts fees[64] or being subject to mortgage prepayment penalties.[65] Consumers in the "deep subprime" category are completely excluded from the markets for certain financial products such as home equity line of credits.[66]

Widespread industry reliance on FICO scores disproportionately subjects credit invisible and credit unscorable consumers to higher risk premiums—i.e., "the cost of being poor."[67] Consumers in the "subprime" and "deep subprime" categories resort to underground banking, high-fees payment systems, prepaid cards, payday loans, or other risky consumer financial products that do not consider credit ratings to meet their daily consumption needs.[68] Because these consumers lack access to the full range of banking services or cannot afford the costs of credit access, they cannot obtain financing for large purchases or engage in activities that typically raise credit scores.[69] As a result, subprime consumers are trapped in a vicious cycle of poverty and indebtedness which further deprives them of the full range of financial services.[70] In sum, while the arrival of automated credit scoring increased access to credit, it created new risks that undermine equal credit access.

B. Current Developments in Consumer Lending

1. The Use of Alternative Data in Consumer Credit Underwriting

The inability of traditional automated methods to fairly assess the profiles of credit invisible and credit unscorable consumers prompted the use of alternative data for consumer credit evaluation. The use of alternative data was pioneered

64. Consumers who overdraft frequently have median credit scores of less than 600, well below what is considered to be a subprime score. *See* Consumer Financial Protection Bureau, *CFPB Unveils Prototypes of "Know Before You Owe" Overdraft Disclosure Designed to Make Costs and Risks Easier to Understand*, CFPB NEWSROOM (Aug. 4, 2017), https://www.consumerfinance.gov/about-us/newsroom/cfpb-unveils-prototypes-know-you-owe-overdraft-disclosure-designed-make-costs-and-risks-easier-understand/.

65. *See* Center for Responsible Lending, *Prepayment Penalties in Subprime Loans* (Jun. 18, 2004), https://www.responsiblelending.org/research-publication/prepayment-penalties-subprime-loans.

66. *See* CONSUMER FIN. PROT. BUREAU, *supra* note 54 at 253.

67. *See* Craig Landes, *The Cost of Being Poor: Why It Costs So Much to Be Poor in America*, FINMASTERS (Sep. 5, 2022, updated Nov. 8, 2023), https://finmasters.com/cost-of-being-poor/.

68. *See generally* Margaret Seikel, *Examining the Factors Driving High Credit Card Interest Rates*, CFPB BLOG (Aug. 12, 2022), https://www.consumerfinance.gov/about-us/blog/examining-the-factors-driving-high-credit-card-interest-rates/; Scott Fulford & Cortnie Shupe, *Consumer Use of Payday, Auto Title, and Pawn Loans: Insights from the Making Ends Meet Survey* 4, Consumer Fin. Prot. Bureau, Rsch. Brief No. 2021-1, (2021), https://files.consumerfinance.gov/f/documents/cfpb_consumer-use-of-payday-auto_title-pawn_loans_research-brief_2021-05.pdf; CONSUMER FIN. PRO. BUREAU, MARKET SNAPSHOT: CONSUMER USE OF STATE PAYDAY LOAN EXTENDED PAYMENT PLANS 2 (2022), https://files.consumerfinance.gov/f/documents/cfpb_market-snapshot-payday-loan-extended-payment-plan_report_2022-04.pdf.

69. *See* Luke Herrine, *Credit Reporting's Vicious Cycles*, 40 N.Y.U. REV. L & SOC. CHANGE 305, 336, 338-39 (2015).

70. *See id.* at 344-46. *See also* Landes, *supra* note 67.

by incumbents in the financial lending market. FICO, for instance, piloted the use of alternative data in "FICO Score XD," in collaboration with the credit bureau Equifax.[71] Unlike the FICO score devised in the 1990s, FICO Score XD compiled data on consumers' cable, cellphone, and utility bill payment histories as proxies for consumer creditworthiness.[72]

Increasingly, however, credit bureaus and rating agencies outsource data collection to third-party data brokers,[73] which are companies that specialize in the scraping and collection of "consumers' personal information" and the "res[ale] or shar[ing] [of] that information with others."[74] These data brokers collect and store transaction data for nearly every U.S. consumer from a wide range of commercial, government, and other publicly available sources.[75] Credit bureaus and reporting agencies use credit brokers to amass enormous quantities of non-traditional "fringe data"—health data, loyalty card data, online subscription data, club membership data, device browser history, consumer complaints, identifying data, court data, and other private information—that are not intuitively relevant to risk-based pricing.[76] These data often serve as "inputs" for a lender's decision to assess the loan applicant's creditworthiness.

71. Ann Carrns, *New Credit Score Systems Could Open Lending to More Consumers*. N.Y. TIMES (Oct. 9, 2015), https://www.nytimes.com/2015/10/10/your-money/new-credit-score-systems-could-open-lending-to-more-consumers.html.

72. Bev O'Shea, *FICO XD: A Credit Score for Those with No Credit*, NERDWALLET (updated Nov. 22, 2021), https://www.nerdwallet.com/article/finance/fico-xd-credit-score.

73. In this Article, I refer to "data brokers" and "data aggregators" interchangeably, although they may differ in many aspects. Data aggregators can be either business-facing (B2B) or consumer-facing (B2C). Business-facing aggregators receive data from a few data brokers, "[provide] some value-added processing, and [repackage] the result in a useable form" for sale or rent. *See* DAVID LOSHIN, BUSINESS INTELLIGENCE 295 (2d ed. 2013). Consumer-facing data aggregators, with the permission of their customers, access and collect information across consumer financial accounts "and put [the information] into a standardized summarized form to help make it easier for consumers to manage their money (e.g., Mint, Yodlee)." Some might "enable other application services to connect to consumers' financial accounts in order to provide new services, such as peer-to-peer transfers and other payment services (e.g., Plaid)." Cheryl R. Cooper, *Open Banking, Data Sharing, and the CFPB's 1033 Rulemaking* 1 (Cong. Rsch. Serv., Rep. No. IN11745, 2021), https://crsreports.congress.gov/product/pdf/IN/IN11745. While some formal differences exist, in practice, most businesses providing data brokerage services tend to overlap with data aggregators because it is more efficient to integrate the two functions in one business entity. In recognition of this trend, I use the terms "data broker" and "data aggregator" interchangeably, refer to both collectively as "data brokers," or refer to them colloquially as "financial intermediaries."

74. *See* FED. TRADE COMM'N, DATA BROKERS: A CALL FOR TRANSPARENCY AND ACCOUNTABILITY i (2014), https://www.ftc.gov/system/files/documents/reports/data-brokers-call-transparency-accountability-report-federal-trade-commission-may-2014/140527databrokerreport.pdf.

75. Of the nine largest data brokers investigated by the FTC, one data broker's database has information on 1.4 billion consumer transactions and over 700 billion aggregated data elements, another data broker's database covers one trillion dollars in consumer transactions, and yet another data broker adds three billion new records each month to its databases. One broker has 3,000 data segments for nearly every U.S. consumer. *See id.* at 46-47.

76. *See* Brief for Respondent at 9-10, Spokeo, Inc. v. Robins, 578 U.S. 330 (2016) (No. 13-1339), 2015 WL 5302538, at *6-7.

Data brokers and fintech companies use machine learning algorithms to make use of the enormous amount of fringe data collected by parsing this "big data,"[77] learning its patterns, and generating a prediction of creditworthiness based on the patterns summarized.[78] After a few iterations, the algorithm matures its decision logic by eliminating contradictory or irrelevant noise data.[79] In this regard, machine learning-based credit underwriting is fundamentally different from conventional automated underwriting models in that it doesn't just summarize statistical patterns. This form of underwriting continuously "learns" from past mistakes and adjusts its future interactions with consumer data inputs each time it makes a prediction.[80]

The three most popular machine learning credit underwriting algorithms[81] to assess credit risk are Random Forest,[82] Artificial Neural Networks,[83] and Boosting.[84] By way of illustration, the learning process of Random Forest

77. "Big data refers to the large, diverse sets of information… [and] can be structured or unstructured. Structured data consists of information already managed by organizational databases," such as tradeline data or formalized credit data stored by credit bureaus. "Unstructured data is information that does not fall into a predetermined format. It includes data gathered from social media sources," networks, websites, or data gathered from personal electronic devices and apps. *See, e.g.*, Troy Segal, *What is Big Data? Definition, How It Works, and Uses*, INVESTOPEDIA (updated Nov. 29, 2022), https://www.investopedia.com/terms/b/big-data.asp.

78. *See* Yinan Liu & Talia Gillis, *Machine Learning in the Underwriting of Consumer Loans*, HARV. L. SCH. CASE STUDIES 8-9 (Mar. 2020), https://projects.iq.harvard.edu/files/financialregulation/files/machine_learning_case_study.pdf.

79. *See* Jason Brownlee, *Why Optimization Is Important in Machine Learning*, MACHINE LEARNING MASTERY (Oct. 12, 2021), https://machinelearningmastery.com/why-optimization-is-important-in-machine-learning/#:~:text=Selection%20as%20Optimization-,Machine%20Learning%20and%20Optimization,or%20maximum%20of%20the%20function.

80. Not all AI algorithmic models "learn" continuously. AI, ML, and deep-learning (DL) (a subset of ML) are three separate concepts, although they are often used interchangeably. Artificial intelligence (AI) is any algorithm, mathematical formula, or technique that enables computers to mimic human decision-making. Machine learning (ML) involves specific AI techniques that give computers the ability to learn without being explicitly programmed to do so. Finally, deep learning (DL) models are a subset of ML. DL models continuously reflect and correct their own mistakes so that they can learn, understand, interpret, and solve problems with a high level of accuracy. *See generally* Matthew McMullen, *All That AI is ML But Not All That is AI is ML*, MEDIUM (Dec. 23, 2020), https://medium.com/nerd-for-tech/-95d38af2f9ea. For purposes of CFPB rulemaking, it is unnecessary to define AI/ML and distinguish between each variation of AI/ML usage in the market. The CFPB only needs to define what makes a model behave like a "black box," regardless of the specific technological underpinnings.

81. Some emerging companies also use their own proprietary machine learning algorithms that have competitive advantage over the three techniques mentioned. These companies treat such algorithms as closely guarded trade secrets, making it impossible to provide a comprehensive view of the industry. Techniques of machine learning also tend to differ depending on the target sector that they are intended to apply to. This Article only provides a glimpse of the industry and its application to credit-risk assessment. *See* Liu & Gillis, *supra* note 78, at 8.

82. Nadège Grennepois, Anca Maria Alvirescu, Margaux Bombail, *Point of View: Using Random Forest for Credit Risk Models*, DELOITTE RISK ADVISORY (Aug. 2019), https://www2.deloitte.com/content/dam/Deloitte/sg/Documents/financial-services/sg-fsi-machine-learning-credit-risk.pdf.

83. Manish Bhoge, *Using the Artificial Neural Network for Credit Risk Management*, ORACLE AI & DATA SCIENCE BLOG (Jan. 23, 2019), https://blogs.oracle.com/ai-and-datascience/post/using-the-artificial-neural-network-for-credit-risk-management/.

84. Jocelyn D'Souza, *A Quick Guide to Boosting in ML*, MEDIUM (Mar. 21, 2018), https://medium.com/greyatom/a-quick-guide-to-boosting-in-ml-acf7c1585cb5/.

includes the following steps: (i) gathering and cleansing data,; (ii) splitting data into a training dataset and a testing dataset,; (iii) training the predictive model with the training dataset based on machine learning algorithms,; and (iv) validating the model with the testing dataset.[85] These steps are common to all machine learning techniques. By repeating these steps, machine learning algorithms are capable of quickly analyzing large volumes of data and detecting patterns that are not apparent to the human eye. Machine learning algorithms generally improve as they process more data, leading to more accurate predictions.

As lenders delegate credit-underwriting decisions to machine learning algorithms, patterns that may have not been apparent to human analysts can suddenly reveal hidden trends that are relevant to constructing a consumer's risk profile.[86] Credit scoring machine learning algorithms trained on alternative data are able to use a consumer's digital footprint to fill in gaps in the consumer's credit history.[87] In this regard, credit underwriting machine learning algorithms present greater access to credit invisible and credit unscorable consumers that are less risky than conventional models may suggest.

2. *"All Data Is Credit Data": Introducing AI to Credit Underwriting*

In 2012, fintech entrepreneur and CEO of ZestAI (formerly ZestFinance) Douglas Merrill told the *New York Times*: "All data is credit data. We just don't know how to use it yet."[88] With a vision to provide credit visibility to the "unbanked" and the "underbanked," ZestAI was one of the first fintech companies to use machine learning algorithms to construct credit risk profiles of prospective loan applicants by mass-processing alternative data.[89] Its aim was to

85. *See, e.g.*, Tony Yiu, *Understanding Random Forest: How the Algorithm Works and Why it Is So Effective*, MEDIUM (Jun. 12, 2019), https://towardsdatascience.com/understanding-random-forest-58381e0602d2; *see also* Paul Wanyanga, *Credit Scoring using Random Forest with Cross Validation*, MEDIUM (Feb. 5, 2021), https://medium.com/analytics-vidhya/credit-scoring-using-random-forest-with-cross-validation-1a70c45c1f31/.

86. *See* Roman Bevz & Olena Domanska, *Artificial Intelligence (AI) for Credit Risk Management in Banking*, AVENGA (Jul. 19, 2022), https://www.avenga.com/magazine/ai-for-credit-risk-management/.

87. *See* Paul Calem, *The Role of Machine Learning and Alternative Data in Expanding Access to Credit: Fintechs' Regulatory Advantage Is to the Detriment of Consumers*, BANK POL'Y INST. (Oct. 6, 2022), https://bpi.com/the-role-of-machine-learning-and-alternative-data-in-expanding-access-to-credit-fintechs-regulatory-advantage-is-to-the-detriment-of-consumers/.

88. Quentin Hardy, *Just the Facts. Yes, All of Them*, N.Y. TIMES (Mar. 24, 2012), https://www.nytimes.com/2012/03/25/business/factuals-gil-elbaz-wants-to-gather-the-data-universe.html?ref=todayspaper; *see also* Emily Rosamond, *"All Data is Credit Data": Reputation, Regulation and Character in the Entrepreneurial Imaginary*, 25 PARAGRANA (ISSUE 2) 112 (2016), https://doi.org/10.1515/para-2016-0032.

89. ZestFinance originally partnered with the Turtle Mountain Band of the Chippewa Indian Tribe to create the subsidiary BlueChip, which is incorporated under tribal law. Because of its tribal lender status, BlueChip (under the control and direction of ZestFinance) was not subject to state usury laws capping interest rates. In 2018, ZestFinance became a target of a class action, in which the plaintiffs alleged that the loans originated by ZestFinance violated Washington usury law (codified in Wash. Rev. Code § 19.52.030), violated the Washington Consumer Protection Act (codified in Wash. Rev. Code § 19.86.020),

help lenders make more accurate credit underwriting decisions based on a wide set of previously inaccessible consumer data.[90] But most financial institutions were skeptical.[91] In 2012, credit underwriting machine learning algorithms were replete with errors and few investors considered them anything more than a costly experiment.[92]

After a decade of rapid improvements in credit scoring machine learning algorithms, lenders using machine learning have obtained a sizable share of the consumer credit underwriting market.[93] According to a 2018 report, 82% of lenders reported making consumer lending decisions using machine learning to process non-traditional and alternative data.[94] Most lenders see opportunities for machine learning to aid in their lending process, and some financial institutions now use, or are experimenting with using, machine learning for credit assessment in mortgage lending.[95] A 2018 survey conducted by Fannie Mae found that "27% of mortgage originators currently use machine learning and artificial intelligence in their origination process and 58% of mortgage originators expect to adopt the technology within two years."[96]

The banking sector has been slow in adopting machine learning in their credit underwriting process due to their existing reliance on FICO scores and reports

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and constituted unjust enrichment under Washington common law. *See* Titus v. ZestFinance, Inc., No. 18-5373, 2018 WL 5084844, at *1 (W.D. Wash. 2018). The case was settled in 2020. Afterwards, ZestFinance rebranded into Zest AI, stopped providing payday loans, and began providing AI-based credit analytical services to other financial institutions and lenders.

90. ZestFinance's LinkedIn page states: "The world's most innovative lenders rely on ZestFinance to do more profitable lending through machine learning. Our Zest Automated Machine Learning (ZAML) software is the only solution for explainable AI in credit, and we automate risk management so our customers can focus on lending safely to more people" ZestFinance, LINKEDIN (accessed Aug. 21, 2022), https://www.linkedin.com/company/zestfinance/; *see also* Steve Lohr, *Big Data Underwriting for Payday Loans*, N.Y. TIMES (Jan. 19, 2015), https://archive.nytimes.com/bits.blogs.nytimes.com/2015/01/19/big-data-underwriting-for-payday-loans/.

91. "A key challenge for the early adoption of AI credit underwriting systems has involved the ability of such systems to generate the specific reasons for adverse credit decisions in accordance with existing standards and without generating confusion or providing inaccurate reasons." BANK POL'Y INST. & COVINGTON, THE FUTURE OF CREDIT UNDERWRITING: ARTIFICIAL INTELLIGENCE AND ITS ROLE IN CONSUMER CREDIT 14 (A.I. Discussion Draft, 2019), https://bpi.com/wp-content/uploads/2019/09/BPI-Artificial-Intelligence-Discussion-Draft-The-Future-of-Credit-Underwriting.pdf.

92. *See id*. at 18.

93. As of April 2022, Arthur, H2O.ai, Fiddler AI, Relational AI, SolasAI, Stratyfy, and Zest AI provide AI diagnostic services or products that reflect the dominant approaches to underwriting consumer credit using commercially available ML models. *See* Blattner, Stark & Spiess, *supra* note 32, at 23-24.

94. *See* AITE GROUP, ALTERNATIVE DATA ACROSS THE LOAN LIFE CYCLE: HOW FINTECH AND OTHER LENDERS USE IT AND WHY 11 (prepared for Experian Info. Sol., Inc., 2018), https://www.experian.com/assets/consumer-information/reports/Experian_Aite_AltDataReport_Final_120418.pdf.

95. *See id*. at 16 (86% of lender-study-respondents believed machine learning could aid in their lending process, although only a "handful" are currently using these models).

96. *See* FANNIE MAE, MORTGAGE LENDER SENTIMENT SURVEY: HOW WILL ARTIFICIAL INTELLIGENCE SHAPE MORTGAGE LENDING 7, 10 (Special Topic Rep., 2018), https://www.fanniemae.com/sites/g/files/koqyhd191/files/migrated-files/resources/file/research/mlss/pdf/mlss-artificial-intelligence-100418.pdf.

by credit reporting agencies.[97] In contrast, non-bank lenders have more readily adopted machine learning. Non-bank lenders have adopted machine learning because they largely rely on digital business models, use newer lending platforms, are not subject to bank-like model risk management requirements, are subject to less consistent examination and oversight, and are incentivized by private equity investors to adapt new technologies.[98] Credit bureaus and companies that develop third-party credit scores (e.g., FICO and VantageScore) are also starting to use machine learning.[99] Machine learning usage is most concentrated in the underwriting of unsecured personal loans and credit cards.[100] Between 2015 and 2019, fintech lenders doubled their share in the unsecured personal loan market and now account for 49% of originated loans.[101] Auto-lending[102] and small business lending[103] are also areas where machine learning underwriting models are in use.

With more credit-underwriting companies embracing the "all data is credit data" approach, the traditional distinction between "relevant" and "irrelevant" data has blurred.[104] For instance, ZestAI's credit scoring machine learning model takes into consideration data that may appear to have little connection with creditworthiness.[105] The model measures "how responsible a loan applicant is" by analyzing the speed they scroll through an online terms-and-conditions disclosure.[106] The model uses the number of social media connections a loan applicant has, the frequency at which a loan applicant deactivates their account, and the number of connections a loan applicant unfriends as proxies to measure risk-taking tendencies.[107] The model also considers spending habits in the

97. *See* Blattner, Stark & Spiess, *supra* note 32, at 24.

98. *Id*. at 25.

99. *Id*.

100. *Id*.

101. *Id*; *see also* EXPERIAN INFO. SOL. INC., FINTECH VS. TRADITIONAL FLS: TRENDS IN UNSECURED PERSONAL INSTALLMENT LOANS 3 (2019), https://www.experian.com/blogs/insights/fintech-vs-traditional-fis-latest-trends-personal-loans/; DBRS, INC., U.S. UNSECURED PERSONAL LOANS—MARKETPLACE LENDERS CONTINUE TO EXPAND MARKET SHARE 3-4 (2019), https://www.dbrsmorningstar.com/research/350589/us-unsecured-personal-loans-marketplace-lenders-continue-to-expand-market-share.

102. Becky Yerak, *AI Helps Auto-Loan Company Handle Industry's Trickiest Turn*, WALL ST. J. (Jan. 3, 2019), https://www.wsj.com/articles/ai-helps-auto-loan-company-handle-industrys-trickiest-turn-11546516801.

103. Trevor Dryer, *How Machine Learning Is Quietly Transforming Small Business Lending*, FORBES (Nov. 1, 2018), https://www.forbes.com/sites/forbesfinancecouncil/2018/11/01/how-machine-learning-is-quietly-transforming-small-business-lending/.

104. *See* Rob Aitken, *'All Data is Credit Data': Constituting the Unbanked*, 21 COMPETITION & CHANGE 274, 281 (2017).

105. *See supra* text accompanying note 92. In this Article, I focus on problems with ZestFinance's original AI credit underwriting model prior to the company's rebranding in 2018. In no way does my criticism imply that ZestAI is presently continuing the problematic practices discussed here.

106. Quentin Hardy, *Big Data for the Poor*, N.Y. TIMES (Jul. 5, 2012), https://archive.nytimes.com/bits.blogs.nytimes.com/2012/07/05/big-data-for-the-poor/.

107. *Id*.

context of the loan applicant's geographic location.[108] For example, "paying half of one's income [on rent] in an expensive city like San Francisco might be a sign of conventional spending, while paying the same amount in cheaper Fresno could indicate profligacy."[109]

Although credit scoring machine learning models have an immense impact on the financial lives of consumers, such models are poorly understood by consumers and regulators. Companies rarely disclose the methods they use for computing credit scores because these methods are often linked to proprietary algorithms that companies guard closely as trade secrets.[110] Likewise, the reasoning that companies give for equating certain behavior with creditworthiness remains opaque. While each company has adopted a distinct methodology for processing the wealth of alternative data collected, the vast majority of fintech companies in the business of credit underwriting have embraced the "all data is credit data" approach because it allows lenders to extract more profits through personalized risk optimization.[111]

However, financial institutions have taken steps to increase visibility and accountability into machine learning model data inputs and the alternative data market more generally. For example, fintech lenders have developed business partnerships and industry initiatives to provide data transparency and reduce bias, in response to popular stakeholder demands for corporate social responsibility.[112] Some of the largest financial institutions have harnessed their market power to reshape the landscape of data aggregation and brokerage. For instance, the payments network giant Mastercard announced in June 2020 its decision to acquire Finicity, a market-leading data broker, to internalize the data collection process.[113] The acquisition enabled Mastercard to monitor the data collection process in-house, rather than to purchase data from third party data brokers. Mastercard's acquisition followed an announcement by Visa to acquire

108. *Id.*

109. *Id.*

110. Under the Defend Trade Secrets Act (codified at 18 U.S.C. § 1839(3)), any piece of information is a trade secret if: (A) the owner takes reasonable measures to keep such information secret; and (B) the information derives independent economic value from (1) not being generally known to the public, and (2) not being legally accessible by anyone who can profit from its disclosure or use. This definition includes algorithms. Even if the inputs are available to the public, it would be difficult for the public to understand the practices of the credit-underwriting industry because variations exist between each company's methodology. Uniform industry standards have not yet been developed because the rapid technological changes in and hyper-competitive nature of this market result in market fragmentation. It is thus currently impossible to construct a complete snapshot of the industry. *See* Robinson & Yu, *supra* note 48, at 13-15.

111. Around 74% of lenders have begun to phase out of traditional credit reporting. 59% of lenders are turning to alternative data in their underwriting process. *See Research Finds Majority of Lenders Now Use Alternative Data in their Underwriting Process*, NOVA CREDIT CORPORATE BLOG (Oct. 24, 2022), https://www.novacredit.com/corporate-blog/alternative-data-research-report-findings.

112. FINREGLAB, DATA DIVERSIFICATION IN CREDIT UNDERWRITING 8 (Oct. 2020), https://finreglab.org/data-diversification-in-credit-underwriting.

113. *Id.* at 7-8.

the data aggregator Plaid.[114] Similarly, banks have also tried to exercise oversight over the process of data aggregation by pushing data brokers to "sign bilateral agreements governing the collection and transmission of consumers' account data from the banks' platforms."[115] Wells Fargo announced in September 2020 that it had signed 17 such agreements with intermediaries and fintech companies that would govern "99% of the information being collected from its platforms for use by other financial institutions."[116] Since these financial institutions are already heavily regulated under federal banking laws, business partnerships and acquisitions such as those of Mastercard, Visa, and Wells Fargo brought the previously unregulated data brokers into the domain of federal regulation.[117]

However, these initiatives and partnerships by financial institutions to exercise oversight over data brokerage fail to address the root problem: lack of public access to the inputs and proxies that credit scoring machine learning algorithms rely on. Thus, consumers still lack sufficient visibility into how certain machine learning algorithms may result in biased credit outcomes. Although business partnerships such as those of Mastercard, Visa, and Wells Fargo may bring data brokers in line with heightened standards of banking regulation—which can mitigate the most egregious forms of arbitrary credit assessment—consumers and other market participants still have no access to the information being processed. Ultimately, lenders prioritize their financial returns and pursue underwriting accuracy only as an instrumental goal. Since the objective of underwriting is to optimize risk-return tradeoffs, banks lack incentives to disclose proprietary information or make it available to the consumer.

C. *Societal Implications of AI Usage in Consumer Lending*

1. *Empirical Evidence: Does AI Facilitate or Stymie Equal Credit Access?*

How "discriminatory" is AI lending compared to other methods of credit underwriting? While the normative debate remains unsettled, empirical analyses suggest that, compared to traditional automated credit scoring methods, AI lending results in fewer cases of discrimination. Whereas traditional methods may disadvantage borrowers who do not have prior credit access, AI and machine learning methods enable lenders to use alternative data to evaluate

114. *Id.*
115. *Id.*
116. *Id.* at 8*; see also* Penny Crosman, *Wells Fargo Says it has Nearly Eliminated Screen-scraping Threat*, AMERICANBANKER.COM (Sep. 24, 2020), https://www.americanbanker.com/news/wells-fargo-says-it-has-nearly-eliminated-screen-scraping-threat.
117. *Id.*

creditworthiness where conventional credit information is not available.[118] The increased use of alternative data also leads to decreased reliance on FICO scores by lenders and financial intermediaries. This decreased reliance on FICO scores mitigates consumer exposure to unfair loan pricing and rejection that results from credit invisibility.[119]

There is no shortage of evidence indicating that AI plays a positive role in facilitating credit access expansion. In a 2019 study concerning the impact of machine learning on the consumer credit underwriting market, the CFPB noted that alternative data usage is positively correlated with the scale of credit coverage.[120] Results from the CFPB study indicate that machine learning with alternative data approves 23-29% more loan applicants[121] and lowers annual average interest rates by 15-17% for approved loans.[122] Compared to low-income loan applicants whose creditworthiness was evaluated under the traditional method, those assessed under the algorithmic method were 13% more likely to be approved for credit extensions.[123] Even after controlling race, ethnicity, and gender variables, expansion of credit access occurred across all population segments.[124] A similar study conducted by the National Bureau of Economic Research (NBER) indicated that, although AI was unable to eliminate discrimination based on an applicant's protected characteristics, "fintech algorithms discriminate 40% less than face-to-face-lenders" in mortgage loan approval and interest rate pricing.[125]

In aggregate, AI-informed FinTech lenders reject consumer loans at a far lower rate than traditional lenders who rely on credit scores, reports, or face-to-face analysis by human loan officers in making lending decisions. In mortgage lending, for instance, face-to-face lenders "reject Latinx and African-American [loan applicants] approximately 6% more often than they reject similarly situated

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118. Empirical studies conducted by economists from the Stanford Graduate School of Business and the Wharton School at University of Pennsylvania indicate that risk-based loan pricing can help lenders mitigate both adverse selection and moral hazard by adjusting interest rates and loan terms based on the assessment of borrower default risk. *See generally* William Adams, Liran Einav & Jonathan Levin, *Liquidity Constraints and Imperfect Information in Subprime Lending*, 99 AM. ECON. REV. 49-84 (2009); Liran Einav, Mark Jenkins & Jonathan Levin, *Contract Pricing in Consumer Credit Markets*, 80 ECONOMETRICA 1387-1432 (2012); Liran Einav, Mark Jenkins & Jonathan Levin, *The Impact of Credit Scoring on Consumer Lending*, 44 RAND J. ECON. 249-274 (2013).

119. *See* Jagtiani & Lemieux, *supra* note 63, at 18-19.

120. Patrice Alexander Ficklin & Paul Watkins, *An Update on Credit Access and the Bureau's First No-Action Letter*, CONS. FIN. PROT. BUR. (Aug. 6, 2019), https://www.consumerfinance.gov/about-us/blog/update-credit-access-and-no-action-letter/.

121. *Id.*

122. *Id.*

123. *See id.*

124. *Id*.

125. For mortgage loans originated on fintech platforms using algorithmic solutions, Latinx and African American loan applicants on average pay 5.3 basis points more in interest for purchases and 2.0 basis points for refinancing. In comparison, Latinx and African Americans pay 7.9 and 3.6 basis points more in interest for home purchase and refinance mortgages respectively because of human bias. *See* Robert Bartlett, Adair Morse, Richard Stanton & Nancy Wallace, 143 J. OF FIN. ECON. 30, 56 (2022).

non-white applicants for both purchase and refinance loans."[126] From 2009 to 2015, traditional lenders rejected around 0.74 to 1.30 million non-white loan applicants who would have been approved absent discrimination.[127] AI-informed lenders, on the other hand, are less likely to discriminate based on race or gender in loan rejection decisions.[128]

The fact that credit underwriting software used by traditional lenders is typically programmed to maximize lending profits explains the disparity between traditional and AI-informed lenders. Lenders generally prefer not to reject loans on discriminatory grounds because such a decision foregoes the opportunity to profit from the transaction.[129] In contrast, lenders favor discriminatory pricing because it allows them to retain the profit opportunity while extracting an above-market rent on vulnerable consumers.[130] Human loan officers, however, may forgo such profit opportunity by rejecting a borrower's loan application, under the influence of their personal biases or animus towards a particular group of people. Since AI can compute default risks with mathematical precision, lenders can profit from price discrimination in transactions that would have been rejected by a human loan officer.[131]

Empirical studies like those conducted by the CFPB and NBER portray a mixed picture of AI bias in credit underwriting. These studies suggest that while AI-informed lenders are not devoid of inherent biases, their credit results are not more discriminatory than human analysts, and the benefits of AI-based credit underwriting in expanding credit access should not be overlooked. These results corroborate the banking industry's general narrative that AI-based credit underwriting creates a win-win for both lenders and borrowers.[132] From a lenders' perspective, AI creates a "Goldilocks Zone" where the consumers' interests for fair lending protection and the banks' interests for profit maximization are evenly balanced.[133] Even for those lenders who support stricter data transparency rules, AI provides a "second-best solution" absent of a less discriminatory alternative.[134] Lenders suggest that the proper focus of AI

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126. *Id.* at 7.

127. *Id.*

128. *See id.*

129. *See id.*

130. *See id.*

131. *See id.*

132. For example, ZestFinance's official website proudly states that lenders who employed Zest's software gained "additional $1.1 million profit per year," while showing a "17% increase in overall approval rate" and "20% increase in approvals for protected classes." ZEST AI, https://www.zest.ai/industry/specialized-lending (last visited Nov. 10, 2023).

133. *See* Bartlett et al., *supra* note 125, at 37 (arguing that fintech has a positive role in loan accept/reject decisions, as "any discrimination in loan rejection rates—as opposed to discrimination in loan pricing—would appear to be inconsistent with the lenders' profit maximization, and that any unprofitable discrimination must reflect human bias by loan officers.").

134. *See* Nydia Remolina, *The Role of Financial Regulators in the Governance of Algorithmic Credit Scoring* 21 (SMU Ctr. FOR AI & DATA GOVERNANCE, WORKING PAPER No. 2/2022, 2022), https://papers.//ssrn.com/sol3/papers.cfm?abstract_id=4057986 (arguing that better algorithms and un-

governance should be to align business incentives with more inclusive data-aggregation and training processes—such as by "remov[ing] bias from data before the model is built."[135]

However, AI-based credit underwriting is currently focused solely on economic factors such as loan approval rates and interest rate pricing. From a "pure economic" perspective, there seems to be little necessity for heightened AI regulation because, after all, the market's embrace of AI has expanded credit access, and the benefits of algorithmic credit underwriting exceed its harms. Yet, this perspective neglects AI's hidden societal costs: encroachments on personal autonomy, erosions of consumer choice, and penalties for certain lifestyles.[136] These costs arguably create deeper and more lasting impacts on systemic inequality that may undermine efforts to deliver distributive justice.

2. Costs of Credit Access: How AI Undermines Individual Autonomy

Concerns Over Digital Unaccountability: Despite expanding credit access, AI and machine learning tools can pose significant risks to transparency, accuracy, and fairness.[137] Opaqueness about what goes into the training data of algorithms and what methods companies use to assess risk already provokes alarm among bank regulators and consumer advocates.[138] Since proprietary algorithms are typically protected as trade secrets, algorithmic inputs are not subject to judicial review or public scrutiny.[139] Thus, consumers face difficulty

biased data do not solve the perils of AI bias in creditworthiness assessment and that regulators should change their approach to focus on data privacy rights, transparency, data availability, and involve fintech companies in sandbox regulation).

135. *See, e.g.*, Sian Townson, *AI Can Make Bank Loans More Fair*, HARV. BUS.REV. (Nov. 6, 2020), https://hbr.org/2020/11/ai-can-make-bank-loans-more-fair; Makada Henry-Nickie, *How Artificial Intelligence Affects Financial Consumers*, BROOKINGS INSTITUTION (Jan. 31, 2019), https://www.brookings.edu/research/how-artificial-intelligence-affects-financial-consumers/.

136. *See infra* Part I.C.2.

137. *See, e.g.*, Joy Buolamwini, *Artificial Intelligence Has a Problem with Gender and Racial Bias. Here's How to Solve It*, TIME (Feb. 7, 2019), https://time.com/5520558/artificial-intelligence-racial-gender-bias/; Michael Akinwumi, John Merrill, Lisa Rise, Kareem Saleh & Maureen Yap, *An AI Fair Lending Policy Agenda for the Federal Financial Regulators*, BROOKINGS CENTER ON REGULATION AND MARKETS (Dec. 2, 2021), https://www.brookings.edu/research/an-ai-fair-lending-policy-agenda-for-the-financial-regulators/; Olga Akselrod, *How Artificial Intelligence Can Deepen Racial and Economic Inequities*, ACLU NEWS & COMMENTARY (Jul. 13, 2021), https://www.aclu.org/news/privacy-technology/how-artificial-intelligence-can-deepen-racial-and-economic-inequities/.

138. *See*, *e.g.*, Pam Dixon & Robert Gellman, *The Scoring of America: How Secret Consumer Scores Threaten Your Privacy and Your Future*, WORLD PRIVACY FORUM (Apr. 2, 2014); Robinson & Yu, *supra* note 48 at 27.

139. Except in rare cases where the trade secret violates another's constitutional right, or if the normal exercise of one's constitutional right involves the disclosure of a trade secret. In such cases, a court will not protect the trade secret from disclosure. *See, e.g.,* Religious Technology Center v. Lerma, 897 F.Supp. 260 (E.D. Va. 1995) (holding that even confidential materials posing substantial dangers to national interests cannot warrant a prior restraint on First Amendment Rights); *Lerma*, 897 F.Supp. at 263 ("if a threat to national security was insufficient to warrant a prior restraint…the threat to plaintiff's…trade secrets is woefully inadequate."). *Cf.* New York Times v. United States, 403 U.S. 713 (1971) (holding that a trade secret owner must show extraordinary harm to obtain a court order enjoining a defendant from disclosing a trade secret that implicates matters of public concern).

when challenging algorithmic decisions that rely on problematic methods or inaccurate data, as any legal or administrative proceeding involving the identification of trade secrets would impose significant fact-finding and economic hurdles on the consumer.[140] While proponents for AI deregulation tend to emphasize that AI underwriting methods are less discriminatory than traditional methods when it comes to interest pricing and approval rates, the opaqueness of AI models erodes the consumers' right to know, understand, and challenge how lenders use consumers' personal information. Such opaqueness also confers to the lender an unfair advantage to exploit informational asymmetries against the borrowers.

Encroachment of Privacy and Autonomy: The utilization of social media data in machine learning also implicates concerns about consumer data privacy and the loss of autonomy, given the breadth of data that is being analyzed. In 2012, Meta (previously "Facebook") filed a patent application regarding a method for "[a]uthorization and authentication based on an individual's social network."[141] The patent application indicated that credit scoring is one of the preferred uses of the invention. The application stated: "[w]hen an individual applies for a loan, the lender examines the credit ratings of members of the individual's social network… If the average credit rating of these members is at least a minimum credit score, the lender continues to process the loan application. Otherwise, the loan application is rejected."[142] Meta's invention aimed to help banks and fintech lenders to reach the "underbanked" and "unbanked" consumer population by constructing an applicant's credit risk profile from their social network.[143] However, this invention would allow lenders, financial intermediaries, and data brokers to probe into a consumer's personal life and commoditize data generated by the consumer's digital footprint on Meta for business purposes without the consumer's consent.

While Meta has not yet implemented its patent for consumer credit underwriting, its potential application—scoring consumers' credit rating based on where they live and what social ties they maintain—also prompts concern that AI can lead to unjustifiable profiling. Such a practice would disproportionately impact people of color. The possibility that a consumer may be financially punished for factors unrelated to their abilities to perform an obligation is inconsistent with the broad legal concept of fairness.[144] Human loan officers

140. *See* Hurley & Adebayo, *supra* note 11, at 166.

141. U.S. Patent No. 9,100,400 B2 (filed Aug. 2, 2012).

142. *Id.*

143. *Id.*

144. Unjustified AI profiling is at least inconsistent with two board concepts of legal fairness: (i) Fundamental Fairness, which is embodied in the Constitution's protection of a citizen's right to privacy under the Fifth Amendment's substantive due process doctrine, and (ii) Contractual Fairness, which protects the consumer's right to know the terms of the contract and void any unconscionable contracts that exploit the consumer's informational asymmetry. *See* Janine S. Hiller, *Fairness in the Eyes of the Beholder: AI; Fairness; and Alternative Credit Scoring*, 123 W. VA. L. REV. 907, 916-19 (2021).

understand that a borrower's residency, ties, and networks are social data points that can reflect their gender, racial, or ethnic backgrounds.[145] Yet, an algorithm cannot discern and exclude all socially-embedded data points from their inputs, even with complex code instructions that addresses every foreseeable possibility for introducing bias in the data scraping and machine learning processes.[146] While an algorithm can easily detect discrete human biases and disregard them as noise in a broad dataset, an algorithm is unable to interpret patterns that carry socially-embedded meanings which are obvious to humans.

Proxy Discrimination Based on Past and Unrelated Factors: Machine learning algorithms can also perpetuate and intensify existing societal biases by generating predictions based on flawed training data reflective of past human prejudices or erroneous judgments.[147] For example, AI may interpret indirect pre-market factors such as lack of access to higher education, high rates of incarceration, and criminal records—outcomes of past societal disparities that are results of human prejudice—as statistical patterns that it recycles into algorithmic inputs.[148] Even "pure economic factors" such as high levels of debt may reflect racial disparities. For example, payday lenders often target minorities who experience short-term liquidity plights more frequently than white populations, causing people of color to accrue higher levels of debt.[149]

Even if the suspect inputs are excluded from the algorithms, AI may still compute discriminatory results because it draws indirect inferences based on facially neutral sources that reflect embedded racial or gender preferences.[150] Discriminatory results occur because machine learning replicates societal biases by scoring consumers based on proxies[151] that reflect suspect factors of race, gender, ethnicity, national origin, religion, marital status, familial association, and age, even if these protected characteristics are excluded from the "inputs" of the algorithm.[152] The AppleCard, for instance, recently drew intense criticism when a male applicant complained that he received a line of credit 20 times higher than that offered to his wife, even though the two filed joint tax returns,

145. *See generally* Joe McKendrick & Andy Thurai, *AI Isn't Ready to Make Unsupervised Decisions*, HARV. BUS. REV. (Sep. 15, 2022), https://hbr.org/2022/09/ai-isnt-ready-to-make-unsupervised-decisions.

146. *See id*.

147. *See* RUHA BENJAMIN, RACE AFTER TECHNOLOGY: ABOLITIONIST TOOLS FOR THE NEW JIM CODE (2019).

148. *See id.*

149. *See, e.g.*, Oren Bar-Gill & Elizabeth Warren, *Making Credit Safer*, 157 U. PA. L. REV. 1 (2008); Cassandra Jones Havard, *On the Take: The Black Box of Credit Scoring and Mortgage Discrimination*, 20 B.U. PUB. INT. L. J. 241 (2011); Gillis, *supra* note 26, at 1175.

150. *See* Gillis, *supra* note 26, at 1184.

151. *See generally* Anya E.R. Prince & Daniel Schwarcz, *Proxy Discrimination in the Age of Artificial Intelligence and Big Data*, 105 IOWA L. REV. 1257 (2020).

152. *See* Gillis, *supra* note 26, at 1184.

lived in the same community, and owned the same property.[153] Goldman Sachs, the issuer of AppleCard, responded to the complaint by noting that the AI device used by the company could not have discriminated against the applicant's wife because the device "[doesn't] even use gender as an input,"[154] "do[es] not know [the applicant's] gender," and does not make decisions "based on factors like gender."[155] However, Goldman's explanation is misleading because a gender-blind algorithm could still be biased against women if it is drawing statistical inference from inputs that correlate with gender, such as purchase history and credit utilization.[156] The AppleCard incident highlights the common misconception that removing faulty algorithmic inputs and proxies for protected characteristics eliminates AI bias.[157]

3. *Digital Redlining: How AI Norm-Policing Amplifies Systemic Inequalities*

The use of machine learning algorithms in credit underwriting can perpetuate bias by excluding vulnerable and marginalized consumers from participating in certain financial markets, resulting in what some have called a "new form of digital redlining."[158] Unlike the discriminatory practice of redlining, where lenders withheld from making loans to consumers from neighborhood banks deemed "hazardous," digital redlining is not a visible set of discriminatory practices. Instead, digital redlining consists of an entire data ecosystem of racialized and gendered transactional costs deployed by lenders in ways that perpetuate systemic inequalities along racial, gender, and class dimensions.[159] In this ecosystem, a consumer is financially penalized with more exploitative loan

153. *See* James Vincent, *Apple's credit card is being investigated for discriminating against women*, THE VERGE (Nov. 11, 2019), https://theverge.com/2019/11/11/20958953/apple-credit-card-gender-discrimination-algorithms-black-box-investigation/.

154. Will Knight, *The Apple Card Didn't 'See' Gender—and That's the Problem*, WIRED (Nov. 19, 2019), https://wired.com/story/the-apple-card-didnt-see-genderand-thats-the-problem/.

155. *See* Neil Vigdor, *Apple Card Investigated After Gender Discrimination Complaints*, N.Y. TIMES (Nov. 10, 2019), https://www.nytimes.com/2019/11/10/business/Apple-credit-card-investigation.html.

156. *See* Ian Carlos Campbell, *The Apple Card doesn't actually discriminate against women, investigators say*, THE VERGE (Mar. 23, 2021), https://theverge.com/2021/3/23/22347127/goldman-sachs-apple-card-no-gender-discrimination/.

157. Knight, *supra* note 154.

158. *See* Robinson Meyer, *Could a Bank Deny Your Loan Based on Your Facebook Friends?* THE ATLANTIC (Sep. 25, 2015), https://www.theatlantic.com/technology/archive/2015/09/facebooks-new-patent-and-digital-redlining/407287/.

159. *See, e.g.*, Linda Morris & Olga Akselrod, *Holding Facebook Accountable for Digital Redlining*, ACLU NEWS & COMMENTARY (Jan. 27, 2022), https://www.aclu.org/news/privacy-technology/holding-facebook-accountable-for-digital-redlining; Nicole Karlis, Digital Redlining: Facebook's Housing Ads Seem Designed to Discriminate, SALON (Aug. 21, 2019), https://www.salon.com/2019/08/21/digital-redlining-facebooks-housing-ads-seem-designed-to-discriminate/; Daniel Leufer, *Computers are Binary, People Are Not: How AI Systems Undermine LGBTQ Identity*, ACCESS NOW (Apr. 6, 2021), https://www.accessnow.org/how-ai-systems-undermine-lgbtq-identity/.

prices and terms than similarly situated consumers simply because she belongs to a marginalized social group.[160]

Digital redlining unjustifiably punishes marginalized social groups. For example, members of the LGBTQ community are consistently penalized for having lower credit ratings and more expensive loans. As a result, members of this community are less likely to participate in markets for essential consumer financial products and have fewer opportunities for upward mobility. Although LGBTQ people tend not to engage in heteronormative consumption and investment activities that banks view as "credit-enhancing," they are twice as likely as non-LGBTQ people to be placed in the subprime and deep subprime risk categories.[161] Over a third (35%) of LGBTQ adults have been denied or excluded from obtaining home equity credit and mortgage loans, compared to 21% of non-LGBTQ adults.[162]

AI-lending exacerbates digital redlining because the underlying logic of AI-lending—risk-return optimization—implicitly protects the status quo. An AI model makes decisions by emulating pre-existing "staple" decisions—norms that can be translated into statistical patterns.[163] These "staple" decisions form the basis of the AI model's learning process. In this process, a machine learning algorithm feeds all available alternative data about a consumer into the model and computes a prediction about the consumer's future credit risk.[164] By design, the machine learning process excludes any "splinter data" that cannot be mapped onto a pre-existing norm.[165] Whether or not the lenders who use such AI models intended to discriminate against marginalized social groups, such "splinter data" often includes consumer datapoints reflecting behavioral patterns that do not fit the idealized confines of working-class heteronormativity.

As illustrated by the examples above, the lenders' embrace of AI in the credit underwriting process has created a market-based "norm-policing" regime that disciplines consumers' choices, behaviors, and microeconomic preferences.[166]

160. *See* Zack Quaintance, *What is Digital Redlining? Experts Explain the Nuances*, GOVERNMENT TECHNOLOGY (Mar. 28. 2022), https://www.govtech.com/network/what-is-digital-redlining-experts-explain-the-nuances.

161. *Credit Reporting and Scoring*, LGBTQ ECONOMICS (accessed Sep. 26, 2022), https://lgbtq-economics.org/issues/credit-reports-and-scores/.

162. *See id.*

163. *See* Jamie Wareham, *Why Artificial Intelligence is Set Up to Fail LGBTQ People*, FORBES (Mar. 21, 2021), https://www.forbes.com/sites/jamiewareham/2021/03/21/why-artificial-intelligence-will-always-fail-lgbtq-people/?sh=4c6e3946301e.

164. *See supra* Part I.B.1; *see also* Artem Oppermann, *Predictive Behavior Modeling: How to Keep Your Customers With AI*, BUILTIN (Jun. 14, 2022), https://builtin.com/machine-learning/predictive-behavior-modeling.

165. *See* Wareham, *supra* note 163.

166. By "norm-policing" regime, I refer to systems of digital surveillance that coerce, pressure, or unduly influence individuals to conform their internal motivations with external social norms through the means of punishment or reward. These systems of digital surveillance may include AI systems or informational technology systems more generally. *See generally* Daniel Villatoro, Giulia Andrighetto, Rosaria Conte & Jordi Sabater-Mir, *Self-Policing Through Norm-Internalization: A Cognitive Solution to*

Both individual discrimination and systemic discrimination prevent consumers from accessing markets for essential consumer financial products as equals. Yet, as the following sections aim to demonstrate, the fair lending laws currently only consider individual discrimination. The fair lending laws lack the legal lexicon to describe systemic inequality or means to redress indirect structural harm in the consumer lending space. To uphold the twin aims of consumer financial protection—fair credit access and equal credit opportunity—fair lending laws must reframe the concept of discrimination.

II. EXISTING LEGAL FRAMEWORKS: THE FAIR LENDING LAWS

Since the 1970s, Congress has striven to build a comprehensive regulatory scheme to ensure the fair and equitable supply of credit to all U.S. consumers. Among Congress' grand pursuits were the eradication of poverty and elimination of all lending practices resulting in unequal access to credit.[167]

This Part assesses how well existing fair lending laws respond to the modern threat of algorithmic discrimination. Since *Inclusive Communities*,[168] federal agencies and the lower courts have sought to expand the coverage of fair lending protection by filling in the statutory gap with anti-discrimination doctrines that recognize disparate impact liability. However, such efforts ultimately fail to provide an adequate remedy to victims of algorithmic discrimination because such efforts tend to mischaracterize the nature and source of algorithmic harm. Additionally, the absence of explicit textual support for the disparate impact liability doctrine in ECOA endangers its future survival considering the Supreme Court's textualist interpretative preference. Meanwhile, a parallel jurisprudential trend to infuse anti-discrimination statutes with common-law tort interpretations may create additional procedural hurdles that prevent the victims of algorithmic discrimination from recovery. This Part suggests that, unless we move beyond our current fixations on disparate impact liability, the threat of algorithmic discrimination will continue to go unchecked.

A. Structure and Enforcement of Federal Fair Lending Laws

Two federal statutes form the core of fair lending protection, which broadly prohibits discrimination in the underwriting of consumer credit: the Equal Credit

the Tragedy of the Digital Commons in Social Networks, 18 JOURNAL OF ARTIFICIAL SCIENCES & SOCIAL SIMULATION, Mar. 31, 2015, at 1.

167. *See* Winnie F. Taylor, *The ECOA and Disparate Impact Theory: A Historical Perspective*, 26 J. L. & POL'Y 575, 631 (2018); Francesca Lina Procaccini, *Stemming the Rising Risk of Credit Inequality: The Fair and Faithful Interpretation of the Equal Credit Opportunity Act's Disparate Impact Prohibition*, 9 HARV. L. & POL'Y REV. S43, S48 (2015); Jamie Duitz, *Battling Discriminatory Lending: Taking a Multidimensional Approach Through Litigation, Mediation, and Legislation*, J. AFFORDABLE HOUS. & CMTY. DEV. L. 101, 107 (2010).

168. *See* Tex.Dep't of Hous. & Cmty. Affs. v. Inclusive Cmtys. Project, Inc., 576 U.S. 519, 519 (2015).

Opportunity Act (ECOA)[169] and Fair Housing Act (FHA).[170] ECOA covers any extension of credit in relation to a consumer transaction, and the (FHA) covers loan transactions involving real estate mortgages. While Congress has divided the responsibilities for implementing the fair lending laws among different federal agencies, under the current divisions of power, the CFPB is primarily responsible for enforcing ECOA,[171] while the Department of Housing and Urban Development (HUD) is tasked with administering FHA.[172]

In addition to the core fair lending statutes, Congress has legislated several consumer financial laws[173] to provide transparency to the market forces, information flows, and lending practices that control consumers' access to credit. These laws include the Home Mortgage Disclosure Act (HMDA), which requires that financial institutions maintain, report, and disclose loan-level information about mortgages[174] and the Fair Credit Reporting Act (FCRA), which governs entities involved in the creation, transmission, and use of consumer reports.[175] Congress gave authority to four bank regulators—the Federal Home Loan Bank Board (FHLBB), the Office of the Controller of the Currency (OCC), the Federal Reserve Board (FRB), and the Federal Deposit Insurance Corporation (FDIC)—to periodically examine the fair lending policies and practices of banks and thrift institutions with respect to credit transactions.[176] ECOA and FHA, together with auxiliary legislation mandating the public disclosure of relevant consumer credit information, comprise the primary legal mechanism protecting consumers of financial services and products from discrimination.

Fair lending laws are enforced by federal administrative agencies such as the CFPB and HUD, the U.S. Department of Justice (DOJ),[177] and private parties.[178] Under the Dodd-Frank Act,[179] The CFPB has authority to bring public

169. The Equal Credit Opportunity Act (codified at 15 U.S.C. § 1691) is the cornerstone anti-discrimination statute dealing with all credit transactions.

170. The Fair Housing Act (codified at 42 U.S.C. § 3601) broadly prohibits discrimination concerning all aspects of a housing transaction, including its rent, sales, brokerage, and financing. The central operative provision is 42 U.S.C. § 3604 (discrimination in the sale or rental of housing and other prohibited practices) (emphasis added).

171. *See* 15 U.S.C. § 1691.

172. *See* 42 U.S.C. § 3601.

173. *See* Adam Levitin, *The Consumer Financial Protection Bureau: An Introduction*, 32 REV. BANKING & FIN. L. 322, 344 (2013).

174. *See* 12 U.S.C. ch. 29; *see also* Cons. Fin. Prot. Bur., Home Mortgage Disclosure (Regulation C), FEDERAL REGISTER (Oct. 28, 2015), vinfo.gov/content/pkg/FR-2015-10-28/pdf/2015-26607.pdf.

175. *See* 15 U.S.C. § 1681 and its implementing rule, Regulation V (codified at 12 C.F.R. § 1022).

176. *See* Walter Gorman, *Enforcement of the Equal Credit Opportunity Act*, 37 THE BUS. LAW. 1335, 1337 (1982).

177. While typically the DOJ is tasked with bringing civil lawsuits to enforce ECOA and FHA, because both Acts allow the CFPB and the HUD to bring suits to enforce their regulations under the Acts, aggrieved parties also complain to the federal agencies so that they may bring legal actions as a remedy for ECOA and FHA violations.

178. *See* Gorman, *supra* note 176.

179. Under Section 1021(a) of the Dodd-Frank Wall Street Reform and Consumer Protection Act of 2010 ("Dodd-Frank Act") (codified at 12 U.S.C. § 5511(a)), Congress established the CFPB's statutory

enforcement actions against any entity for violations of federal fair lending laws (including ECOA) and to coordinate regulatory, investigative, and supervisory activities with other federal and state regulators on matters relating to the administration of fair lending laws.[180] Aggrieved individuals are also entitled to a private right of action under the federal fair lending laws and may sue violators for the recovery of civil damages (both compensatory and punitive), attorney's fees, and applicable equitable and declaratory relief (including injunctions).[181] While an aggrieved party may choose to complain to the federal agency responsible for supervising activities of the creditor or notify the DOJ of an alleged violation, private litigation is the dominant mode by which individuals vindicate their rights under the fair lending laws.[182]

B. The Current State of Anti-Discrimination Doctrines

1. Liability Theories: Disparate Treatment and Disparate Impact

All types of enforcement under the federal fair lending laws—whether through administrative enforcement action, DOJ legal action, or private litigation—must begin with the question of what constitutes a cognizable claim of discrimination. Under the existing doctrine, courts have recognized two theories of discrimination that give rise to action under the federal fair lending laws:[183] disparate treatment and disparate impact.[184]

Disparate treatment discrimination occurs when a creditor treats a loan applicant differently based on protected characteristics such as race, national

purpose as "enforc[ing] Federal consumer financial law consistently for the purpose of ensuring that all consumers have access to markets for consumer financial products and services that market for consumer financial products and services are fair, transparent, and competitive." The CFPB has jurisdiction over a wide variety of financial institutions (both depository and non-depository), such as banks, credit unions, securities brokerage firms, mortgage servicing operations, and fintech companies as long as their services and products relate to consumer finance.

180. *See* 12 U.S.C. § 5493(c)(2)(B).

181. *See* 15 U.S.C. § 1691e(b) and 12 C.F.R. § 1002.16 (establishing a private right of action under the Equal Credit Opportunity Act for civil claims of violation); *see also* 42 U.S.C. § 3613 (providing for the enforcement of the Fair Housing Act by private persons).

182. *See* Gorman, *supra* note 176. It is also important to note that a plaintiff may simultaneously assert claims under both FHA and ECOA. But a plaintiff must choose to recover only under one statute, since ECOA prohibits recovery under both ECOA and FHA for the same transaction;s*ee also* 15 U.S.C. § 1691e(i) ("No person aggrieved by a violation under this subchapter and by a violation of section 3605 of Title 42 shall recover under this subchapter and section 3612 of Title 42, if such violation is based on the same transaction.").

183. The statutory language of ECOA and FHA do not recognize the distinction between disparate treatment and disparate impact. But subsequent caselaw by the federal courts articulated the difference through doctrine. Whereas disparate treatment addresses direct animus towards protected groups, disparate impact assesses disproportionate impact where animus can be inferred. The disparate impact doctrine is recognized by the Supreme Court under FHA. Texas Dep't of Hous. & Cmty. Affs. v. Inclusive Cmty. Project, Inc., 576 U.S. 519, 519 (2015).

184. *See* BD. OF GOV. OF THE FED. RESRV. SYS. (FRB), FAIR LENDING REGULATIONS AND STATUTES: OVERVIEW, CONSUMER COMPLIANCE HANDBOOK, 1-3 (2017), https://www.federalreserve.gov/boarddocs/supmanual/cch/fair_lend_over.pdf.

origin, religion, or sex.[185] This is the standard claim of discrimination that plaintiffs bring against a lender.[186] Although plaintiffs are not required to show that the treatment is motivated by animus or prejudice, courts consider disparate treatment a form of intentional discrimination because "the difference in treatment on a prohibited basis has no credible, nondiscriminatory explanation."[187] Both FHA and ECOA's statutory texts unequivocally recognize disparate treatment claims.

Disparate impact discrimination, by contrast, occurs when a creditor employs facially neutral policies or practices that have an adverse effect on a member of a protected class, unless those policies or practices meet a legitimate business need that cannot reasonably be achieved by less discriminatory alternatives.[188] Unlike the disparate treatment doctrine, the disparate impact doctrine does not require a plaintiff to show that a lender intended to discriminate against them.[189] But a policy or practice that "creates a disparity on a prohibited basis is not, by itself, a proof of violation [of the disparate impact doctrine]."[190]

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185. *See id.*

186. To state a prima-facie claim of disparate treatment under ECOA, a plaintiff must allege the following elements:

(a) The plaintiff is a member of a protected class.
(b) The plaintiff sought to engage in a credit transaction with the defendant.
(c) The defendant rejected the plaintiff's credit application or otherwise negatively treated the plaintiff in the credit transaction, despite the plaintiff's qualifications.
(d) The defendant extended credit or gave more favorable treatment to others of similar credit stature that were not members of the protected class.

See, e.g., Wise v. U.S. Dept. of Agric., 2014 WL 5460606, at *3 (E.D.N.C. 2014). To state a prima-facie claim of disparate treatment claim under FHA, the plaintiff must allege that:

(a) The plaintiff is a member of a protected class.
(b) The plaintiff applied for and was qualified for a loan.
(c) The lender rejected the plaintiff's loan application or approved it with less favorable terms despite the plaintiff's qualifications.
(d) The lender continued to approve loans with more favorable terms for applicants with qualifications similar to the plaintiff that were not members of the protected class.

See, e.g., Gorham-DiMaggio v. Countrywide Home Loans, Inc., 421 Fed. Appx. 97, 100 (2d Cir. 2011); Hood v. Midwest Sav. Bank, 95 Fed. Appx. 768, 778 (6th Cir. 2004).

187. *See id.*

188. *Id.*

189. To state a prima facie claim of disparate impact under ECOA, the plaintiff must allege the following elements:

(a) The defendant has a specific policy or practice relating to an aspect of a credit transaction.
(b) The defendant's policy is outwardly neutral.
(c) The defendant's policy has a significant adverse or disproportionate impact on members of a protected group.

See, e.g., Taylor v. Accredited Home Lenders, Inc., 580 F.Supp. 2d 1062, 1067-68 (S.D. Cal. 2012); Hoffman v. Option One Mortgage Corp., 589 F.Supp. 2d 1009, 1011 (N.D. Ill. 2008). To state a prima facie case for disparate impact under FHA, the plaintiff must show:

(a) A statistical disparity between treatment of protected and non-protected classes.
(b) A robust causal link between a policy and the disparity.

See, e.g., City of Los Angeles v. Wells Fargo & Co., 691 Fed. Appx. 453, 454 (9th Cir. 2017).

190. *See* BD. OF GOV. OF THE FED. RESRV. SYS., *supra* note 185; *see also* Personnel Administrator of Massachusetts v. Feeney, 442 U.S. 256, 258 (1979) (noting that disparate impact discrimination in

While the statutory texts of ECOA and FHA do not explicitly recognize the disparate impact doctrine, this theory has been recognized by the federal courts and by agencies enforcing the fair lending laws. A majority of federal district courts have adopted the view that the language of the fair lending laws does not bar disparate impact claims, although lenders have consistently challenged this view over the past two decades of fair lending litigation.[191] In 2015, the Supreme Court gave a partial answer to this decade-long debate in its landmark decision *Inclusive Communities*.[192] In *Inclusive Communities*, the Court considered whether FHA section 804(a) permits plaintiffs to bring disparate impact claims of racial discrimination.[193] The Court held that FHA permits such claims. Writing for the majority, Justice Kennedy reasoned that FHA must be construed to encompass disparate impact claims because FHA's text explicitly refers to the "consequences of actions and not just to the mindset of the actors" as a basis for imposing discrimination liability.[194] *Inclusive Communities* opened the door for plaintiffs to challenge lender practices or policies that are neutral on their face but have an outsized adverse effect on members of a particular demographic in transactions covered by FHA.

Although there is no equivalent Supreme Court case with respect to ECOA, the federal district courts have expansively interpreted ECOA to allow for disparate impact claims, though the judicial reasonings for these decisions vary from district to district.[195] At the appellate level, prior caselaw in the Fifth, Sixth, Ninth, and D.C. Circuits have all suggested, without directly deciding the issue, that disparate impact claims are actionable under ECOA.[196]

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equal protection analysis implies that "the decision maker selected or reaffirmed a particular course of action at least in part 'because of,' not merely 'in spite of,' its adverse effects upon an identifiable group.").

191. *See infra* Part II.B.3.

192. *See* Inclusive Cmty. Project, Inc., 576 U.S. at 519 (2015).

193. *See id.*

194. *Id.* at 520.

195. *See, e.g.*, Ramirez v. GreenPoint Mortgage Funding, Inc., 633 F. Supp. 2d 922, 930 (N.D. Cal. 2008) (holding that FHA and ECOA permitted disparate impact claims); Hoffman v. Option One Mortgage Corp., 589 F. Supp. 2d 1009, 1011 (N.D. Ill. 2008) (holding that disparate impact claims are not precluded under ECOA and FHA); Taylor v. Accredited Home Lenders, Inc., 580 F. Supp. 2d 1062, 1068 (S.D. Cal. 2008) (holding that ECOA and FHA allow disparate impact claims); Zamudio v. HSBC N. Am. Holdings, Inc., No. 07-4315, 2008 WL 517138, at *2 (N.D. Ill. 2008) (holding that the Supreme Court's decision in Smith v. City of Jackson, 544 U.S. 228 (2005), which allowed disparate impact claims under the Age Discrimination in Employment Act based on the rationale that the ADEA's statutory text explicitly mentions results-oriented phrases indicating congressional intent to prohibit adverse effects, does not by implication bar disparate impact claims under other anti-discrimination statutes that do not contain this same language); Beaulialice v. Fed. Home Loan Mortgage Corp., No. 04-2316, 2007 WL 744646, at *4 (M.D. Fla. 2007) (concluding that *Smith* does not bar disparate impact claims under FHA and the same applies to ECOA); Guerra v. GMAC LLC, No.2:08-cv-01297, 2009 WL 449153 at *3 (E.D. Pa. 2009) (holding that the absence of specific language permitting an effects test in ECOA does not preclude disparate impact claims under ECOA).

196. *See, e.g.,* Haynes v. Bank of Wedowee, 634 F.2d 266, 269 (5th Cir. 1981) (suggesting that disparate impact claims are cognizable under ECOA without deciding its scope or applicability); Golden v. City of Columbus, 404 F.3d 950, 963 (6th Cir. 2005) (stating that "it appears" that disparate impact claims are cognizable under ECOA without reaching the issue); Miller v. Am. Express Co., 688 F.2d 1235, 1240 (9th Cir. 1982) (holding that disparate impact gives rise to a cognizable claim of discrimination

2. *Regulation B: Incorporation of Disparate Impact via Agency Interpretation*

Notwithstanding ECOA's statutory silence on the actionability of disparate impact claims, such claims have prevailed in both private litigation and administrative enforcement actions.[197] In the absence of clear statutory or judicial guidance, litigants have relied on the agencies' compliance opinions, no-action letters, regulations, and interpretative rules to bring disparate impact claims under ECOA. This subsection lays out the structure of 12 C.F.R. §1002,[198] which functions as the CFPB's rulebook for fair lending implementation.

12 C.F.R. §1002 is the principal rule interpreting and implementing ECOA.[199] As originally stipulated by Congress in 1974, ECOA grants the Federal Reserve Board (FRB) rulemaking authority to promulgate regulations "to require that financial institutions and other firms engaged in the extension of credit make that credit equally available to all creditworthy customers."[200] The Act also authorizes the FRB to issue interpretative rules and expound on the meaning of the statute.[201] Pursuant to its statutory authority, the FRB issued 12 C.F.R. §1002 to implement ECOA's prohibition against discrimination on the basis of sex, marital status, race, color, religion, national origin, and age.[202] In 2011, Title X of the Dodd-Frank Act transferred rulemaking authority under ECOA from the FRB to the CFPB.[203] Title X also authorized the CFPB to enforce and interpret a number of "consumer financial laws," which aim to safeguard consumer rights and ensure the "fairness, transparency, and competitiveness" of "markets for consumer financial products."[204]

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under ECOA); Garcia v. Johanns, 444 F.3d 625, 633 (D.C. Cir. 2006) (stating that the court had "no opinion" on the subject [of the applicability of disparate impact theory to ECOA cases] while noting the textual differences between ECOA and FHA).

197. Disparate impact cases brought under ECOA have resulted in multi-million-dollar class action settlements in recent years by some of America's largest corporations, including Ford Motor Credit Company, General Motors Acceptance Corporation, and Nissan Motors Acceptance Corporation. For a full list of recent class settlements brought under ECOA, *see e.g.*, *Case Index – Closed Cases*, NATIONAL CONSUMER LAW CENTER (Apr. 2015), https://perma.cc/T5HL-NWYW; *see also* Francesca Lina Procaccini, *Stemming the Rising Risk of Credit Inequality: The Fair and Faithful Interpretation of the Equal Credit Opportunity Act's Disparate Impact Prohibition*, 9 HARV. L. & POL'Y REV. S43, S44 (2015).

198. Equal Credit Opportunity Act (Regulation B), 12 C.F.R. § 1002 (2011).

199. *See* 12 C.F.R. § 1002.

200. Pub. L. 93-495 § 502 (1974).

201. *See* 15 U.S.C. § 1691a(g) ("Any reference to any requirement imposed under this subchapter or any provision thereof includes reference to the regulations of the Bureau under this subchapter or the provision thereof in question.").

202. Upon the passage of ECOA in 1974, the FRB issued 12 C.F.R. §1002only to enforce ECOA's prohibition against discrimination on the basis of sex or marital status. In December 1976, the FRB amended 12 C.F.R. §1002 to incorporate ECOA's recently expanded coverage to prohibit discrimination on a broader set of protected characteristics, including race, color, national origin, religion, and age. *See* 12 C.F.R. § 202.

203. *See* 12 C.F.R. § 1002.1(a).

204. *See* CFPB, Equal Credit Opportunity (Regulation B): Interim Final Rule with Request for Public Comment, 76 Fed. Reg. 79442, 79444 (Dec. 21, 2011); *see also* Dodd-Frank Act §1021 (codified at 12 U.S.C. § 5511) (stating that the CFPB shall seek to implement and enforce federal consumer financial

12 C.F.R. §1002 outlines two broad prohibitions against discriminatory lending and recognizes both disparate treatment and disparate impact as actionable claims. 12 C.F.R. §1002 states as follows:

> "(a) A creditor shall not discriminate against an applicant on a prohibited basis regarding any aspect of a credit transaction. (b) A creditor shall not make any oral or written statement, in advertising or otherwise, to applicants or prospective applicants that would discourage, on a prohibited basis, a reasonable person from making or pursuing an application."[205]

Subsection (a) encompasses both actual and inferred discriminatory intent, which corresponds to the conventional theory of disparate treatment.[206] Subsection (b) makes illegal any act or policy by the creditor that results in a discriminatory consequence without regard to intention, which corresponds to the theory of disparate impact.[207]

While there is no explicit textual basis in ECOA for a disparate impact claim, the CFPB has pointed to congressional purpose to support its inclusion of disparate impact liability in 12 C.F.R. §1002. The CFPB relied on 12 C.F.R. §1002.6(a), which references the legislative history of ECOA, as support for recognizing disparate impact claims. Specifically 12 C.F.R. §1002.6(a) states that "Congress intended an 'effects test' concept… to be applicable to a creditor's determination of creditworthiness."[208] According to the CFPB's official comment on 12 C.F.R. §1002.6(a), under the "effects test," a creditor can be liable for an ECOA violation for engaging in practices or activities that are "discriminatory in effect because it has a disproportionately negative impact on a prohibited basis, even though the creditor has no intent to discriminate and the practice appears neutral on its face."[209] Similar references to an "effects test" can also be found in the FRB's commentary on 12 C.F.R. §1002.[210]

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laws for the purpose of "ensuring that all consumers have access to markets for consumer financial products and that the markets for consumer financial products are fair, transparent, and competitive.").

205. 12 C.F.R. § 1002.4(a)-(b).

206. *See* CFPB, CFPB Consumer Laws and Regulations – Equal Credit Opportunity Act (ECOA), 2-3 (Jun. 2013), https://files.consumerfinance.gov/f/201306_cfpb_laws-and-regulations_ecoa-combined-june-2013.pdf.

207. *See id.*

208. 12 C.F.R. § 1002.6(a).

209. CFPB, Comment for 1002.6 – Rules Concerning Evaluation of Applications, https://www.consumerfinance.gov/policy-compliance/rulemaking/regulations/1002/Interp-6/.

210. *See* 12 C.F.R. § 1002 (emphasis added). The FRB's commentary to 12 C.F.R. §1002 contains the following reference to the effects test, which cites congressional committee reports as support for ECOA disparate impact liability:

> "*Effects test*. The effects test is a judicial doctrine that was developed in a series of employment cases decided by the U.S. Supreme Court under Title VII of the Civil Rights Act of 1964 (42 U.S.C. § 2000e *et seq*.), and the burdens of proof for such employment cases were codified by Congress in the Civil Rights Act of 1991 (42 U.S.C. § 2000e-2 *et seq*.). *Congressional intent that this doctrine applies to the credit area is documented in the Senate Report that accompanied H.R. 6516, No. 94-589, pp. 4-5; and in the House Report that accompanied H.R. 6516, No. 94-210, p.5.* The Act and regulation may prohibit a creditor practice that is discriminatory in effect because it has a disproportionately negative impact on a prohibited basis, even though the creditor has no intent to discriminate and the practice appears neutral on its face, unless the

Until very recently, federal agencies in charge of various aspects of fair lending enforcement have shared the understanding that disparate impact claims are actionable under ECOA.[211] Both the CFPB and the DOJ have pursued enforcement actions against lenders pursuant to the liability provisions of 12 C.F.R. §1002.[212] However, the validity of 12 C.F.R. §1002's disparate impact provision has encountered legal challenges. Although the DOJ has opined that 12 C.F.R. §1002 remains the "substantive and procedural framework for fair lending" under ECOA, opponents to the proposed rule have challenged the agencies' authority to establish the disparate impact standard in 12 C.F.R. §1002.[213] The following section discusses these challenges in detail, in light of the current political climate and the paradigm shifts in the Supreme Court's disparate-impact jurisprudence.

3. Legal Challenges to ECOA Disparate Impact Liability Theory

Since the inception of ECOA, its disparate impact liability theory has been under assault by lenders, the banking industry, and their allies in the federal government.[214] Challengers argue that the agencies' broad interpretation does not warrant judicial deference because it lacks textual support in the statutory language and is contrary to the Supreme Court's precedent in other discrimination contexts.[215] Despite lenders' protests, a number of federal district courts have deferred to the agencies' interpretative rules in light of ECOA's textual ambiguities.[216] While the Supreme Court's ruling in *Inclusive*

creditor practice meets a legitimate business need that cannot reasonably be achieved as well by means that are less disparate in their impact…"

211. *See infra* Part II.B.3; *see also* Heather Klein, *Testing the "Effects Test" Is Not A Test for Fair Lending Enforcement*, 17 CONSUMER FIN. SERVICES L. REP. 3, 6 (2013) (stating that "although disparate impact is under challenge in the courts, the government continues to enforce the fair lending laws on the basis of that theory.").

212. Under the Obama Administration, the CFPB has pursued claims against auto-lenders under 12 C.F.R. §1002's disparate impact provisions. During the Trump Administration, the CFPB has halted the majority of enforcement actions against lenders on the theory that there was no clear congressional delegation of statutory authority to bring ECOA disparate impact actions. Currently, the CFPB under Biden Administration seeks to revive the disparate impact standard. The CFPB has also opined on the possibility of pursuing such claims against lenders in the algorithmic discrimination context. *See* Andrew Michaelson, Brian Thavarajah & Margaret McPherson, *A Revived Disparate Impact Doctrine Under Biden's CFPB*, LAW360 (Feb. 17, 2021), https://www.kslaw.com/attachments/000/008/593/original/2-17-21_Law360.pdf?1613687065

213. The Equal Credit Opportunity Act, 15 U.S.C §1691 (1974).

214. See Michael Aleo & Pablo Svirsky, *Foreclosure Fallout: The Banking Industry's Attack on Disparate Impact Race Discrimination Claims Under the Fair Housing Act and The Equal Credit Opportunity Act*, 18 B.U. PUB. INT. L.J. 1, 41-49 (2008).

215. *See* Andrew L. Sandler & Kirk D. Jensen, *Disparate Impact in Fair Lending: A Theory Without a Basis & The Law of Unintended Consequences*, 33 BANKING & FIN. SERVS. POL'Y REP. 18, 28 (2014).

216. *See* Treadway v. Gateway Chevrolet Oldsmobile Inc., 362 F.3d 971, at n.3 (7th Cir. 2004) (citation in original) ("The ECOA delegated to the Federal Reserve Board the power to implement regulations in furtherance of carrying out the Act's purpose."); *see also* Powell v. Pentagon Federal Credit Union, No.10-cv-785, 2010 WL 3732195, at *4 (N.D. Ill. 2010) (holding that the Federal Reserve Board's regulations are entitled to substantial deference under *Chevron*.).

Communities quelled opposition to the incorporation of disparate impact liability into FHA and anti-discrimination laws in general, its applicability to ECOA remains contested.

Although the Supreme Court's decision in *Inclusive Communities* has led federal district courts and appellate courts to expansively interpret ECOA and encouraged reliance on 12 C.F.R. §1002, it is unclear whether federal courts will continue to endorse ECOA's disparate impact liability theory. Crucially, the Supreme Court has not yet directly spoken on the issue. Given the current Supreme Court's penchant for textualism, disparate impact claims would likely be disallowed under ECOA since there is no explicit textual support for an "effects test" in ECOA's statutory language.

In *Inclusive Communities*, Justice Kennedy explained that the majority's decision to uphold disparate impact claims was based on both FHA's direct textual reference to a congressional policy of prohibiting acts that causes discriminatory effects and the substantial similarity between FHA's statutory language and that of other anti-discrimination statutes.[217] FHA makes unlawful any act "to refuse to sell . . . or otherwise make unavailable or deny, a dwelling to a person" because of a protected characteristic, while referring to the "consequences of actions" as a basis for imposing liability.[218] Similarly, both Title VII of the Civil Rights Act of 1964 ("Title VII") and the Age Discrimination in Employment Act (ADEA) contained language prohibiting actions that "deprive any individual of employment opportunities or *otherwise adversely affect* his status . . . because of . . . race or age."[219] All three anti-discrimination statutes compared in *Inclusive Communities*—FHA, Title VII, and ADEA—contained effect-oriented phrases such as "otherwise make unavailable" in their operative texts.[220] Justice Kennedy reasoned that, in light of the longstanding judicial interpretation of Title VII and ADEA to encompass disparate-impact claims and congressional reaffirmation of the result, the same logic must be applied to FHA, which shares a similar textual and statutory structure with Title VII and ADEA.[221]

Applying the logic of *Inclusive Communities* to ECOA, it seems unclear whether ECOA recognizes disparate impact claims. Unlike other anti-discrimination statutes, ECOA contains no comparable language indicating the prohibition of acts resulting in adverse impact. ECOA only states that "it shall be unlawful for any creditor to discriminate against any applicant," without

217. Inclusive Cmty. Project, Inc., 576 U.S. at 534-38.

218. *Id*. at 520.

219. *See id.* at 531 (citing Smith v. City of Jackson, 544 U.S. 228, 235 (2005) and Griggs v. Duke Power Co., 401 U.S. 424 (1971)).

220. *See id.*

221. *See id.* at 545.

explicit reference to impact or the consequences of discriminatory acts.[222] A thorough reading of ECOA's operative language supports disparate impact liability because of ECOA's statutory structure and legislative purpose.[223] Yet, ECOA lacks direct textual reference to adverse impact.[224] The textual difference between ECOA and FHA could jeopardize the validity of ECOA disparate impact liability as formulated in the 12 C.F.R. § 1002, which rests on ECOA's broad purpose and legislative history rather than on statutory language.[225]

The textual weakness of ECOA disparate impact is also a point the banking industry belabors. Lenders and their allies argue that the absence of effect-oriented language in ECOA's text implies congressional disapproval of disparate impact claims under ECOA.[226] To support this claim, they have relied on the dicta of two Supreme Court cases outside the fair lending context as their legal arsenal against ECOA disparate impact liability.[227] In *Smith v. City of Jackson*, the Supreme Court indicated that it based its decisions permitting disparate impact claims in employment cases on the specific language in Title VII and not the interpretations of the statute's general purposes.[228] The Court reached its conclusion by applying *Griggs v. Duke Power Company*—one of the first cases to allow disparate impact claims in the Title VII context—which similarly permitted disparate impact claims based on the "effects" language in section 703(a)(2).[229] Although neither *Smith* nor *Griggs* restricts the statutory constructions of other anti-discrimination laws, allies of the banking industry have taken the opportunity to portray both as controlling law that binds the interpretation of ECOA.[230]

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222. 15 U.S.C. § 1691(a); *Cf.* Fair Housing Act, 42 U.S.C. § 3604); Title VII of the Civil Rights Act, 42 U.S.C. § 2000e-2 (1964).

223. *See* Inclusive Cmty. Project, Inc., 579 U.S. at 539-540 (ruling in favor of FHA disparate impact liability based on two purposes of FHA: to "eradicate discriminatory practices within a sector of our Nation's economy" and to "uncover[] discriminatory intent," be it disguised or unconscious). Both purposes fit squarely within the purpose of ECOA, whose legislation was motivated by the desire to ensure fair supply of credit as large portions of the American consumer society become increasingly dependent on financial institutions. *See* Equal Credit Opportunity Act Amendments of 1976, Pub. L. No. 94-239, 90 Stat 251. Moreover, the legislative history of subsequent amendments of ECOA indicates that Congress considered and rejected proposals to eliminate disparate impact liability from ECOA. *See* Equal Credit Opportunity Act Amendments of 1995, H.R. 1699, 104th Cong. (1995); *see* Equal Credit Opportunity Act Amendments of 1997, H.R. 229, 105th Cong. (1997).

224. *See* Francesca Lina Procaccini, *Stemming the Rising Risk of Credit Inequality: The Fair and Faithful Interpretation of the Equal Credit Opportunity Act's Disparate Impact Prohibition*, 9 HARV. L. & POL'Y REV. S43, S49 (2015).

225. *See* Winnie F. Taylor, *The ECOA and Disparate Impact Theory: A Historical Perspective*, 26 J. L. & POL'Y 575, 632-33 (2018).

226. *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. LAW. 829, 830-31, 842 (2006).

227. *See id*. at 831, 832 (discussing cases).

228. *See* Smith v. City of Jackson, 544 U.S. 228 (2005).

229. *See* Griggs v. Duke Power Co., 401 U.S. 424 (1971).

230. *See* Andrew L. Sandler & Kirk D. Jensen, *Disparate Impact in Fair Lending: A Theory Without a Basis & The Law of Unintended Consequences*, 33 BANK. & FIN. SVCS. POL'Y RPT. 18, 28 (2014)

ECOA disparate impact liability will also encounter legislative challenges in anticipation of a likely change in congressional composition. In 2018, with a Republican majority in both the House and Senate, Congress passed a joint resolution preventing the CFPB from using disparate impact analysis in ECOA cases.[231] Former President Donald Trump later signed the resolution into law.[232] The resolution nullified the CFPB's compliance guidance addressed to financial lenders on how to prevent ECOA liability under the disparate impact theory.[233] Starting in 2021 under the Biden administration, the CFPB revived ECOA disparate impact liability, applying it aggressively against the banking industry through Regulation B.[234] While the Biden administration's consumer-friendly posture currently recognizes ECOA disparate impact liability, the doctrine may be short-lived due to its vulnerability to the rapidly changing political climate. For instance, if the next administration aligns with the banking industry, it could easily reverse the CFPB's position. Given the lack of an explicit doctrinal anchor for the theory of ECOA disparate impact liability, consumers will likely face an uphill battle litigating the permissibility of disparate impact in the upcoming term.

For consumers seeking to recover from algorithmic discrimination with respect to a credit transaction, the doctrinal uncertainty of ECOA disparate impact liability suggests a bleak future. Except for mortgage lending, most credit transactions are outside the protection of *Inclusive Communities*, since ECOA governs non-mortgage credit transactions, not FHA. Thus, consumers challenging a discriminatory lending practice or policy would have to either rely on the disparate treatment theory under ECOA or, alternatively, rely on agency enforcement actions bringing disparate impact claims pursuant to Regulation B. However, neither strategy can fully address the concerns of algorithmic victims.

(arguing that there is no statutory basis for allowing disparate impact claims under ECOA, and that the lower courts have misinterpreted *Smith* and *Griggs* by relying on non-statutory references and broad legislative purpose). *But see* Francesca Lina Procaccini, *Stemming the Rising Risk of Credit Inequality: The Fair and Faithful Interpretation of the Equal Credit Opportunity Act's Disparate Impact Prohibition*, 9 HARV. L. & POL'Y REV. S43, S50 (2015) (pointing out that the Supreme Court confirmed that the "availability of disparate impact claims turns solely on Congress's intent to proscribe disparate impact discrimination, as evidenced by the statutory text, the legislative history, the purpose of the statute, [and] the implementing agency's interpretation."). *Cf.* Zamudio v. HSBC N. Am. Holdings, Inc., No. 07-4315, 2008 WL 517138, at 2 (N.D. Ill. 2008) (holding that *Smith* does not by bar disparate impact claims under other anti-discrimination statutes that do not contain this same language); *Cf.* Beaulialice v. Fed. Home Loan Mortgage Corp., No. 04-2316, 2007 WL 744646, at *4 (M.D. Fla. 2007) (concluding that *Smith* does not bar disparate impact claims under FHA and the same applies to ECOA).

231. *See* S.J. Res. 57, 115th Cong. (2018).

232. *See* Pub. L. No. 115-172, 132 Stat. 1290 (2018).

233. *See* CONSUMER FIN. PROT. BUREAU, CONSUMER FINANCIAL PROTECTION BUREAU BULLETIN, 2013-02 (2013), https://files.consumerfinance.gov/f/201303_cfpb_march_-Auto-Finance-Bulletin.pdf; *see also* Winnie F. Taylor, *The ECOA and Disparate Impact Theory: A Historical Perspective*, 26 J.L. & POL'Y 575, 581 (2018).

234. *See* Andrew Michaelson, Brian Thavarajah & Margaret McPherson, *A Revived Disparate Impact Doctrine Under Biden's CFPB*, LAW360 (Feb. 17, 2021), https://www.kslaw.com/attachments/000/008/593/original/2-17-21_Law360.pdf?1613687065.

Bringing a disparate treatment claim entails significant fact-finding costs and evidentiary burden to produce direct evidence pertaining to the decision-making process of the lender-defendant. Additionally, enforcement actions pursuant to 12 C.F.R §1002 disparate impact provisions are unpredictable because they might be at the risk of nullification under judicial review.

C. The "Tortification" of Fair Lending Laws

1. Fusing Tort Concepts in Fair lending Laws: A Brief Legal History

Alongside the Supreme Court's growing embrace of textualism is a parallel trend: the Court's increasing invocation of common-law tort elements to interpret the fair lending statutes. Although neither ECOA nor FHA's operative language mentions the level of intent or causation required to establish a statutory violation,[235] the Court's analysis has focused on implied intent and causation. In short, this judicial "tortification" of the fair lending laws signals the Courts' growing discomfort with delimiting the legal bounds of discriminatory impact and its inclination towards conceptualizing discrimination as discrete instances of misconduct addressable under a fault-based liability regime. This section examines the origins of "tortification" and demonstrates how this trend would further restrict the already-narrowing scope of fair lending protection.

In the 1970s and 80s, the Supreme Court rarely invoked common-law tort concepts to interpret the federal anti-discrimination laws. Over the past few decades, the Court underwent a paradigm shift. It increasingly applied tort elements to discrimination cases, especially those dealing with questions of causation and intent. This paradigm shift coincided with the Court's turn towards textualism, which embodies plain-meaning statutory interpretation.[236] The textualist interpretative framework assumes that, "when Congress used a word in the [anti-]discrimination statutes, it intended those words to have a common law tort meaning, unless otherwise indicated."[237] Under this framework, a court

235. *See* 15 U.S.C. § 1691; *see also* 42 U.S.C. § 3601.

236. The late Justice Antonin Scalia made the following statements embodying the spirit of textualism: "[I]t is simply incompatible with democratic government, or indeed, even with fair government, to have the meaning of a law determined by what the lawgiver meant, rather than by what the lawgiver promulgated. That seems to me one step worse than the trick the emperor Nero was said to engage in: posting edicts high up on the pillars, so that they could not easily be read. Government by unexpressed intent is similarly tyrannical. It is the *law* that governs, not the intent of the lawgiver. That seems to me the essence of the famous American ideal set forth in the Massachusetts constitution: A government of laws, not of men. Men may intend what they will; but it is only the laws that they enact which binds us." ANTONIN SCALIA, A MATTER OF INTERPRETATION 17-18 (1997). *Contra* STEPHEN BREYER, MAKING OUR DEMOCRACY WORK 94-98 (2010) ("[L]inguistic imprecision, vagueness, and ambiguity are often useful, even necessary, statutory instruments. Congress may not know just how its statute should apply in future circumstances where it can see that future only dimly, and new situations will always emerge. Congress may want to consider only one aspect of a complex, detailed subject, and aspect that warrants a few general words that simply point a court in the right direction.").

237. *See* Sperino, *supra* note 24, at 1007 (referencing Staub v. Proctor Hosp., 562 U.S. 411, 417 (2011)).

should construe the words in anti-discrimination statutes by referring to common-law tort meanings and definitions, a method regularly achieved through consulting tort treatises, law dictionaries, and restatements.[238]

Employment discrimination was one of the first areas where tort concepts were aggressively applied. In *Price Waterhouse v. Hopkins*, decided in 1989, the Supreme Court considered whether the plaintiff needed to prove "but-for" cause to establish a violation of Title VII.[239] Justice O'Connor concurred that Title VII was a "statutory employment tort" and should be interpreted "like the common law of torts."[240] Although the Court in *Price Waterhouse* ultimately rejected tort principles and held that it was "not necessary to get into semantic discussions [about] 'but-for' cause," the plurality opinion opened the door for inquiries into the nature of causation required for establishing a Title VII claim.[241] In 1991, Congress responded to *Price Waterhouse* by amending Title VII to clarify that a plaintiff could prevail on a Title VII claim by showing that a protected trait was a motiving factor in an employment decision.[242] Importantly, Congress did not require that a plaintiff show "but for" cause. Congress also refrained from using language mimicking common-law torts and limited the use of defenses that are normally available in tort suits.[243]

Nevertheless, the Supreme Court's move towards "tortification" gained momentum starting in 2009. In *Gross v. FBL Financial Services*, the Court held that ADEA requires the plaintiff to prove "but-for" causation by a preponderance of the evidence.[244] Writing for the majority, Justice Thomas argued that the ordinary meaning of "because of" in ADEA connotes a "but-for causal relationship and thus a necessary logical condition."[245] Although Congress has frequently used the terms "because of" and "on the basis of" interchangeably in anti-discrimination statutes, *Gross* distinguished the two and interpreted the former to carry common-law tort meanings.[246] This time, Congress did not respond to *Gross* like it did in *Price Waterhouse*.

Two years later, in *Staub v. Proctor Hospital*, the Court again invoked tort law principles to interpret the Uniformed Services Employment and Reemployment Rights Act (USERRA). This time, the Court applied two

238. *Id*. at 1108, 1112-14.

239. Price Waterhouse v. Hopkins, 490 U.S. 228, 237 (1989).

240. *Id*. at 264 (O'Connor, J., concurring) (internal quotations omitted).

241. *Id*. at 237 (plurality opinion), 259 (White, J., concurring).

242. *See* Civil Rights Act of 1991, 42 U.S.C. §§ 2000e-2(m), 2000e-5(g)(2)(B).

243. Congress also amended Title VII's provisions on burden of proof in disparate impact cases, and the language of these amendments do not mimic those in common-law torts. *See* 42 U.S.C. §§ 2000e-2(k)(1)(A).

244. Gross v. FBL Financial Services, 557 U.S. 167, 180 (2009).

245. *Id*. at 176 (citing 1 WEBSTER'S THIRD NEW INTERNATIONAL DICTIONARY 194 (1966) and OXFORD ENGLISH DICTIONARY 746 (1933) (both defining "because of" to mean "by reason of, on account of")).

246. *See id*.

additional tort concepts: intent and proximate cause. In *Staub*, Justice Scalia openly embraced common law as a source for textualist statutory interpretation, stating that "we start from the premise that when Congress creates a federal tort it adopts the background of general tort law."[247] While USERRA never mentioned the establishment of statutory tort liability in its text, the Court assumed the statute to be a "federal tort" just like it did in *Gross*.[248] Although *Staub* considered an interpretative question under USERRA, the lower courts have applied *Staub*'s reasoning to cases arising under other anti-discrimination laws due to similarities in statutory text and structure.[249]

Against the backdrop of the "tortification" in the employment discrimination context, the Supreme Court has started to apply a similar interpretative lens to the fair lending laws. In *Bank of America v. City of Miami*, decided two years after the Court recognized FHA disparate impact claims in *Inclusive Communities*, the Court narrowed the protective scope of FHA. In doing so, the Court required plaintiffs to show that a defendant's alleged discriminatory policy or practice was a "direct proximate cause" of the injuries the plaintiff suffered.[250] In the majority opinion, Justice Breyer explained that "a claim for damages under FHA . . . is akin to a 'tort action,'" and is therefore subject to the common law principle that loss is attributable "'to the proximate cause, and not to any remote cause.'"[251] Further, the opinion emphasized that, like Title VII and ADEA, FHA is a statute with "common-law foundations," and the Court's precedents have long recognized its tort roots.[252]

City of Miami went further than any of the Supreme Court's prior discrimination cases in "tortifying" the causation inquiry. In *City of Miami*, the Court used the classic two-pronged analysis in torts, by requiring the plaintiffs to show both actual "but-for" and proximate cause. In *City of Miami*, the question was not whether causality existed but whether the causal chain was close enough to permit recovery. Although the Court recognized the Eleventh Circuit's reasoning that there were "several links in the causal chain" and that the plaintiff "plausibly alleged that none [were] unforeseeable," the Court nonetheless held that the alleged harm was "too remote from the defendant's unlawful conduct."[253] Justice Breyer explained that the proximate cause standard under

247. Staub v. Proctor Hosp., 562 U.S. 411, 417 (2011).

248. *See* 38 U.S.C. § 4301.

249. *See, e.g.*, Davis v. Omni-Care, Inc., 482 Fed. App'x 102, 109 (6th Cir. 2012) (quoting *Staub*, 562 U.S. at 422 (emphasis in original) ("[I]f a supervisor performs an act motivated by antimilitary animus that is *intended* by the supervisor to cause and adverse employment action, and if that act is a proximate cause of the ultimate employment action, then the employer is liable under USERRA.")); Jajeh v. Cnty. of Cook, 678 F.3d 560, 572 (7th Cir. 2012) (quoting the same statement in *Staub*).

250. Bank of Am. Corp. v. City of Miami, 581 U.S. 189, 201 (2017).

251. *Id*. at 201 (citing Meyer v. Holley, 537 U.S. 280, 285 (2003) and Lexmark Intern., Inc. v. Static Control Components, Inc., 572 U.S. 118, 132 (2014)).

252. *Id*. at 203 (citing Anza v. Ideal Steel Supply Corp., 547 U.S. 451, 457 (1991)).

253. *Id*. at 202 (internal quotations omitted).

FHA requires a direct relationship because "[t]he housing market is interconnected with economic and social life . . . [and] a violation of FHA may, therefore, be expected to cause ripples of harm to flow far beyond the defendant's misconduct."[254] Noting that "nothing in the statute suggests that Congress intended to provide a remedy wherever those ripples travel," the Court rejected the Eleventh Circuit's holding that "foreseeability [alone] is sufficient to establish proximate cause."[255] Although *City of Miami* deviated from the foreseeability standard that most state courts use to establish proximate cause, the Court's reasoning followed the standard line of inquiry in common-law torts.[256]

Importantly, in *City of Miami*, the Supreme Court interpreted FHA through the lens of tort law without using the textualist framework that the Court espoused in *Gross* and *Staub*. Justice Breyer clarified the majority's interpretative approach by stating that "[w]e assume Congress is familiar with the common-law rule and does not mean to displace it *sub silentio* in federal causes of cation."[257] Although not a textualist himself, Justice Breyer's opinion echoes the rationale that Justice Scalia articulated earlier in *Staub*: that words in a statute must comport with their plain meaning as reflected in the general corpus of common law and regular usage in the legal community.[258] However, Justice Breyer also emphasized congressional intent and purpose in *City of Miami*. Specifically, Justice Breyer reasoned that Congress must have intended the words to derive a common-law meaning, since Congress was aware of more than a decade of stare decisis applying tort concepts and decided not to amend the key words that courts have consistently held to connote common-law meanings.[259] Although the majority's reasonings in *City of Miami* and *Staub* adhered to different interpretative traditions, both arrived at the same conclusion, forging a consensus between textualists and purposivists on the bench.[260]

Although there is no Supreme Court-equivalent caselaw with respect to ECOA, a cursory overview of recent ECOA cases at the district and appellate levels reveals a widespread adoption of tort concepts. Lower court opinions with respect to the pleading of ECOA violations are replete with references to tort

254. *Id*. (internal quotations omitted).
255. *Id*.
256. *Id*. at 203.
257. *Id*. at 201 (internal quotations omitted).
258. *See Staub*, 562 U.S. at 417.
259. *See* Bank of Am. Corp. v. City of Miami, 581 U.S. 189, 201.
260. *See id.*

notions such as causation[261] and implied intent.[262] One district court opinion even went as far as to draw parallels between the statutory limitation that "ECOA applies only to creditors" and the tort concept of "no duty," although few appellate courts have explicitly adopted this line of reasoning.[263] Read in conjunction with *City of Miami* and *Staub*, these opinions signal the formation of a broad judicial consensus on the tort nature of the fair lending laws.

It is also noteworthy that the "tortification" of fair lending laws has direct implications for the judicial treatment of administrative rules as well. Courts have increasingly read administrative rules to comport with the common-law tort structure. For instance, 12 C.F.R. § 1002.2(l) protects certain defendants from ECOA liability through its definition of "creditor." It states that "a person is not a creditor regarding any violation of the Act or this regulation committed by another creditor[,] unless the person knew or had reasonable notice of the act, policy, or practice that constituted the violation before becoming involved in the credit transaction."[264] Also known as the "Multiple Creditor Rule," 12 C.F.R. § 1002.2(l) absolves a creditor from discrimination liability if that creditor is not reasonably aware of the injurious conduct, even if that creditor's conduct is the actual cause of the victim's injuries.[265] This rule intends to protect subsequent creditors who underwrite or purchase a credit contract (e.g., assignee) without reasonable knowledge of "participation" in the loan origination transaction.[266] Though the rule itself is silent on the required level of notice to "participate" in origination, courts have interpreted the rule to impose a negligence-like reasonability standard. This standard triggers a general obligation under ECOA if, according to the specific factual circumstances, the creditor knows or should have known about the offending conduct.[267] While a textualist reading of 12

261. *See*, *e.g.*, Guerra v. GMAC LLC, No.2:08-cv-01297, 2009 WL 449153 at *4 (E.D. Pa. Feb. 20, 2009) ("In order to properly plead a disparate impact claim, a plaintiff must allege…facts raising a sufficient inference of causation."); Taylor v. Accredited Home Lenders, Inc., 580 F.Supp. 2d 1062, 1068-69 (S.D. Cal. 2008) (holding that the plaintiff's complaint that defendant's policy directly caused a statistical disparity between African American customers and similarly-situated Caucasians in the rate of paying discretionary sufficiently meets the causality requirement in pleading a disparate impact claim under ECOA.); Lapid-Laurel, L.L.C. v. Zoning Bd. of Adjustment, 384 F.3d 442, 466-67 (3d Cir. 2002); Comcast Corp. v. Nat'l Ass'n of Afr. Amer.-Owned Media, 140 S. Ct. 1009 (2020) (holding that a plaintiff has the burden of showing that her membership in a protected class was a 'but-for' cause of her injury, and that a plaintiff's burden to show causation exists at the motion to dismiss stage.).

262. *See* Nia v. Bank of Am., N.A., No.21-cv-01799-BAS-BGS, 2022 WL 1570012 (S.D. Cal. 2022) (finding that the creditor's failure to provide sufficient notice under ECOA supported inference of discriminatory intent, and that the consumer complaints, articles, and social media posts cited by cardholder supported plausible inference of intentional discrimination).

263. *See* Green v. Cen. Mort. Co., 148 F.Supp. 3d 852, 878 (N.D. Cal. 2015).

264. 12 C.F.R. § 1002.2(l).

265. *See id.*

266. *See* John L. Ropiequet & Nathan O. Lundby, *APR Split Class Actions Under the Equal Credit Opportunity Act: The End of History?* 61 CONSUMER FIN. L. Q. REP. 49, 51-52, n. 22 (2007).

267. *See*, *e.g.*, Coleman v. General Motors Acceptance Corp., 220 F.R.D. 64, 77 (M.D. Tenn. 2004) ("[Multiple Creditor Rule] does not require the [loan-originating] entities have knowledge of each individual discriminatory implementation of the policy […] A precise reading of the language suggests that, to be a creditor, a person need only have notice of the policy or practice, not each instance of

C.F.R. § 1002.2(l) would suggest the creation of a bright-line liability rule, courts have applied the rule under a tort-oriented, case-by-case factual inquiry.

Regulators and consumer advocates should worry about the "tortification" trend because it can narrow the protective scope of the fair lending laws. Specifically, "tortification" creates two obstacles for the plaintiff. First, "tortification" applies to the interpretation of the fair lending laws as a whole, affecting both disparate impact and disparate treatment claims. Even if ECOA disparate impact survives both judicial review and congressional challenge in the future, narrowing the statute's "zone of interest"[268] to redress harms a lenders' conduct "directly" and "proximately" caused would dilute the protective effect of ECOA.[269] Lenders could escape liability by outsourcing credit assessment processes to third-party intermediaries or by elongating the "causal chain," adding filters and checkpoints for third party intervention in between the initial data-gathering and the final loan transaction phases.

Second, "tortification" allows judges to disregard the broader congressional purpose of establishing the fair lending regime by ignoring legislative histories and supplanting them with their own understandings of "ordinary meaning" derived from common-law torts.[270] However, reshaping the fair lending statutes in the mold of common-law torts does not align with the present needs for tailor-made AI governance. Additionally, this "tortification" misdirects judicial attention to factual inquiries concerning individual conduct of lenders.[271] "Tortification" shifts the legal focus away from the structures that entrench and

discrimination."); Osborne v. Bank of Amer., Nat. Ass'n, 234 F.Supp. 2d 804 (M.D. Tenn. 2002) ("[K]knowledge, like intent, is a factual issue which may be proved by circumstantial evidence."); In re Armstrong, 288 B.R. 404 (Bankr. E.D. Penn. 2003).

268. A statute's "zone of interest" refers to the type of interests or rights that a statute seeks to protect or harms it aims to address. *See* Bank of Am. Corp. v. City of Miami, 581 U.S. 189, 192(internal quotations omitted) ("whether a plaintiff comes within the zone of interests is an issue that requires us to determine, using traditional tools of statutory interpretation, whether a legislatively conferred cause of action encompasses a particular plaintiff's claim.").

269. *See id.* at 197-199.

270. There is no compelling reason why judges could be more faithful to the statute by relying on legal dictionaries and tort treatises instead of on legislative documents indicating congressional purpose, such as Senate or House reports. *See* John F. Manning, *Textualism as a Nondelegation Doctrine*, 97 COLUM. L. REV. 673, 675 (1997) ("[T]extualist concerns relating to 'genuine' legislative intent and bicameralism and presentment do not alone suffice to explain why textualists reject the interpretative authority of legislative history… [because] textualist judges routinely rely on other extrinsic sources of meaning that do not reflect 'genuine' legislative intent[.]").

271. When members of Congress debated whether ECOA should define the "discrimination" the statute aimed to prohibit as "invidious discrimination," "arbitrary discrimination," or simply "discrimination" without a limiting or explanatory modifier, Congress went with simply "discrimination"—without regard to the violator's state of mind. This indicates that Congress originally intended discrimination liability to hinge on adverse effects, rather than the mental culpability of individual conducts. The courts' reading of ECOA to require "implied intent" and "direct proximate cause" is not faithful to the original congressional purpose. *See* HEARINGS ON H.R. 14856 AND H.R. 14908 BEFORE THE SUBCOMMITTEE ON CONSUMER AFFAIRS OF THE HOUSE COMMITTEE ON BANKING AND CURRENCY, 93rd Cong., 2d Sess. 35, 56-65 (1974).

amplify systemic credit inequality, which Congress intended to eliminate in legislating ECOA.[272]

The "tortification" trend will limit plaintiffs' ability to bring meritorious claims because the tort liability structure will compel them to analogize AI to aspects of human intelligence in their complaints. To bring a legally meritorious claim, complaints of AI discrimination will need to conform with the rigid civil tort formula, which relies on a human-centric standard of conduct. Due to the unpredictability and inexplicability of algorithmic processes in consumer lending, victims of algorithmic harms will be unable to articulate their claims within the purview of the common-law tort liability structure. Therefore, courts will consider algorithmic harm claims meritless, though few would agree that such victims do not deserve legal redress. Given the reasons above, "tortification" of fair lending laws poses an even greater threat to consumer protection than the demise of disparate impact liability. The following section discusses its implications for litigation.

2. *"Tortification" Procedural Hurdles*

One immediate consequence of infusing tort concepts into the interpretation of fair lending laws is to narrow the protective scope of their anti-discrimination provisions by tightening causal and evidentiary standards. Consumers who seek to recover damages from a discriminatory credit decision or loan originating from an algorithmic platform must overcome two procedural hurdles.

Showing Causation: Showing that a causal relation exists between a plaintiff-consumer's injury and a defendant-lender's alleged act of discrimination is already a difficult and costly task for most plaintiffs under the current *Twiqbal* plausibility pleading standard.[273] After *Twiqbal*, a plaintiff must allege claims with "sufficient factual specificity."[274] This standard introduces significant barriers for potential algorithmic harm claims. A potential plaintiff must plausibly plead that multiple, unidentified algorithms working in mutually unrelated ways caused a discriminatory outcome, such as adverse treatment in a loan transaction. Victims of algorithmic discrimination rarely understand what causes their injuries due to deep knowledge gaps about machine learning AI and the opaque world of alternative data in which it operates. As a result, most

272. The legislative origins of ECOA date to the 1970s when various members of Congress introduced bills to address pervasive credit discrimination against groups and communities who were systematically denied equal credit opportunity and financial security—most notably, African Americans and women. *See e.g.*, H.R. 14856, 93rd Cong. (1974); H.R. 14908, 93rd Cong. (1974).

273. *See* Bell Atlantic Corp. v. Twombly, 550 U.S. 544 (2007); Ashcroft v. Iqbal, 556 U.S. 662 (2009). *But see* Colin T. Reardon, Note, *Pleading in the Information Age*, 85 N.Y.U. L. REV. 2170 (arguing that the critics of the *Twiqbal* "plausibility pleading" standard largely ignored the fact that information asymmetries between defendants and plaintiffs are less severe today due to widened access to the Internet).

274. *See* Monette Davis, *Applying Twombly/Iqbal on Removal*, AM. BAR ASS'N. (Apr. 30, 2020), https://www.americanbar.org/groups/litigation/committees/pretrial-practice-discovery/practice/2020/applying-twombly-iqbal-on-removal/.

victims of algorithmic harm would be unable to formulate legally meritorious claims.[275] Many plaintiffs with meritorious claims would be dismissed at the initial pleading stage before having any chance to litigate the issue in court.

The heightened pleading burden would apply to both disparate impact and disparate treatment claims, because the need to establish causal links between the "conduct" and "outcome" lies at the heart of both liability theories. Disparate treatment is concerned with the direct conditioning of credit risk assessment outcomes on a loan applicant's protected characteristics and is considered a form of constructive discriminatory intent.[276] On the other hand, disparate impact, despite its lighter evidentiary burden, requires the plaintiff to show that the adverse effect is casually related to the facially neutral act or policy of the lender.[277] Yet, neither theory fully captures how AI generates decisions. All AI "decisions" are essentially statistical predictions based on a mass intake of correlational patterns. These patterns are typically from datasets summarized from the loan applicant's digital footprints and market-level information.

Even if a plaintiff succeeds in making a legally meritorious claim by plausibly pleading actual causation, they must still prove "proximate cause."[278] As *City of Miami* made clear, plaintiffs bears the burden of proving that, by a preponderance of the evidence, the causal chain of events is "more than foreseeable" in order to satisfy the "direct proximate cause" requirement.[279] Yet, there is no clear judicial guidance on what additional proof is required. In *City of Miami*, the Supreme Court did not clarify what types of harm fall outside the fair lending law's zones of interests. Although the Court determined that Congress could not possibly "intend to provide a remedy wherever those ripples [of harm] travel," the Court did not specify at what point the causal chain is severed or what factors lower courts should consider in making such a determination.[280] Given that both the "proximate cause" and the "zone of interest" inquiries are generally matters of law determined by a judge rather than by a fact-finder,

275. To determine whether a plaintiff has properly pleaded a claim of discrimination under ECOA, a plaintiff must allege that: (i) she is a member of a protected class; (ii) she applied for credit with defendants; (iii) she qualified for credit; and (iv) she was denied credit despite being qualified. Plaintiffs need to show causation in alleging the fourth element. *See e.g.*, Hafiz v. Greenpoint Mortg. Funding, Inc., 652 F.Supp. 2d 1039, 1045 (N.D. Cal. 2009).

276. *See* Gillis, *supra* note 26, at 1198.

277. Under *Inclusive Communities'* holding, plaintiffs brining a disparate impact claim under FHA are still required to sufficiently plead "robust causality" and must point to a specific practice or policy that directly results in the alleged disparity. *See* Tex. Dep't of Hous. and Cmty. Affs. v. Inclusive Communities Project, Inc., 567 U.S. 519, 521 (2015).

278. *See infra* Part II.C.1.

279. *See* Bank of Am. Corp. v. City of Miami, 581 U.S. 189, 200-202.

280. *Id*. at 202 ("The housing market is interconnected with economic and social life…[and] a violation of FHA may, therefore, be expected to cause ripples of harm to flow far beyond the defendant's misconduct… [N]othing in the statute suggests that Congress intended to provide a remedy wherever those ripples travel.").

whether or not a plaintiff satisfies the burden of sufficiently showing causation would be entirely under the presiding judge's discretion.[281]

The causal link is even more tenuous in situations where a financial lender bases a lending decision on third-party agency or data broker credit risk assessments for which the financial lender has no access to the underlying algorithmic inputs. Since data brokers dominate the current credit underwriting market, more consumers are expected to bring cases without sufficient visibility into the causal chain of data processing. In these situations, the causality burden is practically insurmountable for consumers. After *City of Miami*, plaintiffs alleging a disparate impact claim are expected to plausibly plead that the lender's lending practices or policies are a "direct proximate cause" of the plaintiff's injuries.[282] However, a lender cannot be held liable for a disparate impact claim where the independent actions of third parties break the proximate causal chain—even if the misconduct is the actual "but-for" cause of the harm.[283] In essence, anti-discrimination doctrines interpreted within the tort-based causality framework fail to hold acts of algorithmic discrimination accountable because "machine learning . . . is a world of correlation and not causation."[284]

Showing Implied Intent: The notion of intent lies at the core of the disparate treatment theory. Regardless of the actual intent to discriminate, a finding of disparate treatment based on a person's protected characteristics creates an irrebuttable presumption that such discrimination is intentional. Yet, under the disparate treatment theory, it is extremely difficult for plaintiffs at the pleading stage to demonstrate that intentional discrimination is plausible without having access to the algorithmic inputs.

Alleging an act of disparate treatment requires visibility into how credit-underwriting companies allocate consumer data to train algorithms and what proxies the algorithms use to measure creditworthiness. But, in most cases, credit-underwriting companies protect algorithmic inputs as trade secrets, meaning that plaintiffs do not have access to the inputs at least until discovery.[285]

281. The "zone of interest" test is a standing requirement set forth by the Supreme Court and determined by judges through statutory interpretation rather than factual inquiry. *See, e.g.*, Allen v. Wright, 468 U.S. 737, 751 (1984) (stating that a statutory cause of action is presumed to extend only to plaintiffs whose interests "fall within the zone of interests protected by the law invoked."); Bennet v. Spear, 520 U.S. 154, 163 (1997) ("the breadth of [that] zone…varies according to the provisions of law at issue."). Similarly, the "proximate cause" is a legal cause determined by judges instead of by juries or other triers of fact.

282. *City of Miami*, 581 U.S. at 200-202.

283. A plaintiff pleading a disparate impact claim under ECOA would have to satisfy the same "direct proximate cause" requirement, even if a federal court decides that the protection of *Inclusive Communities* (under FHA) would extend to ECOA.

284. *See* Gillis, *supra* note 26, at 1221.

285. Even during the litigation, a trade secret that is properly identified with reasonable particularity is protected from disclosure. Most courts allow the trade secret's owner to identify the trade secret until late in the discovery, but more courts are requiring pre-discovery identification of trade secrets. *See, e.g.,* Joseph Loy, Elliot Scher & Kyle Friedland, *Trade Secret Rulings May Guide on Disclosure in Litigation*,

Since the only conduct that may amount to a "treatment" within the purview of the fair lending laws is the human selection of algorithmic inputs and proxies for machine learning,[286] plaintiffs alleging a disparate treatment discrimination would struggle at the initial pleading stage unless there is visibility into how human actors select and evaluate these proxies and inputs.

3. *Procedural Hurdles Inherent in ECOA Disparate Impact*

Another challenge to algorithmic accountability arises from the procedural obstacles embedded in the concept of disparate impact. Even if a plaintiff survives a motion to dismiss by sufficiently pleading a claim of disparate impact, the likelihood that the plaintiff prevails on the merits is low. This is because, under the fair lending laws, establishing a prima-facie case of disparate impact only creates a rebuttable presumption of discrimination.[287] A defendant can rebut a plaintiff's disparate impact claim by showing that there is a *legally sufficient justification* for the practice by a preponderance of the evidence.[288]

A legally sufficient justification exists where a lender-defendant's interests "could not be served by another practice that has a less discriminatory effect" (i.e., the "less discriminatory alternative" prong) and the challenged practice is "necessary to achieve one or more of its substantial, legitimate, nondiscriminatory interests" (i.e., the "legitimate business necessity" prong).[289] In addition, the justification must have evidentiary support and cannot be hypothetical or speculative.[290] Even if a defendant satisfies this burden, a plaintiff may still establish liability by sufficiently proving that that an alternative practice with a less discriminatory impact could serve the defendant's reasonably legitimate interest.

Less Discriminatory Alternative: In theory, the plaintiff can identify a "less discriminatory alternative" using a process known as "hyperparameter tuning," whereby the plaintiff tests a large number of potential variable combinations for the desired objective which the defendant's model is designed to perform.[291] The

LAW 360 (May 14, 2020); John F. Hornick & Margaret A. Esquenet, *Trade Secret Identification: Prerequisite to Discovery*, FINNEGAN (Apr. 2015). *See also* 29 U.S.C. § 664.

286. Algorithmic credit analysis shifts the locus of decision-making from the human actor to the machine. Through machine learning methods, algorithms remove the decision-making process from the human actor to the computer program. The only human activity that may amount to a discriminatory "treatment" is the selection of inputs for programming and the feeding of data.

287. *See supra* Part II.B.1.

288. *See* 24 C.F.R. § 100.500.

289. 24 C.F.R. § 100.500(b)(1).

290. 24 C.F.R. § 100.500(b)(2).

291. When creating a machine learning model, the programmer does not immediately know what the optimal model architecture is. The machine is typically asked to explore a range of possibilities and select the optimal model automatically. Parameters that define the model architecture are referred to as "hyperparameters" and the process of searching for the ideal model architecture is referred to as "hyperparameter tuning." *See* Jeremy Jordan, *Hyperparameter Tuning for Machine Learning Models* (Nov. 2, 2017), https://www.jeremyjordan.me/hyperparameter-tuning/.

plaintiff's hypothetical result is then measured against the variable combinations from the actual parameters configured for the defendant's AI model architecture.[292] If the tuning yields a disparity that is statistically significant (i.e., 95%), then the plaintiff can show the existence of a "less discriminatory alternative."[293] In practice, however, given that the defendants have exclusive access to the algorithmic inputs and the information necessary for computing the variable combinations for the AI model, a defendant can rebut the plaintiff's claim without difficulty due to pervasive lender-borrower informational asymmetries.

Even if a plaintiff can successfully demonstrate the existence of a "less discriminatory alternative," they must overcome an additional hurdle: showing that the alternative is reasonably adoptable to achieve the defendant's business aims. Yet, the existing legal standard for assessing the sufficiency of "less discriminatory alternatives" is nebulous. Courts have used a variety of loosely defined standards to determine whether the "less discriminatory alternatives" plaintiffs identify would adequately fulfill the defendant's business needs. For example, courts have created judicial tests asking whether such alternatives are "viable," "serving," or "advancing" the defendant's needs.[294] Borrowing a phrase the Supreme Court first used to interpret the disparate impact standard in the Title VII context, the Ninth Circuit has articulated an even stricter test that requires the identified "less discriminatory alternative" to be at least "equally effective" in accomplishing the defendant's legitimate business needs.[295] In FHA context, many courts also vacillate between requiring the plaintiff to show that

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292. *See id.*

293. RELMAN COLFAX PLLC, *Fair Lending Monitorship of Upstart Network's Lending Model*, 9-11THIRD REPORT OF THE INDEPENDENT MONITOR (Sep. 16, 2022), https://www.relmanlaw.com/assets/htmldocuments/PUBLIC%20Upstart%20Monitorship%203rd%20Report%20FINAL.pdf.

294. *See Inclusive Communities* at 533 (explaining that in an FHA case an alternative must have "less disparate impact and serve[] the [entity's] legitimate needs."); Mt. Holly Gardens Citizens in Action, Inc. v. Township of Mt. Holly, 658 F.3d 375, 382 (3d Cir. 2011) (stating that in an FHA case the plaintiffs "must demonstrate that there is a less discriminatory way to advance the defendant's legitimate interest"); Darst-Webbe Tenant Ass'n Bd. v. St. Louis Hous. Auth., 417 F.3d 898, 906 (8th Cir. 2005) ("[T]he plaintiffs must offer a viable alternative that satisfies the Housing Authority's legitimate policy objectives while reducing the revitalization plan's discriminatory impact."); Allen v. City of Chicago, 351 F.3d 306, 313 (7th Cir. 2003) ("To prevail, the officers therefore must demonstrate that an increased percentage of merit-based promotions would be of substantially equal validity as merit-based promotions."); Newark Branch, NAACP v. Town of Harrison, 940 F.2d 792, 798 (3d Cir. 1991) (stating that plaintiffs may prevail "where they are able to suggest a viable alternative to the challenged practice.").

295. *See, e.g.*, Wards Cove Packing Co. v. Atonio, 490 U.S. 642 (1989) (the genesis of the "equally effective" language); *see also* Southwestern Fair Hous. Council, Inc. v. Maricopa Domestic Water Improvement Dist., 17 F.4th 950, 961 (2d. Cir. 2021) ("[T]he burden shifts back to the plaintiff to show the availability of an alternative practice that has less discriminatory impact yet is still equally effective in serving the defendant's legitimate goals."); Hardie v. Nat'l Collegiate Athletic Ass'n, 876 F.3d 312, 315 (9th Cir. 2017) (holding that the plaintiff has failed to show that "an equally effective, less discriminatory alternative" to the defendant's felon-exclusion policy exists, as "he must do so under the three-step analysis for disparate impact set forth in *Wards Cove*.")

the less discriminatory alternative is "equally effective"[296] and adopting a more lax "viable alternative" standard.[297] This indecision creates a lack of clear judicial guidance. Moreover, due to the uncertainty of whether ECOA encompasses disparate impact claims, there is no existing caselaw addressing the sufficiency of "less discriminatory alternatives" in ECOA context.

Legitimate Business Necessity: Furthermore, the courts' refusal to second-guess the lenders' reasonable business judgment effectively eliminates the parties need to litigate what qualifies as a "legitimate business necessity" in a disparate impact claim.[298] In the general non-AI consumer lending context, courts have consistently held that the lender's need to ascertain a borrower's credit risk for loan pricing purposes is always a "legitimate business necessity."[299] A practice is considered "to advance a valid business need if it is predictive of a relevant outcome" (e.g., to calculate asset recovery and loan default risks).[300] When applied to cases involving algorithmic harm, this rule implies that a lender's use of models or proxy variables to ascertain a borrower's

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296. *See, e.g.*, MacPherson v. Univ. of Montevallo, 922 F.2d 766, 733, n.2 (11th Cir. 1991) (interpreting the "equally effective" language in *Wards Cove* to mean that a plaintiff must show, "at the very least," that an alternative is "economically feasible" and declining to decide "whether an alternative practice that is economically feasible but is still more expensive than the employer's current practice can be 'equally effective' within the meaning of *Wards Cove*."); Cureton v. Nat'l Collegiate Athletic Ass'n, 37 F.Supp. 2d 687, 713 (E.D. Pa. 1999) (interpreting "equally effective" to mean "equivalent, comparable, or commensurate, rather than identical."), *rev'd on other grounds*, 198 F.3d 107 (3d. Cir. 1999).

297. *See* Freyd v. Univ. of Oregon, 990 F.3d 1211, 1227 (9th Cir. 2021).

298. Ardent students of corporate law might find this reasoning analogous to the familiar Business Judgment Rule (BJR). *See, e.g.*, In re Caremark Int'l, Inc., 698 A.2d 959 (Del. Ch. 1996); *Business Judgement Rule*, AM. BAR ASS'N (Jun. 15, 2022). Following the logic of BJR, one might ask if there is a point when courts may refuse to defer to the creditor's business judgment by applying some kind of "entire fairness standard" in ECOA disparate impact context. My answer is no. The legitimate business necessity inquiry is much more deferential than BJR because an arm's length credit transaction normally does not involve fiduciary duties. In the corporate context, entire fairness standard kicks in only because certain practices by the manager-agent (*e.g.*, fraud, gross negligence, waste, bad faith, conflicts of interest) create a strong presumption of a breach of fiduciary duty owed to the shareholder-principal. *See, e.g.*, Patrick M. Birney, *Financially Distressed Businesses: Revisiting the Business Judgment Rule and the Entire Fairness Doctrine*, NAT. LAW REV. (May 20, 2020), https://www.natlawreview.com/article/financially-distressed-businesses-revisiting-business-judgment-rule-and-entire. Whereas, in the lending context, the interests of creditor and borrower are presumed to be adversarial. *See* FROST BROWN TODD, *Self-Dealing: When a Fiduciary Relationship Arises in the Lending Context*, (Aug. 3, 2007), https://frostbrowntodd.com/self-dealing-when-a-fiduciary-relationship-arises-in-the-lending-context-2/ ("Courts have traditionally declined to impose [fiduciary] duties on banks in dealing with their customers based on the adversarial nature of the parties' relationship.").

299. *See*, *e.g*., A.B. & S. Auto Service, Inc., v. South Shore Bank of Chicago, 962 F.Supp. 1056, 1061 (N.D. Ill. 1997) ("[In a disparate impact claim under ECOA], once the plaintiff has made the prima facie case, the defendant-lender must demonstrate that any policy, procedure, or practice has a manifest relationship to the creditworthiness of the applicant."); Lewis v. ACB Bus. Services, Inc., 135 F.3d 389, 406 (6th Cir. 1998) (internal quotations omitted) ("[ECOA] was only intended to prohibit credit determinations based on characteristics unrelated to creditworthiness."); Miller v. Countrywide Bank, NA, 571 F. Supp. 2d 251, 258 (D. Mass. 2008) (rejecting the defendant's argument that competitive "market forces" is a legitimate business justification for the discrimination in loan terms among African-American applicants and white consumers, noting that prior caselaw has rejected the "market forces" argument insofar as that it would allow the pricing of consumer loans to be "based on subjective criteria beyond creditworthiness.").

300. Relman Colfax PLLC, *supra* note 293, at 9-11.

creditworthiness would almost always qualify as a "legitimate business necessity." The rule only requires that lenders narrowly tailor the use algorithms to the purpose of ascertaining credit invisible consumer risk profiles, and that the algorithms are not designed to take advantage of credit invisibility by charging a higher rate on such consumers.[301]

However, an AI lender can easily satisfy both elements of the "legitimate business necessity" prong. First, the need to ascertain a consumer's credit risk profile is almost always a "legitimate business objective" under any jurisdiction. The means to carry out the legitimate ends is almost always "narrowly tailored" as long as the lender uses the algorithm under a strictly commercial imperative. Yet, whether a lender narrowly tailors the use of the algorithm for credit-risk analysis is unrelated to the probability that a harm will ensue. A lender may simply instruct the algorithm to scrape and analyze all available data about the consumer. Nevertheless, the algorithm may generate predictions reflecting the biases of past and unrelated human actors and execute the lender's instructions by extracting a higher rate from vulnerable consumers.[302] Depending on what websites the algorithm has visited and what data was trained for machine learning, the same algorithm may or may not result in a discriminatory impact.

Second, lenders are usually not involved in the design of the AI model infrastructure. Whether or not the algorithm is "designed to take advantage" of the consumer is determined before the lender instructs the algorithm to execute its business objective. In other words, the possibility that an algorithm creates a discriminatory impact is unrelated to, and independent of, the lender's instruction.[303] Yet, current rules on what qualifies as a "legitimate business necessity" do not capture this dynamic, giving AI and fintech lenders an easy way to argue their way out of liability. Essentially, the two-pronged *legally sufficient justification* analysis under disparate impact doctrine does not line up with how algorithmic harm unfolds.

III. Existing Avenues for Reform: Limitations and Challenges

Traditional anti-discrimination frameworks only have limited utility for safeguarding consumer's equal access to credit, considering the likely demise of ECOA disparate impact liability theory and the legal hurdles generated by the courts' "tortification" of fair lending laws.[304] While consumer advocates must continue the legal battle to establish ECOA disparate impact, they should also look beyond the disparate impact theory. Our legal system needs new solutions

301. *See* Bartlett et al., *supra* note 125 at 33, 47.
302. *See infra* Part I.C.2.
303. *See id.*
304. *See infra* Parts II.B.3 and II.C.1-2.

to ensure it can address the nascent threats of algorithmic discrimination in the consumer credit underwriting market.

This Part begins by criticizing two existing proposals for a legal response to the risks of algorithmic discrimination: (i) enhanced regulatory scrutiny of algorithmic inputs by ways of mandatory disclosure; and (ii) reform of the disparate impact standard to address problematic algorithmic outputs. Although both the proposals address only a single dimension of algorithmic discrimination, neither of them fundamentally challenge the flawed judicial assumption that AI can conform to human standards of conduct. To remediate this flaw, this Part calls for regulators to consider an alternative harm-based framework as opposed to the traditional conduct-based framework to account for AI discrimination in the enforcement of the fair lending laws.

A. *Limitations of Algorithmic Input Scrutiny*

1. *Legal Uncertainties About Data Privacy and Disclosure Rulemaking*

A dominant approach to AI governance in the consumer lending market is enhanced regulatory visibility into how credit underwriting software design and data-processing mechanisms use algorithmic inputs. A corollary to the existing mandatory disclosure regime,[305] this approach aims to address the problem of input opaqueness by requiring lenders and their business affiliates to disclose AI training data, source codes, and algorithmic formulas to federal agencies.[306] The input scrutiny approach shares the goals of existing disclosure mandates: enhanced algorithmic transparency,[307] facilitation of informed consumer choice,[308] and encouragement of consumer preference towards more socially-

305. For consumer lending other than mortgages, the "mandatory disclosure regime" includes the following federal statutes: (i) Truth in Lending Act (codified at 15 U.S.C. §§ 1601-1667.), which requires lenders to disclose to the consumer certain cost-related information in standardized formats using standardized nomenclature; (ii) Truth in Savings Act (codified at 12 U.S.C. §§ 430-4313), which requires banks to provide to consumers disclosures about terms and costs of deposit accounts and imposes requirements for deposit account advertisements; (iii) Electronic Fund Transfer Act (codified at 15 U.S.C. §§ 1693a-1693r.), providing transparency to wire transfers and remittances. Although none of the existing federal disclosure statutes directly addresses AI-based credit reporting and underwriting, advocates for algorithmic transparency via disclosure draw inspiration from these laws and share the same governing philosophy.

306. *See* CONSUMER FIN. PROT. BUREAU, *CFPB Acts to Protect the Public from Black-Box Credit Models Using Complex Algorithms* (May 26, 2022), https://www.consumerfinance.gov/about-us/newsroom/cfpb-acts-to-protect-the-public-from-black-box-credit-models-using-complex-algorithms/.

307. *See* Jermy Prenio & Jeffery Yong, *Humans Keeping AI in Check—Emerging Regulatory Expectations in the Financial Sector*, FINANCIAL STABILITY INSTITUTE POLICY IMPLEMENTATION NO. 35, at 14-15 (Aug. 2021), https://www.bis.org/fsi/publ/insights35.pdf.*But see* Andrew Burt, *The AI Transparency Paradox*, HARV. BUSINESS REVIEW (Dec. 13, 2019), https://hbr.org/2019/12/the-ai-transparency-paradox.

308. *See generally* Angela A. Hung, Min Cong & Jeremy Burke, *Effective Disclosures in Financial Decisionmaking*, RAND RSCH. REP. RR-1270-DOL (Jul. 2015), https://www.rand.org/pubs/research_reports/RR1270.html.; Jeanne M. Hogarth & Ellen A. Merry,

productive financial products.[309] While promising in theory, this approach may not be feasible due to potential legal challenges, as well as policy design flaws that are reflective of the shortcomings of traditional, fault-based anti-discrimination regimes.

Legal Authority to Mandate Disclosures: While not yet exercised in the algorithmic context, the CFPB has general authority under the DFA to demand financial entities to disclose to their consumers both the individual and market-level data they use as algorithmic inputs for consumer financial services and products. Section 1033 of the DFA provides that, "subject to the rules proscribed by the [CFPB], a consumer financial services provider must make available to a consumer information in the control or possession of the provider concerning the consumer financial product or service that the consumer obtained from the provider."[310] Although the CFPB outlined a set of consumer protection principles in 2017 pursuant to this provision, it has not yet issued rules for implementing section 1033.[311] Currently, the CFPB has only solicited public comments pending the issuance of a final rule.[312] Although the CFPB has not yet released details about its data-sharing rule, this rule, if finalized, could provide consumers a means to access the algorithmic inputs of credit-underwriting software at any time during the loan application for cost comparison and shopping.[313]

Designing Disclosures to Inform Consumer Financial Decisionmaking: Lessons Learned from Consumer Testing, FEDERAL RESERVE BULLETIN (Oct. 21, 2011), https://www.federalreserve.gov/pubs/bulletin/2011/articles/designingdisclosures/default.htm.

309. *See generally* RICHARD THALER & CASS SUNSTEIN, NUDGE: IMPROVING DECISIONS ABOUT HEALTH, WEALTH, AND HAPPINESS (2008); Cynthia Weiyi Cai, *Nudging the Financial Market? A Review of the Nudge Theory*, 60 ACCOUNT. & FIN. 3341, 3357-60 (2020).

310. Consumer Access to Financial Records, 85 Fed. Reg. 71003 (advance notice of proposed rulemaking Nov. 6, 2020).

311. *See* Alex Acree, Pierce Babirak, Shelby Schwartz, Julia Baker, & Chris Napier, *Consumer Financial Data: Legal and Regulatory Landscape*, FINREGLAB (Oct. 2020), https://finreglab.org/wp-content/uploads/2020/10/Financial-Data-White-Paper.pdf.

312. *See* A. J. Dhaliwal, Sherwin Root, Moorari Shah, *CFPB Likely to Delay Data Sharing Rule Until 2023*, SHEPPARD MULLIN RICHTER & HAMPTON LLP, CONSUMER FINANCE & FINTECH BLOG (Jan. 18, 2022), https://www.consumerfinanceandfintechblog.com/2022/01/cfpb-likely-to-delay-data-sharing-rule-until-2023/; *see also* Matt Lehman, *Delay in CFPB's Data Sharing Rule Keeps Financial Institutions Guessing*, RINGCENTRAL (May 10, 2022) (predicting that the CFPB may not implement a rule pursuant to §1033 of the Dodd-Frank Act until late 2022 or some time in 2023), https://www.ringcentral.com/us/en/blog/delay-in-cfpbs-data-sharing-rule-keeps-financial-institutions-guessing/.

313. Through CFPB has not moved forward on issuing a final rule to implement DFA section 1033, in October 2021, the CFPB ordered the six largest technology companies—Amazon, Apple, Facebook, Google, PayPal, and Square—to provide information regarding their payment systems and technologies pursuant to DFA section 1022(c)(4). But this Article will not explore the legal issues pertaining to section 1022(c)(4) in detail, as the provision primarily relates to payment systems rather than consumer lending. *See* CONSUMER FIN. PROT. BUREAU, *CFPB Orders Tech Giants to Turn Over Information on their Payment System Plans*, CFPB NEWSROOM (Oct. 21, 2021); https://www.consumerfinance.gov/about-us/newsroom/cfpb-orders-tech-giants-to-turn-over-information-on-their-payment-system-plans/; *see also* Courtney M. Dankworth, Avi Gesser, Gregory Lyons, James Amler, Caroline Novogrod Swett, Frank Colleluori, Adrian Gonzalez, Anna Gressel & Alexandra Mogul, *Increased Focus by Federal Regulators on AI and Consumer Protection in the Financial Sector*, DEBEVOISE & PLIMPTON LLP, DATA BLOG (Nov.

Potential Legal Issues: Although there is no current or anticipated legal challenge to the CFPB's authority to demand input disclosures under section 1033 of the DFA, it is unclear how the CFPB can, within the statutorily permissible bounds, enforce the disclosure mandate after gaining input access from banks, lenders, and their business affiliates.[314] Since all CFPB powers to regulate financial market disclosure derives from congressional delegation,[315] the contemplated data-sharing rule, if implemented, would likely incite a wave of litigation. Regardless of the form of regulation that the CFPB decides in implementing section 1033, the CFPB must respond to the following questions.

First, who is a "consumer financial services provider"? Does it include the lending institutions' fintech partners, data brokers, AI developers, and other entities located further upstream in the credit supply chain which, nevertheless, do not engage in the business of financial lending? Are they also subject to the disclosure and data-sharing mandate?

Second, in what manner shall such consumer financial services provider "make available consumer information"? Through a standard disclosure form or through indirect disclosure to the agencies? When should the disclosure be made and at what point of the credit transaction?

Third, how will the disclosure mandate interact with information that is exempt or prevented from disclosure? Is there a possible First Amendment challenge in mandating disclosure that unduly interferes with the disclosing party's constitutional right in protected speech in a commercial context?[316]

Fourth, is the CFPB authorized to remove suspect algorithmic inputs that indicate possible discrimination on prohibited characteristics? If yes, under what legal standard shall the CFPB decide for input removal (i.e., disparate impact standard or disparate treatment standard)?

Finally, what is the distinction between "relevant" and "irrelevant" data? As the ZestAI[317] case study in Part I.B.2 of this Article illustrates, one of the key

10, 2021), https://www.debevoisedatablog.com/2021/11/10/increased-focus-by-federal-regulators-on-ai-and-consumer-protection-in-the-financial-sector/.

314. The statutory provision granting the CFPB general rulemaking authority to enforce "federal consumer financial laws" is contained in 12 U.S.C. § 5512.

315. The standard for congressional delegation, ironically, originates from the "non-delegation" doctrine that is implied by the legislative vesting clause of Article I Section I of the Constitution. To enforce the "non-delegation" doctrine, the Supreme Court has required that Congress lays out an "intelligible principle" to govern and guide its delegee (*i.e.*, the agencies). The "intelligible principle" requires that Congress delineate a clear legal framework to constrain the authority of the delegee. *See generally* J.W. Hampton, Jr. & Co. v. United States, 276 U.S. 394 (1928).

316. Ever since *Virginia State Board of Pharmacy v. Virginia Citizens Consumer Council, Inc*., 425 U.S. 748 (1976), it has been settled that First Amendment protections apply to commercial speech. However, mandated disclosures are permissible if they are reasonably related to a substantial government interest even if the warnings are not required to prevent deception so long as the mandated disclosures are (1) purely factual, (2) uncontroversial, and (3) not unjustified or unduly burdensome. *See, e.g.*, Zauderer v. Office of Disciplinary Council of S. Ct. of Ohio, 471 U.S. 626 (1985); Am. Beverage Ass'n v. City of S.F., 916 F.3d 749 (9th Cir. 2019).

317. *See infra* Part I.B.2.

premises of alternative data usage in the credit context is that "all data is relevant" for assessing consumer default risk.

2. *Reasons Why Input Scrutiny Approach Might Not Be Desirable*

One potential application of the CFPB's section 1033 powers would be to create a periodic disclosure regime for data-sharing and confidential review. To avoid unfair or accidental disclosure of legitimate trade secrets by the CFPB, companies subject to CFPB regulatory oversight would disclose relevant information only to the CFPB. The CFPB would then assess all data a company hands over under confidential review. If a company appeals a CFPB decision before a federal court, then the information would become a part of the administrative record, subject to judicial review. If the CFPB finds that the algorithms compute credit scores by giving unreasonable weight to prohibited factors (i.e., race, national origin, religion, or sex) or proxies for prohibited factors (i.e., location, language preferences, social media network, dating history), the CFPB could then bring an enforcement lawsuit against the company or obtain an injunctive order from a federal court. This approach would provide regulatory visibility into the credit-underwriting industry and enhance digital accountability.

However, the input scrutiny approach may not be feasible for two reasons. First, mandatory disclosure of algorithmic inputs may give rise to a constitutional challenge under the Fourth Amendment. A warrantless inspection by the CFPB of a company's algorithms can constitute "unreasonable search and seizure" of private property.[318] Even if the disclosure rule is found to be constitutional,[319] there might be significant industry pushback from the credit-underwriting industry. Second, because information about a person's protected characteristics is embedded in other information about the individual, excluding protected characteristics from algorithmic input cannot guarantee that the algorithm will not infer these characteristics from other trends and uses them to form decisions.[320] Additionally, machine learning algorithms can find spurious correlations when there are none.[321] Thus, prohibiting inputs that are "proxies"

318. U.S. CONST. amend. IV.

319. The dominant judicial test is New York v. Burger, 482 U.S. 691 (1987), which held that a warrantless inspection can be reasonable under the Fourth Amendment because the expectation of privacy in commercial property is attenuated in closely regulated industries, where there is heightened government interest in regulation. But to survive a constitutional challenge, the regulators must show that (i) there is "substantial" government interest underlying the regulatory scheme that purports to authorize the inspection at issue; (ii) the warrantless inspection is "necessary to further the regulatory scheme"; (iii) the inspection program, in terms of capacity and regulatory of its application, provides a constitutionally adequate substitute for warrant.

320. *See* Gillis, *supra* note 26, at 1180-81, 1184.

321. Robin Wigglesworth, *Spurious Correlations are Kryptonite of Wall St's AI Rush*, FIN. TIMES (Mar. 14, 2018), https://www.ft.com/content/f14db820-26cd-11e8-b27e-cc62a39d57a0.

for protected characteristics under the input scrutiny approach does not guarantee enhanced digital accountability.

Even if the CFPB has legal authority to demand algorithmic input disclosure, the CFPB's lack of means to discern "relevant" from "irrelevant" data undermines the effectiveness of input scrutiny. Furthermore, if the CFPB's administrative actions end up in judicial review, it is not clear how courts will determine what data is relevant for credit risk pricing. The "all data is credit data" model challenges the existing legal assumption that there exists a "relevant/irrelevant" dichotomy. Admittedly, quantitative models may help the judicial system better understand the relevance of certain data. For example, some economists have suggested that data might be legally irrelevant when distinctions in loan pricing speak to "the lender's ability to extract rents" from vulnerable borrowers, rather than the need to assess the applicant's creditworthiness.[322] In practice, however, the economists' proposition just opens the door for a battle between expert witnesses. Ultimately, the costs of litigation may have a bottleneck effect that deters victims from seeking legal redress in the first place.

B. Limitations of the Disparate Impact Standard

1. The HUD's New Disparate Impact Standard for AI Discrimination

Another heavily contested arena concerns whether the CFPB should reform its disparate impact standard under ECOA by following the HUD's approach to FHA disparate impact claims. In August 2019, the HUD proposed a new legal framework to assess disparate impact with a specific application to claims of algorithmic discrimination arising under FHA (hereafter "proposed rule"). The HUD's proposed rule was one of the first attempts in the U.S. to determine whether an algorithm violates the fair lending laws. The final rule was adopted in October 2020 and rendered effective in June 2021.

The proposed rule suggests replacing the HUD's prior three-step burden-shifting prima facie framework[323] with a five-element claim that better reflects

322. *See* Bartlett et al., *supra* note 125, at 30, 37.

323. The HUD's prior 2013 rule codified a three-part burden-shifting framework for bringing a prima facie disparate impact discrimination claim, consistent with the legal frameworks on which the HUD and the federal courts have relied: (i) "The plaintiff or charging party is first required to prove as part of the prima facie showing that a challenged practice caused or predictably will cause a discriminatory effect." (ii) "If the plaintiff or charging party makes this prima facie showing, the defendant or respondent must then prove that the challenged practice is necessary to achieve one or more substantial, legitimate, nondiscriminatory interests of the defendant or the respondent." (iii) "If the defendant or respondent meets its burden at step two, the plaintiff or charging party may still prevail by proving that the substantial, legitimate, nondiscriminatory interests supporting the challenged practice could be served by another practice that has a less discriminatory effect." U.S. DEPT. OF HOUS. & URB. DEV., Reinstatement of HUD's Discriminatory Effects Standard, 82 Fed. Reg. 33590, 33591-92 (Jun. 25, 2021) (to be codified at 24 C.F.R. pt. 100). *See also* 78 Fed. Reg. 11460, 11482; Tex. Dep't of Hous. and Cmty. Affs. v. Inclusive

algorithmic practices. Under the proposed rule, a plaintiff must allege that (i) "the challenged policy or practice is arbitrary, artificial, and unnecessary to achieve a valid interest or legitimate objective such as practical business, profit, policy consideration, or requirement of law," (ii) there is "a robust causal link between the challenged policy or practice and a disparate impact on members of a protected class," (iii) the challenged policy or practice has "an adverse effect on members of a protected class," (iv) "the disparity caused by the policy or practice is significant," and (v) "the complaining party's alleged injury is directly caused by the challenged policy or practice."[324]

Under the HUD's new five-element disparate impact framework, defendants will not be able to defeat a plaintiff's disparate impact claim by arguing that there are no less-discriminatory alternatives for the practice pursuing a legitimate business interest. This argument is a significant substantive hurdle for plaintiffs to overcome given that a defendant could justify the challenged act or policy as a matter of reasonable business judgment. Thus, the HUD's new framework increases a plaintiff's likelihood of prevailing on the merits as it disallows a defendant from raising the "less discriminatory alternative" defense.[325]

2. *Unintended Consequences of the New Disparate Impact Standard*

However, the HUD's proposed rule may make it harder for plaintiffs to survive a motion to dismiss at the initial pleading stage, since plaintiffs will need to plead plausibility for five, rather than three, elements to establish a prima facie claim of discrimination.[326] While front-loading a plaintiff's burden of proof can arguably weed out potentially frivolous or meritless lawsuits, it may significantly increase a plaintiff's litigation costs for pre-discovery investigation to garner prima facie evidence.[327] Financially constrained consumers may be discouraged from resorting to legal remedies.

Moreover, the HUD's proposed rule places the burden of proving causation on a plaintiff, which could be an equally—if not more—burdensome procedural obstacle. Given the proposed rule's "robust causal link" requirement, the plaintiff must show a "direct" and "significant" causal link between the plaintiff's injury

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Communities Project, Inc., 567 U.S. 519, 525-527 (2015) (overviewing HUD's 2013 rule's burden-shifting framework).

324. U.S. DEPT. OF HOUS. & URB. DEV., HUD's Implementation of the Fair Housing Act's Disparate Impact Standard. A Proposed Rule by the Housing and Urban Development Department, 84 Fed. Reg. 42854 (Aug. 19, 2019).

325. *See* U.S. DEPT. OF HOUS. & URB. DEV., Reinstatement of HUD's Discriminatory Effects Standard, 82 Fed. Reg. 33592 (Jun. 25, 2021); *see also Inclusive Communities*, 567 U.S., at 542.

326. *See* Comment of Cathy O'Neil, Before the Office of the Assistant Secretary for Fair Housing and Equal Opportunity, HUD: Comment Regarding Docket NO. FR-6111-P-02 (Christopher Bavitz, Mason Kortz, Tea Skela & James Holloway, on behalf of Cathy O'Neil) (Oct. 2019), https://clinic.cyber.harvard.edu/files/2019/10/HUD-Rule-Comment-ONEIL-10-18-2019-FINAL.pdf.

327. *See id.*

and the defendant's alleged discriminatory conduct.[328] The defendant, on the other hand, can defeat a disparate impact claim by simply showing that the machine learning model is not a proximate cause of the disparate impact.[329]

With minor wording alterations, the HUD's 2020 final rule kept the overall five-element disparate impact framework outlined by the 2019 proposed rule.[330] The only textual differences between the proposed and final rule are the wordings of section 100.500(b)(2) (adding the word "disproportionately" before "adverse effect") and section 100.500(b)(5) (changing "injury…directly caused by the challenged policy or practice" to "direct relation between the injury asserted and the injurious conduct alleged").[331] In explaining the changes, the HUD stated that the revision seeks to "more closely adhere to the language of [*City of Miami*]," which "it is intended to codify."[332] *City of Miami* significantly raised the bar in *Inclusive Communities* to impose a stricter and more onerous "direct proximate cause" requirement on the plaintiff to plead a disparate impact discrimination. The HUD's new five-element framework, therefore, will likely create significant barriers preventing plaintiffs seeking to recover from lender's act or policy of algorithmic discrimination in relation to a credit transaction.[333]

Should the CFPB adopt a similar disparate impact standard specifically tailored to algorithmic discrimination, the agency will need to do so through amending the disparate-impact provision under 12 C.F.R. § 1002. However, as noted earlier in Part II, the disparate impact provision of 12 C.F.R. § 1002 may not survive judicial review if challenged in the Supreme Court. If this occurs, an amendment of 12 C.F.R. § 1002's disparate impact standard might be moot.

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328. *Id*.

329. The plaintiff can rebut this defense by showing that the defendant's analysis of causation is based on a flawed method, such as by that an input in the machine learning model is correlated with a prohibited factor. *See* 84 Fed. Reg. 42854.

330. *See* 24 C.F.R. § 100.500. The relevant provision in the 2020 final rule states as follows:

> "At the pleading stage, to state a discriminatory effects claim based on an allegation that a specific, identifiable policy or practice has a discriminatory effect, a plaintiff or charging party must sufficiently plead facts to support each of the following elements:
>
> (1) That the challenged policy or practice is arbitrary, artificial, and unnecessary to achieve a calid interest or legitimate objective such as a practical business, profit, policy consideration, or requirement of law;
>
> (2) That the challenged policy or practice has a disproportionately adverse effect on members of a protected class;
>
> (3) That there is a robust causal link between the challenged policy or practice and the adverse effect on members of a protected class, meaning that the specific policy or practice is the direct cause of the discriminatory effect;
>
> (4) That the alleged disparity caused by the policy or practice is significant; and
>
> (5) That there is a direct relation between the injury asserted and the injurious conduct alleged."

331. *Id*. The HUD changed the original phrasing to "direct relation between the injury asserted and the injurious conduct alleged" in order to closely mirror the majority's holding in *City of Miami*. *See* Bank of Am. Corp. v. City of Miami, 581 U.S. 189, 202-203 (citing Holmes v. Securities Investor Protection Corporation, 503 U.S. 258, 268 (1992)).

332. U.S. DEPT. OF HOUS. & URB. DEV., HUD's Implementation of the Fair Housing Act's Disparate Impact Standard, a Final Rule by the HUD, 85 Fed. Reg. 60288, 60289 (Sep. 24, 2020).

333. *See City of Miami*, 581 U.S. at 202-203.

Moreover, even if 12 C.F.R. § 1002 survives judicial review, the reformed standard may not meaningfully improve the consumer's position because consumers tend to lack understanding of or access to the inputs, structures, and decision-making process of AI credit models. Lastly, like the HUD's five-element rule, the CFPB's proposed amendment of 12 C.F.R. § 1002 may also have the unintended effect of adding to the challenger's (e.g., consumers, applicants) pleading burden.

IV. TOWARDS A HARM-BASED MODEL: PROPOSED "UNFAIRNESS" RULE

Moving from a conduct-based to a harm-based model of AI governance presents several difficult questions. What legal frameworks, other than the existing anti-discrimination statutes, can safeguard equal credit access protection? Upon shifting the focus from lender conduct to consumer injury, what types of harm would constitute injury? What is the source of the consumer injury?

These questions call into question the very foundation of what "discrimination" means under the current legal system. The "discriminatory" nature of an act or policy, as the current fair lending jurisprudence tells us, hinges on the reprehensibility of the lender's conduct. The "tortification" of anti-discrimination statutes reflects this judicial philosophy.[334] However, new modes of systemic discrimination challenge that core judicial presumption. The epitome of such a challenge are AI decision pathways that generate disparate adverse impacts by simply summarizing existing inequalities, involving neither animus nor causation. Unless regulators and consumer advocates move beyond the obsolete conduct-based fair lending regime, the risks of AI discrimination will continue to be unchecked.

However, there may be legal basis to create a harm-based AI governance regime for equal credit access protection. The CFPB's authority to regulate UDAAPs under the Dodd-Frank Act offers an opportunity to redirect our legal focus from lender conduct to consumer harm.[335] This Part explores what a potential "unfairness" rule for AI harm would look like and is divided into four sections. Section A underscores the value of algorithmic transparency and explains why a rule prohibiting the use of "black box" algorithms in credit underwriting is beneficial on public policy grounds. Section B delves into the contents and market implications of the proposed rule. Section C argues that the CFPB has legal authority to adopt such a rule under the three-pronged countervailing balance test for prohibiting "unfair practices" under section 1031(c) of the DFA. Section D discusses counterarguments and provides rebuttals.

334. *See supra* Part II.C.
335. *See* 15 U.S.C. § 5531.

A. Locating the Source of Harm: "Black Box" Algorithms

1. What Makes a Credit Underwriting Algorithm a "Black Box"?

Any attempt to address "black box" models through administrative rulemaking must answer a threshold question of what exactly makes an algorithm a "black box." In data science, an algorithm is often described as a "black box" when it computes a result without explaining how it arrives at the conclusion.[336] In credit underwriting, a "black box" algorithm is one that predicts creditworthiness of consumers without having an explainable, defensible, or justifiable basis for how the model's data inputs relate to its computational outputs.[337] Essentially, both definitions emphasize inexplicability as the hallmark of "black box-ness." That is, users and developers struggle to explain their credit outcomes because the self-learning and adaptive features of such algorithms make them unpredictable.[338]

Since being able to explain credit outcomes depends on the extent to which the algorithm's users and developers understand its logic, there is no definitive threshold for when an algorithm becomes a "black box."[339] Generally, interpreting decision-tree and regression-based algorithmic models does not require additional explanatory algorithms.[340] However, more complex models, such as neural networks, can be difficult to comprehend, since they have "thousands or millions of parameters (i.e., weights)" influencing model behavior and they self-adjust their decision-making patterns to reflect new data inputs.[341] Such models are often considered to be "black boxes" because their behavior cannot be explained even if one has visibility into the models' structure, data inputs, and weights.[342]

Users and developers may be able to shed light on a complex model's behavioral logic by employing Explainable AI (XAI), tools specifically designed to find explanations for models too complex to be understood by humans.[343]

336. *Black Box Machine Learning*, SEON (last visited Dec. 16, 2023), https://seon.io/resources/dictionary/blackbox-machine-learning/..

337. *See* Alexey Surkov, Val Srinivas & Jill Gregorie, *Unleashing the Power of Machine Learning Models in Banking Through Explainable Artificial Intelligence (XAI)*, DELOITTE (May 17, 2022), https://www2.deloitte.com/us/en/insights/industry/financial-services/explainable-ai-in-banking.html.

338. Bryan Yurcan, *How Banks and Shed Light on the "Black Box" of AI Decision-Making*, THE FINANCIAL BRAND (Jun. 29, 2022), https://thefinancialbrand.com/news/data-analytics-banking/artificial-intelligence-banking/how-banks-can-shed-light-on-the-black-box-of-ai-decision-making-147960/.

339. Florian Perteneder, *Understanding Black-Box ML Models with Explainable AI*, DYNATRACE ENGINEERING (Apr. 29, 2022), https://engineering.dynatrace.com/blog/understanding-black-box-ml-models-with-explainable-ai/.

340. *See id*.

341. *Id*.

342. *Id*.

343. *See, e.g.*, Matt Turek, *Explainable Artificial Intelligence (XAI)*, DEFENSE ADVANCED RESEARCH PROJECTS AGENCY (last visited Dec. 13, 2022), https://www.darpa.mil/program/explainable-artificial-intelligence; Blattner, Stark & Spiess, *supra* note 32, at 23-24. Companies that provide XAI

However, experts and researchers are divided on whether XAI brings enough transparency to "black box" model behavior or encourages best industry practices.[344] Some worry that XAI may encourage the adoption of unnecessarily complex models, provide explanations that are not faithful to what the original model computes, or lead to overly complicated decision pathways that are ripe for human error.[345] Additionally, since many XAI tools are open-source software (and public by nature), model developers have expressed concern that XAI may allow competitors to reverse engineer their machine learning techniques and thereby reveal trade secrets behind their proprietary algorithms.[346]

2. *Why Regulating "Black Box" Algorithms Needs to be the CFPB's Priority*

The CFPB has already considered regulating "black box" algorithms. In the *2022-2026 Strategic Plan*, the CFPB stated that it was "particularly concerned about racial equity impacts from the increased usage of data and algorithms in making decisions about people in financial markets" and made fair lending in a "data-driven economy" one of its regulatory priorities.[347] In May 2022, the CFPB Director Rohit Chopra stated that "companies are not absolved of their legal responsibilities when they let a black box model make lending decisions."[348] The *2022-03 Circular* further makes clear that "creditors cannot justify noncompliance with ECOA based on the mere fact that the technology they use to evaluate credit application is too complicated, too opaque in its decision-making, or too new."[349]

Unfortunately, neither the *Plan* nor the *Circular* explain what kinds of AI underwriting models are "too complex" or "too opaque" to be used without

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analytical tools in connection with consumer credit underwriting include: ArthurAI, FiddlerAI, H2O.ai, RelationalAI, SolasAI, Stratyfy, and ZestAI.

344. *See, e.g.*, Agus Sudjianto & Aijun Zhang, *Designing Inherently Interpretable Machine Learning Models*, Presented at ACM ICAIF 2021 Workshop on Explainable AI in Finance (Nov. 3, 2021), https://arxiv.org/pdf/2111.01743.pdf; Mir Riyanul Islam, Mobyen Uddin Ahmed, Shaibal Barua & Shahina Begum, *A Systematic Review of Explainable Artificial Intelligence in Terms of Different Applications and Tasks*, 12 APPLIED SCIS.1353 (2022).

345. *See* Cynthia Rudin, *Stop Explaining Black Box Machine Learning Models for High Stakes Decisions and Use Interpretable Models Instead*, 5 NAT. MACH. INTELL. 206, 207-8 (2019).

346. *See* Caryn Lusinchi, *From Black Box to Glass Box: Transparency in XAI*, ARTHUR AI (Oct. 19, 2022), https://www.arthur.ai/blog/from-black-box-to-glass-box-transparency-in-xai.

347. CONSUMER FIN. PROT. BUREAU, *Consumer Financial Protection Bureau Strategic Plan FY 2022-2026*, at 7 (Spring 2022), https://files.consumerfinance.gov/f/documents/cfpb_strategic-plan_fy2022-fy2026.pdf.

348. CONSUMER FIN. PROT. BUREAU, *CFPB Acts to Protect the Public from Black-Box Credit Models Using Complex Algorithms* (May 26, 2022), https://www.consumerfinance.gov/about-us/newsroom/cfpb-acts-to-protect-the-public-from-black-box-credit-models-using-complex-algorithms/.

349. *See id*. *See also* CONSUMER FIN. PROT. BUREAU, *Consumer Financial Protection Circular 2022-03* (May 26, 2022), https://www.consumerfinance.gov/compliance/circulars/circular-2022-03-adverse-action-notification-requirements-in-connection-with-credit-decisions-based-on-complex-algorithms/.

violating ECOA.[350] To date, the CFPB has not promogulated any rules or issued any guidance on how users and developers of AI credit models can comply with ECOA's anti-discrimination and adverse action notice requirements.[351]

Without clear rules, lenders using credit-underwriting algorithms cannot be certain about their compliance with ECOA. The CFPB should provide legal clarity by prioritizing addressing "black box" AI usage during the remainder of this term. Specifically, the CFPB should prohibit the usage of "black box" AI models and craft safe-harbors that incentivize the market's use of harmless, explainable, and ECOA-compliant ("white-box") models. The following are policy grounds for adopting a new algorithmic transparency rule:

(1) Incentivizing Market Adoptions: Legal uncertainty regarding what kinds of algorithms may violate ECOA prevents national banks, federally insured lenders, and other highly regulated financial institutions from adopting AI. As a result, less-regulated entities such as payday lenders, auto lenders, and small business lenders currently dominate the AI lending market. Having a safe-harbor rule separating "white-box" from "black box" models can remove that roadblock and encourage more regulated and safer lenders to use AI technologies in a beneficial, fair, and equitable fashion.[352]

(2) Promoting Best Practices: Having a well-defined safe harbor promotes using simpler models that are more clearly interpretable, and disincentivizes lenders from using algorithms that are unnecessarily complex for the underlying purposes.[353]

(3) Providing Guardrails for Innovation: By narrowing the scope of prohibition to only opaque and unexplainable "black box" algorithms, the CFPB would send a signal to the market that it supports technological innovations to enhance the accuracy and fairness of the credit underwriting process. The CFPB's adoption of a safe-harbor rule would also facilitate the market's usage of XAI to help lenders fulfill their obligations under ECOA.[354]

(4) Protecting Consumer Data Privacy: Lenders that use algorithms for credit underwriting should not take more information than necessary from consumers and should not take any information without a consumer's consent. "White-White box" models preserve a consumer's right to know how credit

350. Brett J. Ashton, *Recent Developments in Fair Lending Discrimination as a UDAAP Violation and Algorithmic Redlining*, KRIEG DEVAULT LLP (Jun. 2, 2022), https://www.kriegdevault.com/insights/recent-developments-in-fair-lending-discrimination-as-a-udaap-violation-and-algorithmic-redlining.

351. Adverse action notice requirement refers to lender's obligation to explain any adverse actions taken against a consumer within a reasonable timeframe. Under 12 C.F.R. § 1002.9, a creditor taking an adverse action against a loan applicant is required to deliver to the applicant "a notification in writing" containing "a statement of specific reasons" for the adverse action "within 30 days" after taking such action. *See* 12 C.F.R. § 1002.9.

352. *See* Surkov, Srinivas & Gregorie, *supra* note 32.

353. *See* Perteneder, *supra* note 32.

354. *See* Blattner, Stark & Spiess, *supra* note 32, at 23-24.

assessments use their personal data and helps lenders comply with adverse action notice requirements under ECOA.[355]

(5) Preventing Consumer Harm: Victims of AI discrimination often lack sufficient understanding of the nature, extent, and source of their harms. Consequently, such victims tend to face significant pleading and evidentiary hurdles. Even technologically sophisticated consumers struggle to challenge these decisions because they have no access to the model's inputs, parameters, and decision logic, which are often protected as trade secrets.[356] Prohibiting "black box" models would increase algorithmic transparency and enable consumers to challenge discriminatory lending decisions.

B. Proposed Rulemaking: Prohibiting Black Box Usage as "Unfair"

1. Policy Design Under Dodd-Frank Act Section 1031(b): Defining "Unfairness"

This section discusses what a proposed rule prohibiting "black box" AI models might look like. Under section 1031(b) of the Dodd-Frank Act, the CFPB "may prescribe rules applicable to a covered person or service provider identifying as unlawful unfair, deceptive, or abusive acts or practices ["UDAAPs"] in connection with [or the offering of] . . . a consumer financial product or service[.]"[357] Such rules "may include requirements for the purpose of preventing such acts or practices."[358] Congress delegated broad authority to the CFPB to define UDAAPs and address them through either prohibitive or prophylactic means.[359]

(1) Defining the "Unfair" Practice: Pursuant to its power under section1031(b), the CFPB should identify as "unfair" the practice of using "black box" machine learning algorithms in connection with any aspect of a credit transaction involving the underwriting of consumer credit which has a disparate impact on race, sex, religion, or national origin. The CFPB should further define a "black box" algorithm as "any algorithmic model or machine learning technology used in connection with the underwriting of consumer credit

355. 12 C.F.R. § 1002.2(c)(1)defines "adverse action" as: "(1) A refusal to grant credit in substantially the amount or on substantially the terms requested in an application unless the creditor makes a counteroffer (to grant credit in a different amount or on other terms), and the applicant uses or expressly accepts the credit offered; (2) A termination of an account or an unfavorable change in the terms of an account that does not affect all or substantially all of a class of the creditor's accounts; or (3) A refusal to increase the amount of credit available to an applicant who has made an application for an increase." *See* 12 C.F.R. § 1002.2(c)(1); *see also* Sarah Ammermann, *Adverse Action Notice Requirements Under the ECOA and the FCRA*, CONSUMER COMPLIANCE OUTLOOK (2013), https://www.consumercomplianceoutlook.org/2013/second-quarter/adverse-action-notice-requirements-under-ecoa-fcra/#footnotes.

356. *See supra* Part I.C.2.

357. 12 U.S.C. §5531(b).

358. *Id*.

359. *See* Ashton, *supra* note 350.

(whether or not the model is designed specifically for the use of credit underwriting), where the relationship between the model's input and outputs lacks a clearly explainable correlation to an applicant's creditworthiness or likelihood of default."[360] In adopting this definition, the CFPB will also need to clarify some additional issues.

(2) What is "Clearly Explainable"? Explainability raises several difficult questions. Should the proposed rule require algorithmic models to be self-explainable by design? Or is it permissible for the model to be *post-hoc* explainable through the use of XAI? Should the proposed rule require the model to be explainable at any given point in time? What if a model's explainability changes over time without substantial interference by the model's developers or users? What degree of explainability is required? Will partial explainability suffice?

Given the complexity of model explainability as a technical issue and the ever-changing nature of AI technological innovation, the CFPB need not provide a definitive, bright-line rule for the above questions. The CFPB should determine what is "clearly explainable" on a case-by-case according to the factual circumstances. Nevertheless, certain factors should guide the inquiry of whether a model satisfies the "clearly explainable" requirement. These factors are not exhaustive and are meant to be a guide for compliance:

(a) Whether drivers of the model's behavior can be interpreted by developers and users without the need of additional XAI tools;
(b) Whether such drivers can be described or otherwise communicated to the consumers in a readily understandable form;
(c) If the model's design is not self-explanatory, whether the use of different XAI tools would yield substantially different, inconsistent, or opposite explanations for its behavior;
(d) Whether the model's design is unnecessarily complex for achieving the lender's underlying purposes; and
(e) The availability of simpler alternatives that would achieve the lender's purposes with the same substantial level of accuracy and effectiveness.

360. A possible legal response might be that the CFPB does not have the power to incidentally define what makes a model a "black-box" because the proposed rule has not identified the design of such models to be itself an "unfair practice." Under this logic, opponents to the proposed rule might argue that CFPB does not have power under section 1031(b) to define what a "black box" is unless the CFPB demonstrates that the design of the model itself (1) generates substantial consumer injury, (2) that injury is not reasonably avoidable, and (3) that injury is not outweighed by countervailing benefits to consumers or to competition. However, the CFPB need not address this issue. Although this issue has not yet been litigated, the language of section 1031(b) grants CFPB the legal authority to define components of a practice that the CFPB identifies as "unfair, deceptive, or abusive." If the CFPB has power to define an overall practice as "unfair," it would necessarily have the power to define individual components of the practice to be "unfair." Defining what "black box," "explainability," and "defensibility" means is necessary and integral to the CFPB's exercise of section 1031(b) power to identify "black box AI/ML model usage" as "unfair." *See generally* CONSUMER FIN. PROT. BUREAU, *Unfair, Deceptive, or Abusive Acts or Practices (UDAAPs) Examination Procedure*, *in* CFPB SUPERVISION AND EXAMINATION MANUAL 1748 – 1766 (Mar. 2022), https://files.consumerfinance.gov/f/documents/cfpb_supervision-and-examination-manual_2022-09.pdf.

(3) Safe-Harbor for "White-Box" Algorithmic Models: If a model is "self-explainable" by design, then that model is a "white-box." A lender's use of "white-box" models for credit underwriting will not be deemed "unfair" under the proposed rule. However, the usage of "white-box" models by itself will not automatically satisfy the lenders' obligations under ECOA and 12 C.F.R. § 1002. The lender must meet the independent and separate requirements of adverse action notice and non-discrimination under ECOA.

(4) Rebuttable Presumption of Compliance: Alternatively, if the algorithmic model meets the "explainability" requirement— but only through the use of XAI in *post-hoc* rationalization— then the model meets the legal presumption that it is not a "black box." But that presumption is rebuttable if the challenger (e.g., consumer, applicant) shows, by a preponderance of the evidence, any one of the following:

(a) Using various XAI tools to shed light on the model's logic would yield substantially different, inconsistent, or opposite explanatory conclusions about the AI model's behavior;[361]
(b) The XAI only partially explains the model's logic and leaves out significant portions of the model's behavior that are more directly relevant to the consumer's credit outcome;[362]
(c) The XAI's conclusions about the model's behavior patently contradict reasonable and more plausible interpretations of the original model (had XAI not been used);[363] or
(d) Any other factual circumstances that seriously undermine the integrity of the XAI used to explain the model's logic.

Then, the burden should shift back to the model's user (or developer) to demonstrate that the model is still explainable by other reasonable means for its underlying purposes, notwithstanding the above factors. This burden-shifting framework should preserve the consumer's right to challenge bad-faith XAI usage while not compromising the lender's incentives to increase model explainability using XAI.

2. *Expected Market Impact of the Proposed "Unfairness" Rule*

This section discusses the anticipated impacts that the proposed rule will have on the landscape of consumer lending. After considering the relevant policy

361. This factor is a proxy for assessing whether the XAI tool which the lender uses to explain model behavior is a faithful interpretation of the original model outcome. If different XAI tools (not chosen by the lender) yield significantly different results in ways that are inconsistent with the original interpretation, then it undermines the integrity of the original XAI interpretation. This prevents lenders from selectively choosing XAI tools that are biased.

362. This factor is a proxy for assessing whether the XAI tool offers a substantially complete and reasonable explanation of the model logic to the extent that it accurately describes how the model makes credit decisions.

363. This factor is a proxy for evaluating whether the XAI's explanations about the model logic is consistent with the established norms of data science or other reasonable standards accepted by the credit underwriting industry.

trade-offs, this section concludes that the proposed rule will be net-beneficial for the market.

(1) Positive Market Impact: Eliminating the use of "black box" models levels the playing field for competition in the fintech lending market and boosts the market adaptation of interpretable, transparent algorithmic models for credit underwriting. Many lenders have hesitated to adopt algorithmic models—or adapted them in forms that limit much of their value—due to uncertainty about an important threshold question: given that AI machine learning models can be more complex and less transparent than the models they would replace, how can lenders determine which particular models can be trusted and comply with ECOA?[364] The proposed rule will remove that uncertainty by having a "white box" safe harbor and narrowing prohibition to only "black box" models.

The proposed rule will also likely encourage the banking sector to use machine learning technologies in a safe and equitable fashion, as AI underwriting is on the whole more accurate than traditional underwriting and less susceptible to human error.[365] For instance, credit reports that credit-reporting agencies prepare are susceptible to errors introduced by consumers (e.g., self-reporting errors), furnishers (e.g., providing outdated or inaccurate data), or user information-processing systems (e.g., tradeline matching errors).[366] In contrast, AI decision-making has fewer points of human intervention (and pathways of human error) and scrapes information that covers a wider range of consumer activities.[367]

Additionally, the proposed rule is expected to facilitate the development and adoption of XAI technologies. Currently, the global XAI market size is estimated to grow from $4.4 billion in 2021 to $21 billion by 2030.[368] Most growth in XAI adoption is concentrated in the healthcare, retail, logistics, and telecom sectors.[369] XAI adoption in credit underwriting is still in its incipient stage due to regulatory uncertainties. Since the rebuttable presumption rule allows lenders to use XAI to satisfy the "explainability" requirement, the proposed rule will likely have a positive impact on the market adoption of XAI for credit

364. *See* Blattner, Stark & Spiess, *supra* note 32, at 12.

365. *See supra* Part I.C.1.

366. *See generally* CONSUMER FIN. PROT. BUREAU, *Key Dimensions and Processes in the U.S. Credit Reporting System: A Review of How the Nation's Largest Credit Bureaus Manage Consumer Data*, CFPB MARKETS RESEARCH & REPORTS 23-26 (Dec. 2012).

367. *See generally* Naveen Joshi, *Does AI Improve Human Judgement?*, FORBES (Feb. 3, 2022), https://www.forbes.com/sites/naveenjoshi/2022/02/03/does-ai-improve-human-judgment/?sh=132e3ada7638.

368. *See generally* EXPLAINABLE AI MARKET BY OFFERING, BY DEVELOPMENT, BY TECHNOLOGY, BY END-USE INDUSTRY, BY APPLICATION – GLOBAL OPPORTUNITY ANALYSIS AND INDUSTRY FORECAST, 2021-2030 (2021).

369. *See generally* EXPLAINABLE AI MARKET SIZE, SHARE ANALYSIS 2023 TO 2027, KEY PLAYERS, COMPETITIVE WEAKNESS, AND STRENGTHS (2022).

underwriting. As the XAI market grows the become more competitive, the use of XAI will become more transparent and industry best practices will form.

(2) Potential Market Concerns: Understandably, model developers might be concerned that granting a safe-harbor to "white-box" models may confer a market advantage to developers of simpler and self-explanatory models over complex ones. They might argue that the proposed rule sacrifices model accuracy for interpretability. However, data science research suggests that there is not always a trade-off between accuracy and interpretability.[370] When considering problems that have structured data with "naturally meaningful features" (i.e., mapping attributes for real-world contents), there is often "no significant difference in performance between more complex classifiers and much simpler classifiers after preprocessing."[371] Although the proposed rule might have the effect of discouraging the usage of unnecessarily complex models, the proposed rule increases the price transparency of algorithmic models and helps users (e.ge., lenders) to better compare the quality and efficacy of such models for their underlying purposes.

Another concern is that the proposed rule's explainability requirement might accomplish little beyond just increasing the compliance costs of fintech lenders. True, lenders may satisfy the "explainability" burden by purchasing XAI services. We expect some lenders to do so, since it can be more costly to replace entire model systems than to purchase XAI services to explain existing ones. However, this rule ensures that *post-hoc* explainability through XAI usage will not give lenders the same protections as using simpler self-explanatory models. Lenders have a choice of either (1) using XAI but only receiving the benefit of the rebuttable presumption, or (2) following the best practice of using self-explanatory AI models and enjoying the protection of the "white-box" safe-harbor.

Finally, model developers might be worried that the proliferation of XAI services jeopardizes their intellectual property rights.[372] While this is a legitimate concern, the risk of trade secrets misappropriation[373] is minuscule compared to the benefits of algorithmic transparency and market competition that this rule confers. Developers should bear the burden to internalize the costs of adopting

370. *See* Cynthia Rudin, *Stop Explaining Black Box Machine Learning Models for High Stakes Decisions and Use Interpretable Models Instead*, 5 NAT. MACH. INTELL. 206, 207 (2019).

371. *Id*.

372. *See e.g.,* Michael Ridley, *Explainable Artificial Intelligence (XAI): Adoption and Advocacy*, 41 INFORMATION TECHNOLOGY AND LIBRARIES 1, 4 (2022); Caryn Lusinchi, *From Black Box to Glass Box: Transparency in XAI*, ARTHUR AI (Oct. 19, 2022), https://www.arthur.ai/blog/from-black-box-to-glass-box-transparency-in-xai.

373. A trade secret is misappropriated when anyone acquires the information through improper means or improperly discloses it without the owner's consent, whether intentionally or unintentionally. *See* 18 U.S.C. § 1839(5). Section 1839(6) defines "improper means" as any activity including theft, bribery, misrepresentation, corporate espionage, or inducement of breach of contract. *See* 18 U.S.C. § 1839(6).

safety protocols to prevent the leakage of proprietary information.[374] Their ability to enforce their intellectual property rights in court is also unharmed by the proposed rule.[375]

C. Legal Authority to Define "Black Box" Model Usage as "Unfair"

This section evaluates the validity of the proposed "unfairness" rule if it is subjected to judicial review. In sum, this section argues that the proposed rule passes the countervailing balance test set forth by section 1031(c) of the DFA, which outlines the CFPB's authority to proscribe rules prohibiting "unfair" practices.

Under section 1031(c), the CFPB "shall have no authority to declare an act or practice . . . to be . . . unfair, unless the Bureau has a reasonable basis to conclude that: (A) the act or practice causes or is likely to cause substantial injury to consumers which is not reasonably avoidable by consumers; and (B) such substantial injury is not outweighed by countervailing benefits to consumers or to competition."[376] By legislating section 1031(c) in broad terms, Congress granted the CFPB the authority to define unfairness on a "flexible, incremental basis" to accommodate the evolving needs of consumer protection while balancing competing market interests.[377]

1. Usage of "Black Box" Algorithms Causes Substantial Consumer Injury

A "substantial injury" under section 1031(c)(1)(A) of the DFA typically involves monetary harm.[378] Although the harm cannot be speculative, the statute

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374. For the proprietary algorithm to be protected as a trade secret, the owner must take reasonable measures to prevent the proprietary information relating to the algorithm from being leaked to the public. The information must also derive independent economic value from (1) not being known to the public and (2) not being readily ascertainable by others through proper (*i.e.*, legal) means. *See* 18 U.S.C. § 1839(3).

375. Owners of the misappropriated trade secret may sue for lost profits, unjust enrichment, and reasonable royalties either under federal law (*i.e.*, Defend Trade Secrets Act) or under state law (*i.e.*, Uniform Trade Secret Acts). *See* James V. Fazio & Kevin M. Cloutier, *Diminution in Value as a Measure of Damages for Trade Secrets Misappropriation*, 13 NAT'L L. REV. (Mar. 16, 2021). The Defend Trade Secrets Act (DTSA) expressly states that federal trade secrets law does not preempt state law. This gives the owner the flexibility to weigh costs and benefits of brining parallel actions or bring the lawsuit only in state or federal court. But DTSA has a statute of limitation of 5 years, whereas the Uniform Trade Secrets Act (UTSA) has a statute of limitations of 3 years. *See, e.g.*, Randy Kay, Kelsey I. Nix & Douglas L. Clark, *Are Federally Protected Trade Secrets on the Horizon? Key Things to Know About the Defend Trade Secrets Act of 2015*, JONES DAY INSIGHTS (Nov. 2015), https://www.jonesday.com/en/insights/2015/11/are-federally-protected-trade-secrets-on-the-horizon-key-things-to-know-about-the-defend-trade-secrets-act-of-2015 ; *Defend Trade Secrets Act (DTSA),* ABRAHAMS KASLOW & CASSMAN LLP (Nov. 16, 2019), https://akclaw.com/defend-trade-secrets-act-dtsa/.

376. 12 U.S.C. § 5531(c)(1).

377. *See* Am. Fin. Servs. Ass'n v. FTC, 767 F.2d 957, 967 (D.C. Cir. 1985).

378. FED. TRADE COMM'N, *Policy Statement on Unfairness* (Dec. 17, 1980). Congress later amended the FTC Act to include this specific standard in the Act itself. *See* 15 U.S.C. § 45(n).

does not require actual harm.[379] "A significant risk of concrete harm [is] sufficient."[380] According to the CFPB's *UDAAP Examination Procedure*, "foregone monetary benefits or denial of access to products or services, like that which may result from discriminatory behavior, may also cause substantial injury."[381] Here, the practice of using "black box" AI models for credit underwriting exposes some consumers to significant risks of suffering adverse actions—loan rejection, unfavorable loan terms and interest rates, denial of a credit line increase—even though similarly-situated consumers would not receive such adverse actions.[382] These risks of adverse action can be translated into concrete monetary amounts in the form of forgone monetary benefits and credit opportunities.

(1) Measuring Injury: To measure the magnitude of substantial injury, the CFPB generally "assesses the aggregate injurious consequences that the specific practice causes or is likely to cause for consumers."[383] Thus, for the practice at issue in the proposed rule, the magnitude of injury is the aggregate injurious impact of all adverse actions undertaken against consumers because the model used for credit underwriting has a disparate impact on race, sex, religion, or national origin. The practice of using "black box" algorithms "need not injure a substantial number of consumers; it only requires that a target portion of consumers incur substantial injury."[384]

In addition to actual monetary harms, non-white consumers suffer the harm of not being able challenge a discriminatory lending decision informed by "black box" models. The opaque nature of "black box" model behavior prevents consumers from gathering sufficient evidence to allege an ECOA violation or otherwise negotiate with lenders to obtain better terms.[385] Thus, algorithmic opaqueness creates a substantial risk that these consumers will lose access to financial services or the safeguards to their economic rights.[386] Such harms can be calculated in monetary terms if we consider any claim to enforce a consumer right to be measurable in the form of judicially-awarded compensatory damages.

Although the CFPB lacks data on the precise monetary harm caused by "black box" model usage, the CFPB is not required to "calculate a precise total dollar figure for the aggregate injury" to conclude that the injury is "substantial" under section 1031(c)(1)(A). Computing an exact dollar figure would not only

379. *See* CONSUMER FIN. PROT. BUREAU, *supra* note 360, at 2.
380. *Id*.
381. *Id*.
382. *See* 12 C.F.R. § 1002.2(c)(1) (defining adverse action).
383. *See* 82 Fed. Reg. 54591 (Nov. 17, 2017).
384. FED. TRADE COMM'N, *Policy Statement on Unfairness* (Dec. 17, 1980).
385. *See supra* Part II.C.2.
386. *See id*.

be impractical, but also "represents a level of exactitude that is not required of or attained by the FTC" or the CFPB under the UDAAP authorities.[387]

(2) Degree of Discriminatory Impact: Critics may point out that AI credit models are, in the aggregate, "less discriminatory" than traditional automated underwriting methods and face-to-face lending.[388] Indeed, even counting the impact of "black box" models, AI credit underwriting is, on the whole, resulting in fewer loan rejections than conventional credit underwriting. This is especially the case in mortgage lending, auto-lending, and credit card markets. However, a practice does not need to be the "most discriminatory" in order to create "substantial consumer injury." Such injury is "substantial" under section 1031(c)(1)(A) if any portion of the consumer population suffers a disproportionately adverse monetary impact, (even if less discriminatory than other methods).

Critics might also argue that AI will "naturally find proxies for race, given that there are large income and wealth gaps between races."[389] "Unintentional proxy discrimination by AIs is virtually inevitable" because the nature of machine learning is that it replicates existing human cognitive and societal biases.[390] However, the fact that AI bias merely replicates existing inequalities does not diminish the resulting injury to consumers.

2. *Discriminatory Injury Is Not Reasonably Avoidable by Consumers*

An injury is not "reasonably avoidable" if the consumer is coerced into a transaction, hindered from exercising consumer choice, or if the transaction occurs without her knowledge or consent.[391] For an injury to be "reasonably avoidable" under section 1031(c)(1)(A), "consumers must have the practical means to avoid it, and the actions that a consumer is expected to take must be reasonable."[392] This element of the "unfairness" test is rooted in the *FTC Policy Statement*'s recognition that "consumers ordinarily can be relied upon to select products that best meet their needs without regulatory intervention."[393]

(1) Inability to Avoid Discrimination: A defining characteristic of discrimination is that consumers do not choose to be discriminated against. That is, they are involuntary victims of prejudicial and biased decision pathways because of immutable characteristics (e.g., race, color, sex). Whether the adverse

387. 82 Fed. Reg. 54591 (Nov. 17, 2017).

388. *See, e.g.,* Bartlett et al., *supra* note 125.

389. *See generally* Aaron Klein, *Reducing Bias in AI-based Financial Services*, BROOKINGS INSTITUTION (Jul. 10, 2020), https://www.brookings.edu/research/reducing-bias-in-ai-based-financial-services/.

390. Anya E.R. Prince & Daniel Schwarcz, *Proxy Discrimination in the Age of Artificial Intelligence and Big Data*, 105 IOWA L. REV. 1257 (2020)

391. CONSUMER FIN. PROT. BUREAU, *supra* note 360, at 1749.

392. *Id*.

393. FED. TRADE COMM'N, *Policy Statement on Unfairness* (Dec. 17, 1980).

effect is a result of intentional disparate treatment or unintentional disparate impact, consumers have no control over the impact and no practical means to avoid it (i.e., one cannot change her race or ethnicity). The CFPB's *UDAAP Examination Procedure* also makes clear that "consumers cannot reasonably avoid discrimination."[394]

(2) Invisibility of the Injury: When a harmful practice is hidden from consumer view, consumers cannot reasonably be expected to avoid injury by selecting alternative substitutive products. When a consumer selects among an array of consumer financial products, the consumer has no visibility into how their creditworthiness will be evaluated by the lenders. "Black box" algorithms exacerbate that problem, since neither the lender, developer, nor consumer understands what causes the model to exhibit a disparate impact in computing a credit outcome.

(3) Availability of Substitute Products: Critics will likely point out that consumers can avoid using the products fintech lenders offer and by choosing from a range of substitutive alternatives that do not use AI methods for credit underwriting. However, consumers lack meaningful choice because consumers cannot distinguish whether a model is a "black box" when applying for a loan. Moreover, since lenders often tout AI credit underwriting as being more accurate (and less discriminatory) than traditional credit underwriting,[395] consumers tend to believe that that the credit result is fair, even if the lender used a model that would qualify as a "black box." Thus, the lack algorithmic transparency renders the question of consumer choice meaningless. Here, the CFPB's *UDAAP Examination Procedure* also makes clear that "the key question is not whether a consumer would have made a better choice."[396] Rather, the proper question is "whether an act or practice hinders a consumer's decision-making."[397]

3. *Injury Outweighs Countervailing Benefits to Consumers or to Competition*

To be "unfair," section 1031(c)(1)(B) requires the identified act or practice to be "injurious in its net effects." That is, the consumer injury "must not be outweighed by any offsetting consumer or competitive benefits that are also produced by the act or practice."[398] In measuring net-effects, the injuries and

394. CONSUMER FIN. PROT. BUREAU, *supra* note 360, at 1749.

395. *See*, *e.g.*, Sebastian Larsson, *How Artificial Intelligence (AI) Improves Credit Underwriting*, EVISPOT (last visited Jan. 6, 2023), https://evispot.ai/how-artificial-intelligence-ai-improves-credit-underwriting/; Ginimachine, *Why AI in Commercial Underwriting is Rewriting the Future of Lending* (Jul. 12, 2022), https://ginimachine.com/blog/ai-in-commercial-underwriting/.

396. *See* CFPB UDAAP Examination Procedures, *supra* note 360, at 1749-1750.

397. *Id*. at 1749.

398. *Id*. at 1750.

benefits shall be measured in accordance with the principle of proportionality (i.e.g., aggregate injuries measured against aggregate benefits).[399]

(1) Offsetting Benefits to Consumers: Discrimination can both harm and benefit consumers. Some consumers are adversely impacted based on their protected characteristics, while others are unfairly privileged because of these characteristics. Consumers of certain backgrounds (e.g., white, male) may obtain a windfall from the lender's use of "black box" models. Generally, consumers who appear more creditworthy than they actually are benefit from the opaqueness of "black box" AI credit underwriting processes. These benefits manifest in the form of increased credit lines, lower interest rates, better loan terms, and higher loan approval rates. However, whereas privileged consumers get a windfall, consumers who are discriminated against suffer the additional injury of not being able to challenge discriminatory lending decisions informed by "black box" algorithms. From a lender's perspective, the use of "black box" algorithms may also cause them to lose revenue because the algorithm underestimates the default risk of privileged consumers.[400]

(2) Offsetting Benefits to Market: It is possible that a "black box" AI algorithm might be less discriminatory due to its complexity. This reflects the belief that there is a trade-off between model accuracy and explainability.[401] However, this is only a scant possibility, as leading experts in data science challenge the view that increasing model complexity necessarily enhances accuracy (and consequently sacrifices explainability).[402] The speculative benefits of having more accurate (but less transparent) models do not outweigh the concrete consumer injuries of adverse action caused by algorithmic opaqueness.

D. *Anticipated Legal Response to the Proposed "Unfairness" Rule*

1. *Response 1: The CFPB Cannot Conflate "Unfairness" and "Discrimination"*

If implemented, the proposed rule will likely invite pushback from users and developers of models that will be considered "black box" under the proposed

399. *See id.*

400. *See, e.g.*, David Nickerson, *Credit Risk, Regulatory Costs and Lending Discrimination in Efficient Residential Mortgage Markets*, 15 J. RISK FINANCIAL MANAG. 197 (2022); Ryan Browne & MacKenzie Sigalos, *AI Has a Discrimination Problem. In Banking, the Consequences Can Be Severe*, CNBC (Jun. 23, 2023), https://www.cnbc.com/2023/06/23/ai-has-a-discrimination-problem-in-banking-that-can-be-devastating.html.

401. *See, e.g., supra* note 394; Shannen Balogh & Carter Johnson, *AI Can Help Reduce Inequality in Credit Access, But Banks Will Have to Trade-Off Fairness for Accuracy*, BUSINESS INSIDER (Jun. 30, 2021), https://www.businessinsider.com/ai-lending-risks-opportunities-credit-decisioning-data-inequity-2021-6?r=US&IR=T.

402. *See* Cynthia Rudin, *Stop Explaining Black Box Machine Learning Models for High Stakes Decisions and Use Interpretable Models Instead*, 5 NAT. MACH. INTELL. 206, 207-8 (2019).

rule. Since the proposed rule categorizes the use of models having a discriminatory effect as unfair, opponents to the proposed rule might raise a legal challenge along the following lines:[403]

> "The CFPB's conflation of unfairness and discrimination ignores the text, structure, and legislative history of the Dodd-Frank Act. For example, the Dodd-Frank Act discusses "unfairness" and "discrimination" as two separate concepts and defines "unfairness" without mentioning discrimination. The Act's legislative history refers to the CFPB's antidiscrimination authority in the contexts of ECOA and HMDA, while referring to the CFPB's UDAAP authority separately."[404]

Rebuttal 1: Nothing in the statute indicates that a "discriminatory" act or practice cannot simultaneously be "unfair." The statutory language of section 1031(c) of the DFA is plain and simple.[405] As long as an act or practice causes substantial injury to consumers that they cannot reasonably avoid, where the injury is not outweighed by countervailing benefits to consumer or competition, that practice is "unfair."[406] There is no textual limitation in section 1031(c) against categorizing a "discriminatory" practice as "unfair" as long as the three statutory elements are met.[407] The statutory structure of the DFA also supports this interpretation . When the DFA transferred rulemaking authority under ECOA from the Federal Reserve Board to the CFPB, it also transferred to the CFPB the power to interpret and enforce a number of "federal consumer financial laws"[408] to safeguard consumer rights and ensure the "fairness, transparency, and competitiveness" of "markets for consumer financial products."[409] This suggests the CFPB's UDAAP power under the DFA is not limited to what it "inherited" from the FTC, and that the CFPB may draw authority from ECOA to enforce the general statutory purpose of DFA.[410]

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403. *See* CONSUMER FIN. PROT. BUREAU, *CFPB Targets Unfair Discrimination in Consumer Finance* (Mar. 16, 2022), https://www.consumerfinance.gov/about-us/newsroom/cfpb-targets-unfair-discrimination-in-consumer-finance/.

404. INDEP. CMTY. BANKERS OF AM., *Unfairness and Discrimination: Examining the CFPB's Conflation of Distinct Statutory Concepts*, 3 (Jun. 2022), https://www.icba.org/docs/default-source/icba/advocacy-documents/reports/unfairness-and-discrimination-examining-the-cfpbs-conflation-of-distinct-statutory-concepts.pdf

405. *See* 12 U.S.C. § 5531(c).

406. *See* CONSUMER FIN. PROT. BUREAU, *supra* note 403.

407. *See* Stephen Hayes & Kali Schellenberg, *Discrimination Is "Unfair": Interpreting UDA(A)P to Prohibit Discrimination*, Relman Colfax LLP, Prepared for Student Borrower Protection Center,15 (Apr. 2021), https://protectborrowers.org/wp-content/uploads/2021/04/Discrimination_is_Unfair.pdf.

408. "Federal consumer financial law" is defined to include two sets of distinct sets of authority: the CFPB's organic authority under Consumer Financial Protection Act (Title X of the Dodd-Frank Act), and authority under preexisting federal laws that have been transferred to the CFPB under the Dodd-Frank Act. *See* 12 U.S.C. § 5481(14). *See also* Levitin, *supra* note 173, at 344.

409. *See* CFPB, *supra* note 205. *See also* Dodd-Frank Act § 1021 (codified at 12 U.S.C. § 5511) (stating that the CFPB shall seek to implement and enforce federal consumer financial laws for the purpose of "ensuring that all consumers have access to markets for consumer financial products and that the markets for consumer financial products are fair, transparent, and competitive.").

410. The DFA also amended a section of the Truth in Lending Act (TILA), authorizing the CFPB to prescribe regulations to prohibit "abusive or unfair lending practices that *promote disparities* among consumers of equal credit worthiness but of different race, ethnicity, gender, or age." This is the classic language of disparate impact. 15 U.S.C. § 1639b(c)(3)(C) (emphasis added).

Rebuttal 2: Legislative history suggests that Congress intended for the "unfairness" concept to be flexible and adaptive. An adaptive problem requires an adaptive solution. When Congress originally envisioned the concept of "unfairness" under the section 5 of the FTC Act, it decided to leave enough flexibility to the FTC to define various "unfair practices," recognizing that it is impossible to embrace all unfair practices in statutory form.[411] The concept of "unfairness" was meant to be defined incrementally to keep up with the evolving societal needs to regulate new markets and products.[412]

The FTC's 1980 *Policy Statement* also reflects this adaptive, market-oriented approach.[413] When Congress codified the *Policy Statement* in section 1031(c) of the DFA, it intended the meaning of "unfairness" to carry a similarly adaptive meaning under the CFPB's jurisdiction.[414] Section 1031(c)(2) of the DFA exemplifies this in authorizing the CFPB to consider "established public policies" in defining an "unfair" practice.[415]

2. *Response 2: The Concept of "Discrimination" Excludes "Unfairness"*

Additionally, opponents to the proposed unfairness rule may raise the following legal challenge:

> "The CFPB's view of "unfairness" is inconsistent with decades of understanding and usage of that term in the Federal Trade Commission Act and with the enactment of ECOA. Congress gave the CFPB the same "unfairness" authority that it gave to the Federal Trade Commission in 1938, which has never included discrimination. It makes no sense that Congress would have enacted ECOA in 1974 to address discrimination in credit transactions if it had already prohibited discrimination through the FTC's unfairness authority. For the same reason, Congress could not have intended 1938 for unfairness to "fill gaps" in civil rights laws that did not exist."[416]

Rebuttal 1: The CFPB's "unfairness" power is not confined to what was originally granted to the FTC. Because the aim of the DFA is to address evolving societal demands for consumer protection,[417] Congress adopted a malleable view of the CFPB's power and broadly delegated discretion.[418] Even though "unfairness" under section 1031(c) of the DFA follows the same three-pronged analysis under section 5 of the FTC Act, what is "unfair" under DFA depends on

411. *See* Am. Fin. Servs. Ass'n v. FTC, 767 F.2d 957, 967 (D.C. Cir. 1985) (discussing the evolution of the FTC's authority to identify and proscribe "unfair" practices).

412. *See id.*

413. FED. TRADE COMM'N, *Policy Statement on Unfairness* (Dec. 17, 1980).

414. The language of the FTC *Policy Statement* and Dodd-Frank Act § 1031(c) is almost identical.

415. 12 U.S.C. § 5531(c)(2).

416. INDEP. CMTY. BANKERS OF AM., *supra* note 404, at 3.

417. *See* 12 U.S.C. § 5511(a)-(b).

418. *See* 12 U.S.C. § 5531(b) ("The Bureau may prescribe rules applicable… identifying as unlawful unfair, deceptive, or abusive acts or practices in connection within any transaction with a consumer for a consumer financial product or service, or the offering of a consumer financial product or service. Rules under this section may include requirements for the purpose of preventing such acts or practices.").

the statutory scheme that the CFPB is charged to administer. Even in section 5 of the FTC Act, Congress adopted a malleable view of "unfairness" and broadly delegated discretion to the FTC. In the subsequent amendments, Congress "had not at any time withdrawn the broad discretionary authority originally granted to the FTC to define unfair practices on a flexible, incremental basis."[419] Moreover, the fact that the FTC can bring enforcement actions under the section 5 of the FTC Act to challenge discriminatory mark-up practices in auto-lending suggests that the FTC Act's concept of "unfairness" has also grown to encompass disparate impact discrimination (even though the FTC has no power to enforce ECOA).[420]

Rebuttal 2: The CFPB's definition of "unfairness" warrants judicial deference because its exercise of power under section 1031(c) is not arbitrary or capricious. The Supreme Court has made clear in *Chevron* that, in reviewing an agency's construction of a statute which Congress has left the agency to interpret and administer, the courts must give deference to the agency's interpretation, unless it is arbitrary and capricious.[421] Both the text and the structure of DFA clearly indicates that Congress intended for the CFPB to define "unfairness." Section 1031(b) of the DFA explicitly grants the CFPB the power to define and prohibit "unfair" practices.[422] While section 1031(c) functions as a general limitation on the CFPB's "unfairness" power,[423] it only mandates what the CFPB *should* consider, rather than what the CFPB *cannot* consider in defining an act or practice as "unfair."[424] This notion—that Congress intended section 1031(c) to operate as the floor, rather than the ceiling, of the CFPB's "unfairness" power—is reinforced by section 1031(c)(2)'s authorization of the CFPB to consider established public policies for defining "unfairness."[425] Essentially, the CFPB may identify a practice as "unfair" as long as the CFPB has a reasonable basis to conclude that the practice causes unavoidable substantial consumer injury and is net-injurious to consumer welfare. The CFPB's interpretation should be upheld under *Chevron* since defining "discrimination" as "unfair" is consistent with the text of the statute and is neither arbitrary nor capricious.

419. Am. Fin. Servs. Ass'n v. FTC, 767 F.2d 957, 967 (D.C. Cir. 1985).

420. *See, e.g.*, Complaint, FTC v. Liberty Chevrolet, Inc., 20-CV-3945 (S.D.N.Y. May 21, 2020); Complain, FTC v. N. Am. Auto. Servs., 1:22:cc-01690 (E.D. Tex. Mar. 31, 2022).

421. Chevron U.S.A., Inc. v. Nat. Res. Def. Council, Inc., 467 U.S. 837, 844 (1984).

422. 12 U.S.C. § 5531(b).

423. 12 U.S.C. § 5531(c)(1). The relevant statutory provision states that the CFPB "shall have *no authority*" to declare an act or practice of be unfair unless it passes the three-prong countervailing balance test, rather than the CFPB "has authority." Although this language operates as a restraint on CFPB's power to identify "unfair" acts, the text is silent on what cannot be unfair.

424. Section 1031(c) of DFA is a limiting provision, while section 1031(b) is an enabling provision. The language of §1031(c) provides that "the Bureau shall have no authority." *See* 12 U.S.C. § 5531(c). Read in juxtaposition with section 1031(b)'s statement that "the Bureau may proscribe rules applicable," it suggests that any exercise of section 1031(b) power that complies with the section 1031(c) limitation is reasonable and appropriate. *See* 12 U.S.C. §5531(b).

425. *See* 12 U.S.C. § 5531(c)(2).

Rebuttal 3: Congress gave the CFPB two separate powers to enforce its statutes, so that the removal of the CFPB's power to bring enforcement actions under one statute would not invalidate the CFPB's power to regulate by rulemaking under another.[426] Even if the disparate-impact provision of 12 C.F.R. § 1002 is overruled in judicial review, it does not affect the validity of the proposed rule— as the CFPB's exercise of "unfairness" power under section 1031(d) does not hinge on actionability of disparate impact claims under ECOA.[427] A bar against bringing a disparate impact claim in a lawsuit does not prohibit the CFPB from regulating discriminatory practices by rulemaking.[428] In other words, the CFPB's power under DFA to prohibit unfair practices via public regulation is not dependent on a consumer's ability to bring private claims of discrimination under ECOA.

CONCLUSION

This Article has sought to answer the question of how AI challenges assumptions about discrimination in credit transactions by delineating judicial trends in the "tortification" of fair lending laws and by underscoring the adverse consequences they have for consumer rights. This Article argues that the fair lending laws fail to adequately protect consumers from the risks of algorithmic harm because such frameworks do not capture the essential characteristics of algorithmic decision-making. The principal limitation of the fair lending laws is their misplaced fixation on "lender conduct" rather than "consumer harm."

This Article has explored a number of policy designs such as disclosure, input scrutiny, and reforming the disparate impact standard under ECOA to effectuate moving from a conventional conduct-based to harm-based paradigm for equal credit access protection. After evaluating the benefits and limitations of each option, this Article has arrived at the conclusion that the most feasible regulatory option to address algorithmic harms is to invoke the CFPB's UDAAP power under the Dodd-Frank Act.

To provide actionable roadmaps for legal reform, this Article has proposed a rule to prohibit the usage of "black box" algorithms for credit underwriting as unfair under section 1031 of the Dodd-Frank Act. The proposed "unfairness"

426. *See id.*

427. Congress created in ECOA a private right of action for injured consumers, whereas in DFA, Congress granted the CFPB the power to prohibit unfair practices by public regulations. These are mutually independent powers. Only Congress, not the CFPB, could have provide for that. Thus, the CFPB's determination under DFA that its unfairness power extends to discrimination does not authorize consumers to bring private claims under DFA. Under this logic, a court's invalidation of disparate impact claims under ECOA does not take away the CFPB's power to prohibit practices resulting disparate impact via public regulation. *See* Jeff Sovern, *Why the CFPB is Right That it Can Act Against Discrimination Using its Unfairness Power*, PUBLIC CITIZEN CONSUMER LAW & POLICY BLOG (May 1, 2022), https://pubcit.typepad.com/clpblog/2022/05/why-the-cfpb-is-right-that-it-can-act-against-discrimination-using-its-unfairness-power.html.

428. *See id.*

rule, while not intended as a panacea, can hopefully provide a means to redress systemic discrimination by directly addressing sources of algorithmic harm. Ultimately, the proposed rule seeks to redress inequities in credit access in a society where the immutable, protected characteristics of an individual are intertwined with the socioeconomic feedback loops of indebtedness, poverty, and disempowerment.