ADDING FAIRNESS TO FAIR LENDING CASES: HOW COMPREHENSIBLE DISCLOSURES COULD KEEP AI-BASED CREDIT SCORING ACCOUNTABLE TO BORROWERS

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INTRODUCTION

For many, accessing credit is an early and crucial step toward achieving the American Dream.[1] In nearly every form of commercial activity, lending plays an indispensable role in helping participants acquire the financial means necessary to engage in future transactions.[2] The vast scope of commerce affected by lending includes, among other activities, all dealings made possible by obtaining "personal loans, credit cards, home loans, student loans, car loans, small business loans, and loan modifications."[3] Yet before any lending agreement can be reached, a lender typically makes some assessment of the loan applicant's creditworthiness.[4] This process requires evaluating the applicant's ability to punctually repay both the borrowed sum and any applicable interest.[5] Because these evaluations determine an applicant's eligibility for a loan, as well as the key terms of any agreement the creditor may offer,[6] a just society must insist that only legitimate factors be considered when attempting to establish an applicant's creditworthiness.

Unfortunately, the availability of credit in the United States is at times influenced not only by sound business considerations but also by indefensible prejudice.[7] Given the sizeable impact lending decisions

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1 *See* Sahiba Chopra, *Current Regulatory Challenges in Consumer Credit Scoring Using Alternative Data-Driven Methodologies*, 23 VAND. J. ENT'M'T & TECH. L. 625, 625 (2021).

2 *See* Julia Kagan, *What is the Equal Credit Opportunity Act (ECOA)?*, INVESTOPEDIA (Oct. 2, 2022), https://www.investopedia.com/terms/e/ecoa.asp.

3 *See id.*

4 *See Credit Evaluation and Approval*, INC. (Feb. 6, 2020), https://www.inc.com/encyclopedia/credit-evaluation-and-approval.html.

5 *Id.*

6 *Id.*

7 *See, e.g.*, Robert Bartlett et al., *Consumer-Lending Discrimination in the FinTech Era* 1, 3, 5 (Nat. Bureau Econ. Rsch., Working Paper 25943), https://www.nber.org/papers/w25943; Deb-

have on the lives of credit applicants, lending has long been a preferred tool for those seeking to discriminate.[8] Such discrimination is frequently traced to government and private entities alike and may appear in both overt and hidden forms.[9] Perhaps the most dramatic example of lending discrimination in the United States was the widespread use of "redlining" techniques by government mortgage lenders to segregate neighborhoods throughout the country based on race.[10]

Acknowledging the pernicious effects of biased lending decisions, Congress passed the Equal Credit Opportunity Act (ECOA) of 1974, which prohibits certain discriminatory lending practices.[11] Specifically, the ECOA forbids lenders from "discriminat[ing] against any applicant . . . on the basis of race, color, religion, national origin, sex or marital status, or age . . . ."[12] The scope of the ECOA's prohibition, however, has been the subject of lengthy debate, due largely to an ambiguous portion of the statutory text.[13] On one side of the issue are those who believe that the phrase "on the basis of" means that Congress intended the ECOA to prohibit only intentional discrimination.[14] On the other side are those who believe that the identical language reveals an intent to outlaw certain "facially neutral" practices that may nonetheless have a discriminatory effect.[15] This latter

bie Gruenstein Bocian et al., *Lost Ground, 2011: Disparities in Mortgage Lending and Foreclosures*, CTR. FOR RESPONSIBLE LENDING (Nov. 2011), http://www.responsiblelending.org/mortgage-lending/research-analysis/Lost-Ground-2011.pdf; Jean Folger, *The History of Lending Discrimination*, INVESTOPEDIA (Aug. 12, 2022), https://www.investopedia.com/the-history-of-lending-discrimination-5076948; MARGERY AUSTIN TURNER & FELICITY SKIDMORE, MORTGAGE LENDING DISCRIMINATION: A REVIEW OF EXISTING EVIDENCE 14 (1999).

8 *See* Aaron Klein, *Credit Denial in the Age of AI*, BROOKINGS INST. (Apr. 11, 2019), https://www.brookings.edu/research/credit-denial-in-the-age-of-ai/ [hereinafter Klein, *Credit Denial*].

9 *See id.*

10 *See id.*; Kagan, *supra* note 2.

11 *See* U.S. Dep't of Justice, *The Equal Credit Opportunity Act* (Nov. 14, 2022), https://www.justice.gov/crt/equal-credit-opportunity-act-3.

12 15 U.S.C. § 1691(a).

13 *See* Winnie F. Taylor, *The ECOA and Disparate Impact Theory: A Historical Perspective*, 26 J.L. & POL'Y 575, 578-80 (2018) [hereinafter Taylor, *The ECOA and Disparate Impact Theory*].

14 *See* Peter N. Cubita & Michelle Hartmann, *The ECOA Discrimination Proscription and Disparate Impact—Interpeting the Meaning of the Words That Are Actually There*, 61 BUS. L. 829, 831, 834 (2006); *see also* Taylor, *The ECOA and Disparate Impact Theory*, *supra* note 13, at 579.

15 *See, e.g.*, 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, S43, S45 (2015); Taylor, *The ECOA and Disparate Impact Theory*, *supra* note 13, at 580.

theory of harm, which is recognized by other civil rights statutes, is referred to as disparate-impact discrimination.[16] In early 2021, the Biden Administration signaled its intent to have the Consumer Financial Protection Bureau (CFPB), the federal agency that leads the government's ECOA enforcement efforts,[17] recognize disparate-impact discrimination claims under the ECOA.[18] Later that year, and almost immediately after taking office, CFPB director Rohit Chopra[19] delivered official remarks reinforcing that view and signaled the CFPB's commitment to making disparate-impact claims a centerpiece of the Bureau's policy goals.[20]

Although the ECOA has, for several decades, proved an effective anti-discrimination tool, recent criticism has highlighted the statute's inadequacies in dealing with new forms of lending and credit scoring.[21] Particularly concerning is the rise of credit-scoring methodologies that utilize "alternative data" and artificial intelligence (AI).[22] When the ECOA was enacted, lending institutions were comprised mostly of banks, and credit scoring was based primarily on the applicant's past dealings with other lenders.[23] Recently, however, the lending industry

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16 *See* Winnie F. Taylor, *Eliminating Racial Discrimination in the Subprime Mortgage Market: Proposals for Fair Lending Reform*, 18 J.L. & POL'Y 263, 273 n.38 (2009) [hereinafter Taylor, *Eliminating Racial Discrimination*].

17 The ECOA is also enforced by other federal agencies, including the Department of Justice, the Federal Trade Commission, the Office of the Comptroller of the Currency, the Federal Reserve Board, the Federal Deposit Insurance Corporation, and the National Credit Union Association. *See* U.S. Dep't of Justice, *supra* note 11.

18 Andrew Michaelson, Brian Thavarajah, & Margaret McPherson, *A Revived Disparate Impact Doctrine Under Biden's CFPB*, LAW 360 (Feb. 17, 2021, 3:26 P.M.), https://www.law360.com/articles/1353795/.

19 *See Senate Confirms Rohit Chopra to Lead the Consumer Financial Protection Bureau*, NPR (Oct. 1, 2021, 10:45 A.M.), https://www.npr.org/2021/10/01/1042310553/cfpb-senate-confirms-rohit-chopra-watchdog-consumer-financial-protection-bureau.

20 *See Remarks of Director Rohit Chopra at a Joint DOJ, CFPB, and OCC Press Conference on the Trustmark National Bank Enforcement Action*, CONSUMER FIN. PROT. BUREAU (Oct. 22, 2021), https://www.consumerfinance.gov/about-us/newsroom/remarks-of-director-rohit-chopra-at-a-joint-doj-cfpb-and-occ-press-conference-on-the-trustmark-national-bank-enforcement-action/ [hereinafter *Remarks of Director Rohit Chopra*].

21 *See, e.g.*, Chopra, *supra* note 1, at 638; Janine S. Hiller, *Fairness in the Eyes of the Beholder: AI; Fairness; and Alternative Credit Scoring*, 123 W. VA. L. REV. 907, 920, 922-24 (2021); Eric Knight, *AI and Machine Learning-Based Credit Underwriting and Adverse Action under the ECOA*, 3 BUS. & FIN. L. REV. 236, 238, 240 (2020).

22 *See* Knight, *supra* note 21, at 237-38.

23 *See* Aaron Klein, *Reducing Bias in AI-based Financial Services*, BROOKINGS INST. (July 10, 2020), https://www.brookings.edu/research/reducing-bias-in-ai-based-financial-services/ [hereinafter Klein, *Reducing Bias*].

has been revolutionized by the development of computer algorithms that use AI and machine learning to predict an applicant's creditworthiness from a slew of unconventional data points.[24] This has led to significant increases in credit access among the traditionally underserved, as those who previously lacked sufficient credit history to be adequately scored can now apply for credit from lenders who use alternative data.[25] Yet, such innovation also comes with a substantial downside. Because AI-based credit-scoring technologies possess analytical capabilities that far exceed human ability, even the creditors that use those technologies are often unable to explain how a particular lending decision has been made.[26] This opacity is concerning because it means that credit decisions could be made through the unwitting use of data that serves as a proxy for the protected categories of information about credit applicants that the ECOA places off limits.[27] In such a case, the ECOA's disclosure requirements, which compel an agency to inform applicants of the reasons behind unfavorable lending decisions, would be rendered almost useless.[28] In other words, AI-based credit-scoring models could be discriminating unintentionally and in a way that prevents easy detection or correction.

Given the ECOA's clear shortcomings in the face of AI-based credit-scoring technology, many commentators have called for an updated regulatory framework.[29] This has led to a profusion of policy recommendations aimed at dealing with a lending industry so dramatically affected by technological change.[30] Yet, while many of these proposals are clever and would, if implemented, reflect an improvement over the status quo, they too often seem to downplay or ignore political realities.[31] Further, many feasible proposals champion disclosure

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24 *See id.*

25 *See id.*

26 *See* Andrew D. Selbst & Solon Barocas, *The Intuitive Appeal of Explainable Machines*, 87 FORDHAM L. REV. 1085, 1088-89 (2018).

27 *See id.* at 1092; Knight, *supra* note 21, at 255.

28 *See* Knight, *supra* note 21, at 255.

29 *See, e.g.*, Chopra, *supra* note 1, at 641-42; Hiller, *supra* note 21, at 933; Knight, *supra* note 21, at 255.

30 *See, e.g.*, Chopra, *supra* note 1, at 641-42; Hiller, *supra* note 21, at 932-35; Knight, *supra* note 21, at 255.

31 *See, e.g.*, Vlad A. Hertza, *Fighting Unfair Classifications in Credit Reporting: Should The United States Adopt GDPR-Inspired Rights In Regulating Consumer Credit?*, 93 N.Y.U. L. REV. 1707, 1730, 1740 (2018) (calling on Congress or federal regulators to adopt rules similar to those of the European Union's General Data Protection Regulation (GDPR), with which to amend the ECOA); Hiller, *supra* note 21, at 932-35 (advocating for federal regulators to require that

requirements that would ultimately prove unhelpful, given the inherent "inscrutability and nonintuitiveness" of AI-based credit-scoring systems.[32] Perhaps in recognition of such difficulties, the CFPB has expressed its comfort in bringing suits under the ECOA as currently written, relying on the disparate-impact theories used as recently as the Obama Administration.[33] This indicates that, at least for the foreseeable future, the major developments in this area of law will occur via judicial enforcement rather than through legislative reform.[34]

Accordingly, this Comment will depart from those common modes of analysis that focus, at least primarily, on legislative or regulatory change. Instead, this Comment seeks to establish a framework that will allow for a better judicial application of disparate-impact claims brought under the ECOA. Specifically, this Comment argues that reviewing courts should integrate an expanded transparency requirement into the burden-shifting framework that applies to disparate-impact cases under the ECOA, as first articulated in *Texas Department of Housing v. Inclusive Communities*.[35] Under this modified framework, lenders asserting a business-necessity defense would be required to reveal, not only the internal features of their credit-scoring algorithm but also extrinsic details describing the broader context in which the algorithm operated when making the challenged lending decisions.[36] This requirement would present plaintiffs with the best opportunity to surmount an algorithm's inherent inscrutability and nonintuitiveness[37] by ensuring that defendants do most of the work to provide a comprehensible account of how their proprietary algorithms operate.[38]

computer programmers incorporate concepts of legal fairness into their algorithms and subject them to regular testing); Klein, *Reducing Bias*, *supra* note 23 (arguing for a uniform regulatory framework that would replace the current split across federal enforcement agencies, state and federal governments, etc.).

32 *See* Selbst & Barocas, *supra* note 26, at 1090; *infra* Analysis Section I.

33 *See* Michaelson, Thavarajah, & McPherson, *supra* note 18.

34 *See id.* (predicting that the CFPB will bring enforcement actions for alleged disparate-impact discrimination).

35 Tex. Dep't of Hous. & Cmty. Affs. v. The Inclusive Cmtys. Project, Inc., 576 U.S. 519, 527 (2015).

36 *See* Selbst & Barocas, *supra* note 26, at 1129-30.

37 *See id.* at 1090.

38 This would not require defendants to inculpate themselves. Instead, it would simply require defendants to make accurate and comprehensible descriptions of how their algorithms worked within the context of making the challenged lending decisions. *See infra* Analysis Section II.

The Background section of this Comment will present an overview of AI-based credit scoring, the relevant provisions of the ECOA, judicial precedent applying disparate-impact claims under the ECOA, and the three-part burden-shifting framework applied by the Supreme Court in *Inclusive Communities*. Scholarly work praising and criticizing the framework will also be presented and assessed against reasonable alternatives. Then, the Analysis section will explain how an expanded transparency requirement could be integrated into a modified, but readily implementable, version of the *Inclusive Communities* burden-shifting framework that would better advance the policy goals of the ECOA. The Analysis section will explain how the proposed transparency requirement would help plaintiffs in the short term without requiring dramatic legislative or regulatory change, and the Conclusion section will reflect on those benefits.

BACKGROUND

This section will begin by explaining the fundamentals of AI-based credit scoring. In addition to describing the most impactful ways in which AI-based credit-scoring methods have revolutionized operations within the lending industry, this section will devote particular attention to the social benefits and costs of this new technology—both of which are considerable. Concrete examples of such costs will show how seemingly neutral, algorithmic-based lending decisions can result in shocking discrepancies that prevent equal access to credit. Then, this section will introduce the ECOA, the primary statutory instrument by which the government attempts to prevent discriminatory lending. An overview of the legislative history and purpose behind the ECOA will follow, along with highlights of the key developments in the statute's enforcement history. Next, a description of judicial precedent involving disparate-impact claims brought under the ECOA and related statutes will introduce the burden-shifting framework established by the Supreme Court in *Inclusive Communities*. Finally, this section will conclude by analyzing the leading scholarly assessments of the *Inclusive Communities* framework and by examining the viability of the alternative approaches these scholars have proposed.

I. UNEQUAL CREDIT ACCESS AND AI-BASED CREDIT-SCORING MODELS

As suggested above, developments in alternative data, and their ready application to credit-scoring, have already yielded significant transformations in the lending industry.[39] By using predictive techniques such as machine learning,[40] AI-based credit-scoring systems can help creditors make lending decisions without relying solely on traditional forms of credit-scoring data.[41] Moreover, because AI-based credit scoring is still in its infancy, subsequent transformations are sure to come.[42] Yet, this potential must be evaluated in full recognition of the pervasive difficulties many people continue to face when attempting to access credit.

Even today, many Americans face considerable difficulty—and sometimes repeated failure—in their attempts to access "mainstream credit" from traditional lenders such as banks, credit unions, or payday loan companies.[43] The primary source of such difficulty is usually the fact that these citizens have "limited access to credit because they have little or no credit history."[44] Even though credit reporting agencies are in the business of compiling credit records on as many consumers as possible, a 2015 study conducted by the CFPB found that an estimated twenty-six million consumers (roughly eleven percent of the United States' adult population) were entirely without agency-created credit records.[45] The CFPB labels such consumers as "credit invisibles."[46] Moreover, the study revealed that, even among consum-

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39 *See* Klein, *Reducing Bias*, *supra* note 23.

40 Machine learning is a type of AI that "rel[ies] on computing power to sift through big data to recognize patterns and make predictions without being explicitly programmed to do so." Knight, *supra* note 21, at 237-38 (cleaned up).

41 *See* Klein, *Reducing Bias*, *supra* note 23.

42 *See, e.g.*, *AI and Alternative Data Could Help Millions Gain Access to Credit*, LSU MEDIA CENTER, (Sept. 20, 2022), https://www.lsu.edu/mediacenter/news/2022/09/wfl_lending.php (encouraging the continued development of "[s]marter underwriting algorithms").

43 *See* Michael M. Aphibal & Chrys D. Lemon, *Use of "Alternative Data" in the Underwriting of Consumer Credit: A Useful Roadmap Begins to Develop*, FINTECH L. REP., Nov.-Dec. 2017, at 1.

44 *See id.*

45 KENNETH P. BREVOORT, PHILIPP GRIMM, & MICHELLE KAMBARA, CONSUMER PROT. FIN. BUREAU, DATA POINT: CREDIT INVISIBLES, CONSUMER PROTECTION FINANCIAL BUREAU 4, 6 (2015).

46 *Id.*

ers with such records, nineteen million (roughly 8.3 percent of the United States' adult population) had records "that were treated as unscorable" by a traditional or "commercially-available credit scoring model."[47] In most cases, a consumer's credit record is considered "unscorable" because it contains either insufficient data or "no recently reported activity."[48]

Although the sheer magnitude of the segment of the population that the CFPB study deems as "credit invisible" or having only "unscorable" credit records is concerning in its own right, the study illuminates another alarming feature of contemporary credit access in the United States.[49] As the study makes clear, difficulty in accessing credit disproportionately affects racial minorities and those with lower incomes.[50] Specifically, the study notes that "Blacks and Hispanics are more likely than Whites or Asians to be credit invisible or to have unscored credit records."[51] While only nine percent of Whites and Asians are credit invisible, roughly fifteen percent of Blacks and Hispanics fall into this category.[52] Similarly, while only seven percent of Whites have unscored records, this figure is nearly doubled for Blacks and Hispanics, thirteen and twelve percent of whom, respectively, have unscored records.[53] Further, these disparities "are observed across all age groups, suggesting that these differences materialize early in the adult lives of these consumers and persist thereafter."[54] While disheartening, these findings of stark racial discrepancies in credit access are, unfortunately, consistent with the results of other studies.[55]

With so many potential customers denied access to traditional means of obtaining capital, "some lenders and fintech companies have begun to use alternative data to evaluate the creditworthiness of con-

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47 *Id.* at 4.

48 *Id.*

49 *See id.*

50 *Id.* at 6.

51 KENNETH P. BREVOORT, PHILIPP GRIMM, & MICHELLE KAMBARA, CONSUMER PROT. FIN. BUREAU, DATA POINT: CREDIT INVISIBLES, CONSUMER PROTECTION FINANCIAL BUREAU 6 (2015).

52 *Id.*

53 *Id.*

54 *Id.*

55 *See, e.g.*, Bartlett et al., *supra* note 7, at 5-6; Bocian et al., *supra* note 7, at 3-4; TURNER & SKIDMORE, *supra* note 7, at 2.

sumers who have no credit report."[56] As its name suggests, alternative data is frequently defined in the negative, by comparing it to what it is not.[57] The opposite of alternative data is what is now referred to as "traditional data," or that information that has historically been included "as part of a credit application, such as income or length of time in residence."[58] The simplest definition of alternative data, then, is any information "that is not 'traditional' and is not found in a [conventional] credit report."[59] More specifically, alternative data often includes information related to "rent, insurance, or utility payments; checking account transaction data, such as deposits, withdrawals, and transfers; or data that some consider to be related to a consumer's stability, such as frequency of changes in residences, employment, phone number, email, or education."[60] Creditors that use alternative data collect this data in a multitude of ways, which range from having applicants fill out extensive questionnaires and application materials to having a machine conduct its own research on the applicant, or some combination of these two methods.[61]

Using these inputs, non-traditional credit-scoring companies and lenders can assess the creditworthiness of a loan applicant in ways previously thought impossible. This ability has been compounded by concurrent developments in AI and machine learning.[62] Specifically, these twin developments have enabled creditors to "find empirical relationships between new factors and consumer behavior."[63] This has led industry spectators to make the remarkable, yet cogent observation that "[i]f there are data out there on you, there is probably a way to integrate it into a credit model."[64] Accordingly, there are, of course, numerous instances of lenders using non-traditional data to make sound lending decisions without discrimination against any protected group.[65] For example, algorithms have been documented to

56 *See* Aphibal & Lemon, *supra* note 43, at 1.

57 *See id.* at 2.

58 *Id.* at 1.

59 *Id.* at 2.

60 *Id.* at 1-2.

61 *See, e.g.*, *An Incredible Alternative to Questionnaire-Based Research*, AURIS (Aug. 9, 2018), https://genylabs.io/the-need-for-an-alternative-to-questionnaire-based-research/.

62 *See* Klein, *Credit Denial*, *supra* note 8.

63 *Id.*

64 *Id.*

65 *See, e.g.*, Mikella Hurley & Julius Adebayo, *Credit Scoring in the Era of Big Data*, 18 YALE J.L. & TECH., 148, 175-76 (2016).

view "[s]ocial-media posts about a car breakdown" as "indicat[ing] a risky borrower."[66] In a similar vein, other credit-scoring algorithms use "how quickly a loan applicant scrolls through an online terms-and-conditions disclosure" on the theory that fully reading these documents "could indicate how responsible the individual" will be with their borrowing."[67]

Of course, capabilities of this sort present both significant opportunities and risks. On one hand, creditors who utilize such data are often opening a door to those who may have been blocked out by traditional credit-scoring methods.[68] On the other hand, "just because there is a statistical relationship does not mean that it is predictive, or even that it is legally allowable to be incorporated into a credit decision."[69] Moreover, illegality may occur even without the knowledge of the person or organization using the AI-based credit-scoring system.[70] There are several potential sources of this problem. In one scenario, the programmers designing the algorithm may unknowingly incorporate features that reflect their own unconscious biases.[71] In another scenario, even neutrally designed algorithms using alternative data may discriminate against applicants based on protected characteristics through the use of "proxy" data, even though such discrimination is not known to, or intended by, the potential lender.[72]

To appreciate the staggering potential that exists for unmeasured and otherwise unmonitored discriminatory lending decisions, it is helpful to consider a few illustrative examples. First, proxy discrimination is often difficult to guard against because the data that serves as a proxy for information about an applicant's membership in a protected class frequently bears no intuitive connection to that class.[73] A useful thought experiment describes a lender using an AI-based credit-scoring algorithm that treats the applicant's use of a Mac or PC as a key factor in determining the applicant's ultimate creditworthiness.[74] Over time, and after numerous applications, the algorithm determines—correctly—that Mac users are more likely than PC users to

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66 *See* Knight, *supra* note 21, at 245.
67 Hurley & Adebayo, *supra* note 65, at 164.
68 *See* Aphibal & Lemon, *supra* note 43, at 2.
69 *See* Klein, *Credit Denial*, *supra* note 8.
70 *See* Aphibal & Lemon, *supra* note 43, at 2.
71 Bartlett et al., *supra* note 7, at 5-6.
72 *See* Aphibal & Lemon, *supra* note 43, at 2.
73 Klein, *Credit Denial*, *supra* note 8.
74 *Id.*

pay back their loans, even controlling for other factors.[75] Although using the applicant's computer type as a screening mechanism may seem innocuous at first glance, this decision quickly becomes more problematic when it is learned that Mac users are disproportionately white.[76] A similar dynamic can play out with other categories of seemingly neutral data, as such data can unexpectedly correlate significantly with protected characteristics of the applicants.[77]

Second, even data that seems more obviously linked to protected data can be difficult to exclude from AI-based credit-scoring methods. This is because the programmers who design the algorithm, as well as the business operators that implement it, are often completely unaware of the specific data the algorithm ends up using to make its final decisions concerning an applicant.[78] For example, a hiring firm was recently shocked to discover that its AI-based hiring technology ended up "develop[ing] a bias against female applicants."[79] Ultimately, this bias was manifested by the algorithm's tendency to "exclude resumes of graduates from . . . women's colleges."[80] Examples like this indicate how blatant and substantial discrimination can result from AI-based algorithms, even when there is no discriminatory intent on the part of those using the technology. It also helps explain the results of a recent study conducted using data from two million mortgage applications, which found that black families were "80% more likely to be denied by an algorithm when compared to white families with similar financial and credit backgrounds."[81] The increasing prevalence of AI-based credit-scoring algorithms, coupled with the fact that the businesses designing and utilizing these technologies are often unable to restrain them from making discriminatory decisions, strongly illustrates the need for developing an adequate and sensible regulatory response.[82]

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75 *Id.*

76 *Id.*

77 *See* Hurley & Adebayo, *supra* note 65, at 182 (explaining how borrowers' zip codes appear to be "facially neutral" data, but "can easily serve as a proxy for a sensitive characteristic like race").

78 Klein, *Credit Denial*, *supra* note 8.

79 *Id.*

80 *Id.*

81 *See Remarks of Director Rohit Chopra*, *supra* note 20.

82 *See, e.g.*, Chopra, *supra* note 1, at 626-27.

II. A BRIEF OVERVIEW OF THE ECOA

Passed in 1974, the ECOA reflects an avowed Congressional intent "to eliminate unfair lending practices that inhibit equality in the credit industry due to factors unrelated to an applicant's creditworthiness."[83] Pursuant to the Dodd-Frank Wall Street Reform and Consumer Protection Act, the CFPB is the federal agency that takes the lead in enforcing the ECOA,[84] even though the CFPB shares this enforcement responsibility with other federal agencies, including the Department of Justice and the Office of the Comptroller of the Currency.[85] Unsurprisingly, then, the CFPB also takes the lead in enforcing Regulation B, which "provide[s] the substantive and procedural framework for fair lending."[86]

In their early years, ECOA lawsuits "focused primarily on prohibiting the unfair treatment of women by lenders due to sex and marital status."[87] This narrow focus undoubtedly resulted because, before the ECOA's enactment, "the credit industry held many assumptions about women that undermined their ability to obtain credit."[88] The ECOA's initial, exclusive focus on women was quick to change, however.[89] Indeed, only two years after the original statute's enactment, Congress adopted the Equal Credit Opportunity Act Amendments of 1976, which "extended the ECOA's protection against discrimination to include the applicant's race, color, age, religion, national origin," and other characteristics.[90] Gradually, the scope of ECOA lawsuits also began to reflect the broad list of protected characteristics described in the statutory text.[91] Importantly, the ECOA was passed during a period in which there were also great

83 *See* Taylor, *The ECOA and Disparate Impact Theory*, *supra* note 13, at 576.

84 *See* Request for Information on the Equal Credit Opportunity Act and Regulation B, 85 Fed. Reg. 46600 (proposed Aug. 3, 2020); *see also CFPB Takes Action Against Fifth Third Bank for Auto-Lending Discrimination and Illegal Credit Card Practices*, CONSUMER FIN. PROT. BUREAU (Sept. 28, 2015), https://www.consumerfinance.gov/about-us/newsroom/cfpb-takes-action-against-fifth-third-bank-for-auto-lending-discrimination-and-illegal-credit-card-practices/.

85 John Gore & Alexander Maugeri, *Banks Need to Gird for Tough Fair Lending and Housing Enforcement*, JONES DAY (Nov. 12, 2021), https://www.jonesday.com/en/insights/2021/11/banks-need-to-gird-for-tough-fair-lending-and-housing-enforcement-bloomberg-law.

86 U.S. Dep't of Justice, *supra* note 11; *see also* 12 C.F.R. pt. 1002; 15 U.S.C. § 1691(a).

87 *See* Taylor, *The ECOA and Disparate Impact Theory*, *supra* note 13, at 579.

88 *Id.* at 602.

89 *See id.* at 600.

90 *Id.*

91 *See id.* at 579.

changes "in the way lenders dispensed consumer credit."[92] As time has passed, however, the enforcement policies of the DOJ and the CFPB when applying the ECOA have perceptibly varied based on the policy preferences of most presidential administrations.[93] Despite these variations in enforcement, historical analysis shows that "Congress inextricably linked the ECOA and disparate impact liability from the statute's beginning."[94] This linkage is reflected in both the legislative history of the ECOA and its early case law.[95] A similarly important development that reinforced the cognizability of disparate-impact claims under the ECOA was the introduction of early, substantive amendments to the ECOA that noticeably shunned "requirement[s] that ECOA plaintiffs must show that lenders intentionally violated the statute in order to recover punitive damages."[96]

III. APPLYING DISPARATE-IMPACT THEORY TO THE ECOA

As previously noted, the ECOA declares that "[i]t shall be unlawful for any creditor to discriminate against any applicant, with respect to any aspect of a credit transaction on the basis of race, color, religion, nation original, sex or marital status, or age."[97] The language of this prohibition has served as the inevitable starting point for debates over whether disparate-impact claims are cognizable under the statute.[98] Although the question is undoubtedly of profound importance, it has received surprisingly little discussion in the case law.[99]

While the Supreme Court has resolved the applicability of disparate-impact theory in many other statutory contexts,[100] "the Ninth Cir-

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92 *Id.* at 598.

93 *See, e.g.*, Katy O'Donnell, *Mulvaney: Rate of Violations to Factor in Future CFPB Actions*, POLITICO (May 29, 2018).

94 Taylor, *The ECOA and Disparate Impact Theory*, *supra* note 13, at 581; *see* Amendments to Regulation B to Implement the 1976 Amendments to the Equal Credit Opportunity Act, 42 Fed. Reg. 1242, 1246, 1255 (Jan. 6, 1977); *see also* Equal Credit Opportunity; Revision of Regulation B; Official Staff Commentary, 50 Fed. Reg. 48,018 (Nov. 20, 1985).

95 *See* Taylor, *The ECOA and Disparate Impact Theory*, *supra* note 13, at 599.

96 *See id.* at 601.

97 15 U.S.C. § 1691(a).

98 *See, e.g.*, Andrew L. Sandler & Kirk D. Jensen, *Disparate Impact in Fair Lending: A Theory without a Basis & the Law of Unintended Consequences*, BUCKLEY LLP (July 13, 2012), https://buckleyfirm.com/sites/default/files/disparateimpactwhitepaper.pdf.

99 Taylor, *The ECOA and Disparate Impact Theory*, *supra* note 13, at 622.

100 *See, e.g.*, Tex. Dep't of Hous. & Cmty Affairs v. The Inclusive Cmtys. Project, Inc., 576 U.S. 519, 545-46 (2015) (upholding disparate impact theory under the Fair Housing Act); E.E.O.C. v. Abercrombie & Fitch Stores, Inc., 575 U.S. 768, 775 (2015) (upholding disparate

cuit is the only federal appellate court to [have] directly answer[ed] the question."[101] In upholding disparate-impact claims under the statute, the Ninth Circuit noted that "not requiring proof of discriminatory intent is especially appropriate in the analysis of ECOA violations because 'discrimination in credit transactions is more likely to be of the unintentional, rather than the intentional, variety.'"[102] In *Miller v. Am. Express Co.*, the Ninth Circuit relied heavily on the ECOA's legislative history, quoting the following passage from the Senate Report to the 1976 ECOA Amendments: "In determining the existence of discrimination . . . courts or agencies are free to look at the effects of a creditor's practices as well as the creditor's motives or conduct in individual transactions."[103]

Although not explicitly ruling on the issue, the Fifth Circuit has also indicated that recognizing disparate-impact liability is likely appropriate under the ECOA.[104] In a similar fashion, the Sixth Circuit and the D.C. Circuit have implied, without deciding, that the ECOA covers disparate-impact claims.[105] It should be noted, however, that the D.C. Circuit appeared at least somewhat skeptical that the ECOA recognized disparate impact discrimination.[106] Specifically, the D.C. Circuit concluded that "[b]oth Title VII and the Age Discrimination in Employment Act (ADEA) prohibit actions that otherwise adversely affect a protected individual" and that "the Supreme Court has held that this [particular] language gives rise to a cause of action for disparate impact discrimination under Title VII and the

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impact theory under Title VII of the Civil Rights Act of 1964); Smith v. City of Jackson, 544 U.S. 228, 239-40 (2005) (upholding disparate impact theory under the Age Discrimination in Employment Act of 1967); Raytheon Co. v. Hernandez, 540 U.S. 44, 53 (2003) (upholding disparate impact theory under the Americans with Disabilities Act).

[101] Taylor, *The ECOA and Disparate Impact Theory*, *supra* note 13, at 622 (citing Miller v. Am. Express Co., 688 F.2d 1235 (9th Cir. 1982)).

[102] *Miller*, 688 F.2d at 1239 (quoting Cherry v. Amoco Oil Co., 490 F. Supp. 1026, 1030 (N.D. Ga. 1980)).

[103] S. Rep. No. 94-589, at 4 (1976), *as reprinted in* 1976 U.S.C.C.A.N. 403, 406.

[104] *See* Taylor, *The ECOA and Disparate Impact Theory*, *supra* note 13, at 622 (citing Haynes v. Bank of Wedowee, 634 F.2d 266, 269 n.5 (5th Cir. 1981)). It is perhaps interesting that the Fifth Circuit seemed to rely heavily on the then-current version of the ECOA regulations in reaching its conclusion. *See Haynes*, 634 F.2d at 269 n.5 (citing 12 CFR § 202.6(a) n.7) ("ECOA regulations endorse use of the disparate impact test to establish discrimination . . . .").

[105] Taylor, *The ECOA and Disparate Impact Theory*, *supra* note 13, at 622 (citing Garcia v. Johanns, 444 F.3d 625, 633 (D.C. Cir. 2006); Golden v. City of Columbus, 404 F.3d 950, 963 n.11 (6th Cir. 2005) ("Neither the Supreme Court nor this Court have previously decided whether disparate impact claims are permissible under ECOA. However, it appears that they are.")).

[106] *See* Taylor, *The ECOA Disparate Impact Theory*, *supra* note 13, at 622.

ADEA."[107] Yet, while pointing out that the "ECOA contains no such language," the D.C. Circuit still implied that the ECOA likely recognizes disparate-impact claims.[108] Thus, it seems fair to observe that the state of the case law before the Supreme Court's *Inclusive Communities* decision, while unresolved, had a decidedly pro-disparate-impact tilt.

The Supreme Court's *Inclusive Communities* decision moved the federal judiciary a considerable step closer to recognizing ECOA-based disparate impact liability. Although the case concerned the Fair Housing Act (FHA)[109] and not the ECOA,[110] the Court's reasoning has significant relevance for interpreting the latter statute.[111] The Court focused strongly on the FHA's "results-oriented language," which is similar to language in other antidiscrimination statutes, as well as "the [FHA's] statutory purpose."[112] The relevant portion of the FHA's text reads:

> [I]t shall be unlawful—(a) To refuse to sell or rent after the making of a bona fide offer, or to refuse to negotiate for the sale or rental of, or otherwise make unavailable or deny, a dwelling to any person because of race, color, religion, sex, familial status, or national origin.[113]

From this, the Court found that "the phrase 'otherwise make unavailable' refers to the consequences of an action rather than the actor's intent."[114] Because both the FHA and the ECOA were designed to prevent discriminatory lending and both statutes share the identical textual prohibition "it shall be unlawful . . . to discriminate against" phrasing, many commentators have noted that recognizing disparate impact liability under one statute should entail a similar recognition with respect to the other.[115]

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107 *Garcia*, 444 F.3d at 633 n.9 (cleaned up).

108 *See id.*

109 42 U.S.C. §§ 3601-31.

110 *See* Tex. Dep't of Hous. & Cmty Affairs v. The Inclusive Cmtys. Project, Inc., 576 U.S. 519, 525 (2015).

111 *See Attorney General Josh Stein Leads Coalition to Urge CRPB to Protect Consumers from Credit Discrimination*, N.C. DEP'T OF JUST. (Sept. 5, 2018), https://ncdoj.gov/attorney-general-josh-stein-leads-coalition-to-urg-d1/.

112 *See Inclusive Cmtys. Project*, 576 U.S. at 545-46 (2015).

113 42 U.S.C. § 3604(a).

114 *See Inclusive Cmtys. Project*, 576 U.S. at 534 (citing United States v. Giles, 300 U.S. 41, 48 (1937)).

115 *See Attorney General Josh Stein*, *supra* note 111.

Yet, this was not the sole or even primary takeaway from the *Inclusive Communities* case. Instead, the opinion's main significance derives from the Court's use of a specific three-step, burden-shifting framework.[116] This framework is worth describing in full detail, as courts' adoption of the framework has made it decidedly more difficult to prevail on a disparate-impact claim, even if such claims are more widely recognized in the first place.[117] First, "the plaintiff 'has the burden of proving that a challenged practice caused or predictably will cause a discriminatory effect.'"[118] This requires the plaintiff to show that the defendant's policy, and the defendant's policy alone, caused the challenged injury.[119] Second, if the plaintiff was successful at the first step, "the burden shifts to the defendant to 'prove that the challenged practice is necessary to achieve one or more substantial, legitimate, nondiscriminatory *interests*.'"[120] Analyzing such interests is "analogous" to assessing Title VII's "business necessity standard" in employment discrimination cases.[121] Finally, if the defendant can make such a showing, the burden shifts back to the plaintiff, who can still prevail by showing that "the challenged practice could be served by another practice that has a less discriminatory effect."[122]

Commentators quickly noted that this framework creates a formidable hurdle for plaintiffs, regardless of the nature of the challenged practice.[123] It requires the plaintiff, not the defendant—who presumably holds the most knowledge about the challenged practice—to prove that the defendant's practice caused a disparate-impact injury.[124] Further, the framework "allows respondents to defend disparate-impact claims by presenting a legitimate policy rationale."[125] This is why the "substantial, legitimate, nondiscriminatory interest[ ]" language is potentially troubling.[126] Expressed another way, the sec-

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116 *See* Andrew Michaelson et al., *The Implications of a Revived Disparate Impact Doctrine Under a Biden CFPB*, KING & SPALDING (Dec. 17, 2020), https://www.kslaw.com/news-and-insights/the-implications-of-a-revived-disparate-impact-doctrine-under-a-biden-cfpb.

117 *See id.*

118 *Inclusive Cmtys. Project*, 576 U.S. at 527 (quoting 24 CFR § 100.500(c)(1)).

119 *See Inclusive Cmtys. Project*, 576 U.S. at 527.

120 *Id.* (quoting § 100.500(c)(2)) (emphasis added).

121 *Id.* at 541.

122 *Id.* (quoting § 100.500(c)(3)).

123 DAVID H. CARPENTER, CONG. RSCH. SERV., R44203, DISPARATE IMPACT CLAIMS UNDER THE FAIR HOUSING ACT 2, 11 (2015).

124 *See id.* at 8-9, 11.

125 *See* Michaelson, *supra* note 116 (cleaned up).

126 *See* C.F.R. § 100.500(c)(2).

ond stage of the burden-shifting framework would allow defendants to escape liability by showing only that their interest in applying the disputed credit-scoring technique was "legitimate" and "nondiscriminatory," apparently irrespective of any discriminatory effects the technique might have inflicted on the plaintiffs.[127] Such a result seems to be wholly at odds with disparate-impact theory in general, as the framework privileges the defendant's intent, rather than scrutinizing the effects of the defendant's credit-scoring policy.

The difficulty that the framework imposes on plaintiffs is particularly acute in fair lending cases where the defendant is accused of discriminating via an AI-based credit-scoring method. Because algorithmic credit scoring uses data in inscrutable and nonintuitive ways,[128] plaintiffs cannot be expected to know which data was decisive, or necessary, to the final credit decision at issue—at least under traditional disclosure methods.[129] Faced with their accusers' severe confusion, defendants may be tempted to portray the complicated internal dynamics of their own algorithms as justification for the lending decisions informed by that algorithm.[130] Despite the considerable weaknesses of the *Inclusive Communities* burden-shifting framework, however, it seems unlikely that today's relatively conservative Supreme Court would abandon that framework in the foreseeable future.

IV. AN ASSESSMENT OF LEADING LEGISLATIVE AND REGULATORY PROPOSALS

Since this Comment is concerned with practicality, this section assesses the leading proposals that scholars have already proffered as means of alleviating the discriminatory impact of AI-based credit-scoring methods. Much has been written with this goal in mind, but the most popular approach taken by scholars is to propose significant changes to existing legislative and regulatory schemes.[131] This is a

127 *See id.*

128 *See* Selbst & Barocas, *supra* note 26, at 1090.

129 *See* Michael Akinwumi et al., *An AI Fair Lending Policy Agenda for the Federal Financial Regulators*, BROOKINGS INSTITUTE (Dec. 2, 2021), https://www.brookings.edu/research/an-ai-fair-lending-policy-agenda-for-the-federal-fi nancial-regulators/ (explaining that lenders' adverse action disclosures under the ECOA are rarely "consumer-friendly or useful").

130 *See* Selbst & Barocas, *supra* note 26, at 1136.

131 *See, e.g.*, Chopra, *supra* note 1, at 626-27; Hiller, *supra* note 21, at 932-35; Knight, *supra* note 21, at 256.

broad characterization, of course, and proposals in this category range from decidedly modest to startlingly ambitious. Nevertheless, it is important to explicitly recognize this shared feature of such proposals because it is precisely this feature that makes the solutions' prompt implementation unlikely. Despite unaccommodating political realities, these proposals frequently advocate for making significant adjustments to existing statutes and regulations, with a sizeable number going even further by arguing for comprehensive legislative overhauls.[132] A similarly ambitious but distinct line of approach calls for mandating changes to the algorithmic codes themselves.[133]

Among the most far-reaching proposals from recent scholarship are those that urge for the adoption of a European Union-style data privacy framework.[134] Such a proposal undoubtedly has distinct benefits. First, it would require upfront that credit agencies realize that they cannot run their algorithms against some data, so long as such decisions lack transparency.[135] This prohibition would reflect a core provision of the General Data Protection Regulation (GDPR), which stipulates that "[p]ersonal data shall be . . . processed lawfully, fairly and in a transparent manner in relation to the data subject."[136] Second, and perhaps most advantageously, this proposal would help create greater uniformity in the American regulatory system, which consists of federal, state, and local actors.[137] The problem with such proposals, however, is that they fail to account for the extremely polarized politics of today's United States.[138] Indeed, it is unlikely that such a comprehensive change would be enacted for the sole purpose of updating the ECOA in particular or even for a broader

132 *See, e.g.*, Chopra, *supra* note 1, at 626-27; Hiller, *supra* note 21, at 932-35; Knight, *supra* note 21, at 256.

133 *See* Hiller, *supra* note 21, at 932, 933-35.

134 *See, e.g.*, Hertza, *supra* note 31, at 1729-41.

135 *See id.* at 1732.

136 *Id.* at 1730 (cleaned up).

137 *See e.g.*, Paul Andersen, *H.R. 8152 – The American Data Privacy and Protection Act: The United States' Solution for the Current "Patchwork" of Data Privacy & Protection Laws*, U. MARYLAND LAW SCHOOL, https://www.law.umaryland.edu/ Programs-and-Impact/Business-Law/JBTLOnline/22-to-23-AY/HR8152/ (last accessed Nov. 30, 2022) (explaining that the adoption of a GDPR-style framework would achieve efficiencies by converting a patchwork regulatory system into a more unified one); *see also* Hertza, *supra* note 31, at 1729-41. If Congress were to adopt such legislation, it would affect the operation of not just the ECOA, but countless other statutes involving personal data or data privacy issues.

138 *See* Hertza, *supra* note 31, at 1729-41 (describing the sweeping effects of a GDPR-style framework without accounting for the political obstacles to implementation).

attempt to prevent credit discrimination in general. A new data privacy framework of the kind envisioned by these authors would have a sweeping impact on many other areas of law.[139]

Equally far-reaching solutions are those that suggest subjecting lenders' AI-based credit-scoring methods to some form of an audit.[140] Although this approach may initially seem simple, further examination reveals it would involve considerable difficulties.[141] As a preliminary matter, one must choose which type of entity should conduct the audit. Options include existing government regulators who already struggle to manage their broad and growing purviews; newly created government regulators, who would have a more targeted authority; private auditors; or even creditors themselves, subject to adequate government scrutiny.[142]

Yet difficulties will arise irrespective of the option chosen. To begin with, there are currently no official standards, governmental or otherwise, that would govern a general algorithmic audit, let alone one specifically designed to seek evidence of potential disparate-impact discrimination.[143] This means that, while anti-discrimination audits may be a burgeoning industry for private companies, there is no guarantee that such audits would be useful.[144] Further, even if these audits were shown to be useful in revealing discriminatory outcomes, many companies would not want to get audited in the absence of an express requirement from the government.[145] A possible reason for such reluctance would be the fact that creditors who are informed by auditors of discriminatory problems with their algorithms would then lose plausible deniability of such problems when the companies are defendants in court, a development that would be especially unwelcome to creditors if they find themselves unable to fix the identified problems.[146] Additionally, even if audits were eventually shown to be

139 *See id.*

140 *See, e.g.*, Akinwumi et al., *supra* note 129.

141 *See, e.g.*, Alfred Ng, *Can Auditing Eliminate Bias from Algorithms?*, THE MARKUP (Feb. 23, 2021, 8:00 A.M.), https://themarkup.org/ask-the-markup/2021/02/23/can-auditing-eliminate-bias-from-algorithms (last visited Jan. 2, 2022); Cathy O'Neil, Comment Letter Regarding Docket No. FR-6111-P-02 (Oct. 18, 2019), http://clinic.cyber.harvard.edu/files/2019/10/HUD-Rule-Comment-ONEIL-10-18-2019-FINAL.pdf.

142 *See* Ng, *supra* note 141.

143 *Id.*

144 *Id.*

145 *Id.*

146 *See id.*

reliable and accountable to society, that scenario would almost certainly require some form of government oversight. This, in turn, would require government agencies to first develop auditing standards and competencies of their own, even if the role of such agencies were limited to supervising the audits performed by private companies.[147]

Less ambitious proposals often center on devising ways to incorporate legal methods of fairness into the AI-based credit-scoring models themselves.[148] These proposals are imaginative and have the benefit of dealing with potential discrimination at an early stage.[149] Although not foolproof—because an appreciable degree of monitoring would still have to take place to ensure that companies were complying with these limitations during the algorithm design phase—this approach would significantly alleviate the burden of regulatory agencies.[150] Unfortunately, however, the lag time on such proposals would likely be quite substantial, as agencies would have to develop new competencies to first catch up and then keep pace with the algorithm designers.[151]

The most common variant of the relevant scholarly proposals involves attempts to unify the disparate enforcement mechanisms on the front end, and then leverage such efficiencies to bring about heightened regulatory scrutiny.[152] Such consolidation, the theory goes, will help agencies more quickly develop necessary capabilities to regulate changes in credit-scoring algorithms that are unlikely to ever slow down.[153] These proposals, however, share the same weaknesses plaguing the first—the country's unfavorable political climate—albeit to a less serious degree.[154] Among these calls is an interesting proposal to eliminate the adverse action notice requirement of the ECOA,[155] which requires lenders to inform those whose credit applications have been denied (or approved on less favorable terms) of "the specific reasons for the [adverse] action taken."[156] The rationale behind this particular proposal is a recognition that the level of speci-

147 *Id.*

148 *See* Hiller, *supra* note 21, at 932-35.

149 *See id.* at 934.

150 *See id.* at 935.

151 *See id.* at 928, 934-35.

152 *See, e.g.*, Klein, *Credit Denial*, *supra* note 8.

153 *See id.*

154 *See id.*

155 Knight, *supra* note 21, at 251-52.

156 12 C.F.R. § 1002.9.

ficity required in the adverse action notice requirements is difficult to meet and burdensome for AI-using creditors to provide alongside every rejected application.[157] Also, even if creditors could describe the exact reasons an application was denied, such reasons would need to explain the "integrat[ion of] thousands of data points," which would likely be "utterly incomprehensible" to the applicants without meaningful context.[158]

A final category of solutions that must be addressed consists of proposals that unfortunately do not seem to account for what scholars Andrew D. Selbst and Solon Barocas describe as the inherent "inscrutability and nonintuitiveness" of AI-based credit-scoring systems.[159] As Selbst and Barocas explain, "the property of inscrutability suggests that [algorithms] available for direct inspection may defy understanding," while "nonintuitiveness suggests that even where [algorithms] are understandable, they may rest on apparent statistical relationships that defy intuition."[160] Together, these properties mean that adopting reforms that simply call for more extensive disclosure of algorithmic inputs are likely doomed to fail.[161] The authors see this failure as an inevitable consequence of adhering to such solutions because human minds will almost certainly be unable to draw the necessary inferences between the inputs utilized by a given algorithm and how the algorithm uses those inputs in a discriminatory and unnecessary way.[162]

Despite Selbst's and Barocas's helpful identification of these algorithmic problems, relying on human intuition to explain AI-based credit models is precisely what many proposals seem to suggest.[163] For example, Mikella Hurley and Julius Adebayo constructed a model statute that would require the increased disclosure of credit-scoring algorithms' inputs.[164] The model statute would also prohibit the use of certain inputs by forbidding the use of any algorithms that "treat as significant any data points or combinations of data points that are highly correlated to sensitive characteristics and affiliations."[165]

157 Knight, *supra* note 21, at 240-41.
158 *See id.* (cleaned up).
159 *See* Selbst & Barocas, *supra* note 26, at 1087-89.
160 *Id.* at 1091.
161 *See id.* at 1136-38.
162 *See id.*
163 *See id.* at 1086.
164 *See* Hurley & Adebayo, *supra* note 65, at 195.
165 *Id.* at 200 (cleaned up).

Together, these suggestions reveal that the authors may harbor two flawed beliefs. First, the input-disclosure requirement indicates a belief that simply "pull[ing] back the curtain" on algorithmic inputs will allow regulators to grasp how the examined algorithms function.[166] Second, the authors seem to believe that a prohibition on the use of variables that are "highly correlated" with protected characteristics can be enforced, even though they do not define what "highly correlated" means in an algorithmic context.[167] This is no small issue. As another commentator has noted, it is very difficult to determine when a variable is too closely related to, or too highly correlated with, protected information,[168] especially when the variable is listed, without further context, as simply informing the ultimate rejection decision.

The above observations reveal that a helpful way of assessing potential solutions to the problem of algorithmically caused disparate-impact discrimination may be to take a more generalized approach that analyzes whether the solutions are input- or outcome-focused.[169] Although disclosure-based proposals often carry the promise of meaningful change, they frequently suffer from at least one of the following two general forms of weakness. First, input-focused proposals often fail to account for the sheer volume of data points a credit-scoring algorithm is likely to assess in performing its function.[170] Second, outcome-focused proposals require an auditing competency that necessitates expensive and lengthy development.[171] Related to this setback is the additional problem of determining which entities are best suited to conducting the necessary audits.[172] Finally, assessing how these solutions interact with the predictably invoked business-necessity defense is an important but often neglected step in devising a workable solution.

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166 *Id.* at 195.

167 *See id.* at 200, 205-06 (the authors include the phrase in their "Model Act" without providing a definition).

168 *See* O'Neil, *supra* note 141.

169 *See* Talia Gillis, *The Input Fallacy*, 106 MINN. L. REV. 1175, 1246 (2019).

170 *See id.* at 1240-41; O'Neil, *supra* note 141.

171 *See* O'Neil, *supra* note 141; Ng, *supra* note 141.

172 *See* O'Neil, *supra* note 141; Ng, *supra* note 141.

ANALYSIS

Section I of this Analysis begins by focusing on the limitations that hamper the current formulation of the *Inclusive Communities* burden-shifting framework, especially as applied to ECOA disparate-impact claims involving AI-based credit scoring. As illustrated below, the heart of this analysis will turn on how the second stage of the burden-shifting framework—where the defendant simply shows that the challenged policy was applied as a business necessity, thus furthering a "nondiscriminatory interest"—is problematic. Section II of this Analysis will then set forth a possible solution, which contemplates courts requiring defendants to do most of the work in providing comprehensible and context-based descriptions of their algorithms.

I. THE LIMITATIONS OF THE *INCLUSIVE COMMUNITIES* BURDEN-SHIFTING FRAMEWORK WHEN APPLIED TO AI-BASED CREDIT SCORING

To prevail in disparate-impact cases, defendants must demonstrate that the challenged practice that caused a discriminatory effect was implemented as a business necessity.[173] This defense is required whenever the plaintiff can satisfy its prima facie burden of showing that the defendant's practice "caused or predictably will cause" a measurable disparity.[174] As previously noted, the defendant must at this second stage, "prove that the challenged practice is necessary to achieve one or more substantial, legitimate, nondiscriminatory interests."[175] Although this language may sound imposing, the defendant can meet this requirement "by presenting a legitimate policy rationale."[176] In disparate-impact cases where the challenged practice is the defendant's AI-based credit-scoring method, this rationale would take the form of the defendant arguing that its algorithm is the best way the defendant can make legitimate credit-scoring decisions.[177] This form of defense is particularly convenient to defendants because

[173] *See, e.g.*, Tex. Dep't of Hous. & Cmty. Affairs v. The Inclusive Cmtys. Project, Inc., 576 U.S. 519, 531-32 (2015).

[174] *See id.* at 527.

[175] *Id.* (quoting 24 C.F.R. § 100.500(c)(2)) (emphasis added) (cleaned up).

[176] *See* Michaelson et al, *supra* note 116.

[177] *See* Selbst & Barocas, *supra* note 26, at 1136 (explaining how a hypothetical defendant's chief engineer might seek to justify the defendant's credit-scoring decisions by testifying that the defendant simply follows the algorithm's treatment of input data).

the inherent complexity of the decision-making process effectively operates as a black box.[178] In fact, because the operations of AI-based algorithms are largely inscrutable and nonintuitive on their own,[179] CFPB Director Rohit Chopra may not have exaggerated when he described AI-based credit-scoring algorithms as "black boxes behind brick walls."[180]

Given that the *Inclusive Communities* burden-shifting framework traces its origins to discriminatory hiring cases from the 1970s[181]—a period that long predates the advent of modern credit-scoring algorithms—it is perhaps wholly unsurprising that the judicial developments that have afforded so much deference to this initial framework are woefully inadequate in the context of AI-based lending. Accordingly, the following section argues that courts should adopt an expanded transparency requirement capable of easy integration into the *Inclusive Communities* burden-shifting framework. Such a requirement would require defendants to do most of the work in providing comprehensible and contextual explanations of how their own algorithms operate, thus allowing for a more robust judicial analysis of credit-scoring algorithms.

II. ADDING AN EXPANDED TRANSPARENCY REQUIREMENT TO THE SECOND STAGE OF THE *INCLUSIVE COMMUNITIES* BURDEN-SHIFTING FRAMEWORK WHEN THE DEFENDANT RELIES ON ALGORITHMIC DECISION MAKING

As Selbst and Barocas noted, increased algorithmic complexity has led to AI-based credit-scoring models that are inscrutable and nonintuitive.[182] These authors explain that requiring defendants to provide extensive documentation revealing the context in which algorithms operate is necessary to overcome those twin hurdles.[183] Without such context, attempts to explain an algorithm would rely solely

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178 *See* Hurley & Adebayo, *supra* note 65, at 158 (explaining how "companies treat their [algorithms] as closely guarded trade secrets," which frustrates attempts to develop "a comprehensive picture" of how the algorithms function).

179 *See* Selbst & Barocas, *supra* note 26, at 1090.

180 *See Remarks of Director Rohit Chopra*, *supra* note 20.

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

182 *See* Selbst & Barocas, *supra* note 26, at 1090.

183 *See id.* at 1129-30.

on that algorithm's "internal mechanics," which would, in turn, "force [examiners] to rely on intuition to guess at why the [algorithm's] rules are what they are."[184] Because algorithmic complexity frustrates virtually all attempts at intuition-driven explanation, examiners need to also understand "the institutional and subjective process behind [an algorithm's] development."[185] Specifically, Selbst and Barocas define the relevant context surrounding an algorithm as revealed through: "(1) the values and constraints that shape" the problems the algorithm attempts to solve, "(2) how these values and constraints inform the development" and functioning of the algorithm, and (3) how algorithmic outputs "inform final decisions."[186] To ensure credit applicants, plaintiffs, and courts can obtain answers to these questions, Selbst and Barocas sensibly advocate for "a regime of mandated documentation."[187]

Although the documentation regime conceptualized by Selbst and Barocas could be implemented in a variety of ways,[188] disclosure via litigation would provide several distinct advantages. First, lenders already face extreme difficulty complying with detailed, ex-ante disclosure requirements.[189] The ECOA's adverse action notice requirements, for example, require a level of specificity that is difficult to satisfy and burdensome for AI-using creditors to provide alongside every rejected application.[190] Second, expanding this type of requirement to include necessary contextual documentation would only add to those burdens. Indeed, creditors would understandably "be reluctant to publish [disclosures] that reveal[ ] operating strategy, perceived constraints, or even embedded values" underpinning their algorithms.[191] Third, designing ex-ante disclosure requirements to be less burdensome while still retaining their usefulness would require legislative or regulatory changes unlikely to soon materialize.[192] Fourth, contextual documentation made available during litigation

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184 *Id.* at 1129.

185 *Id.* at 1130.

186 *See id.*

187 *Id.* at 1136.

188 *See* Andrew D. Selbst & Solon Barocas, *The Intuitive Appeal of Explainable Machines*, 87 FORDHAM L. REV. 1085, 1133-35 (2018) (discussing the possibility of mandating periodic disclosures of algorithmic performance via algorithmic impact statements or audits).

189 *See* Knight, *supra* note 21, at 240-41.

190 *See id.*

191 *See* Selbst & Barocas, *supra* note 26, at 1135.

192 *See* Knight, *supra* note 21, at 240-41, 256.

would allow for "the prepared documents to remain private but available as needed for accountability."[193] In other words, the defendant's disclosures, while sufficiently comprehensible and contextual, would be limited to what is necessary to properly adjudicate a given case. Finally, judicially compelled disclosure, at least in this Comment's proposed form, would place the burden on the defendant to explain the defendant's own algorithmic model, thus avoiding many of the costs and uncertainties that would plague alternative systems of ex-ante impact statements or audits.[194]

Considering the above, this Comment proposes that the second step of the *Inclusive Communities* burden-shifting framework should be modified to include an expanded transparency requirement. This requirement would compel defendants to provide contextual information about their AI-based credit-scoring models and a comprehensible explanation of how their models resulted in the challenged lending decisions. Given the difficulty of constructing intuitive explanations from contextual disclosures, it will not be enough, as Selbst and Barocas seem to suggest,[195] to rely on plaintiffs to fully capitalize on any disclosures defendants might make during pretrial discovery or cross-examination at trial. Rather, courts should not view defendants as having successfully made a business-necessity defense unless defendants provide comprehensible accounts of how their algorithms led to the challenged lending decisions. This approach will not require defendants to inculpate themselves, but it will ensure that defendants do most of the work in explaining how their AI-based credit-scoring methodologies led to the challenged decisions.[196] This expanded transparency requirement will give plaintiffs the best opportunity available to them under the *Inclusive Communities* framework to show that the defendants' models, when taken in context, tend to have discriminatory effects. Further, even if a defendant can make this more rigorous showing of a true business necessity, the defendant's testimony will equip the plaintiff with a comprehensible description of

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193 *See* Selbst & Barocas, *supra* note 26, at 1135.

194 *See* Knight, *supra* note 21, at 240-41 (explaining the costs of various ex-ante disclosure requirements).

195 *See* Selbst & Barocas, *supra* note 26, at 1129 (explaining the downsides of using intuition to explain findings which depart form human intuition such as findings stemming from machine learning models).

196 *See id.* at 1136.

the algorithm that the plaintiff can use when attempting to meet the rebuttal burden in the third step of the burden-shifting framework.[197]

In response to this proposal, many will undoubtedly argue that making slight adjustments to the Court's existing burden-shifting framework would provide insufficient protection to the minority groups that routinely bear the brunt of discrimination. It is important, however, that any proposed solution should be designed in a way that does not deprive society of the appreciable benefits that AI-based credit-scoring methods can provide.[198] Studies show that the primary beneficiaries of AI-based credit scoring are those who experience difficulty accessing credit under traditional credit-scoring methods.[199] As Selbst and Barocas note, policies that prevent lenders from using algorithms that the lenders themselves may find difficult to explain risk "forgo[ing] the increased accuracy that would result from a richer and more advanced analysis."[200] Accordingly, any solution should be carefully tailored in such a way that it does not make the widespread use of these technologies practically impossible or legally proscribed. Instead, legal reform should attempt to strike the balance of holding users of AI-based credit-scoring methodologies accountable without preventing their ability to expand credit access.

The principal benefit of a judicially implemented disclosure requirement is that it would allow the reviewing court to exercise a significant degree of flexibility. In fair lending cases, this flexibility would permit courts to make particularized assessments of each defendant creditor.[201] Such discretion is extremely useful in AI-based fair-lending cases because it protects the innovative potential of credit-scoring technologies to a degree that other solutions likely cannot.[202] Further, judicial review prevents defendants from getting away with supplying only pro forma disclosures of the kind likely to fill ex-

197 *See* Pauline T. Kim, *Data-Driven Discrimination at Work*, 58 WM. & MARY L. REV. 857, 922-23 (2017) (explaining that being able to interpret a model allows for debate on whether a model's use is acceptable).

198 *See* Sarah Auchterlonie & Jason Downs, *Proxy Problems—Solving for Discrimination in Algorithms*, JD SUPRA (Feb. 3, 2022), https://www.jdsupra.com/legalnews/proxy-problems-solving-for-6190627/; Knight, *supra* note 21, at 237-38, 257-58.

199 *See* MICHAEL A. TURNER ET AL., GIVE CREDIT WHERE CREDIT IS DUE: INCREASING ACCESS TO AFFORDABLE MAINSTREAM CREDIT USING ALTERNATIVE DATA 3 (2006).

200 *See* Selbst & Barocas, *supra* note 26, at 1111.

201 *See id.* at 1137 (acknowledging that an accounting of a credit model will allow courts to make evaluations of the subjective decisions of creditors).

202 *See id.* at 1136.

ante disclosure forms, such as the ECOA's adverse action notices. A regime of limited but meaningful algorithmic disclosures mirrors Jeanne C. Fromer's suggested reforms to trade secrets law, in which she argues that algorithm developers should be required to disclose only those features that are believed crucial to the ultimate result.[203] By conducting an ex-post assessment of the defendant's algorithm that focuses only on the decision-determinative inputs in the specific cases before them, courts would leave significant aspects of the algorithm protected from over-disclosure.

Finally, it is notable that the CFPB has previously described its own regulatory policy as reflecting something of a dual mandate: "The Bureau's mission includes both protecting consumers from unlawful discrimination and fostering innovation."[204] To this end, it is imperative that any proposed solution—legislative, regulatory, or judicial—be crafted so as not to impose on creditors antidiscrimination policies and disclosures so burdensome that they prevent the use of cutting-edge technologies or stifle future innovations. Instead, reforms should erect sturdy guardrails sufficient to protect the most vulnerable and otherwise leave new credit-scoring technologies to continue developing in their most benign and fruitful ways.

CONCLUSION

Although AI and related technologies have dramatically reshaped the way in which creditors assess loan applications, the fundamental need for fair lending laws remains as urgent as ever. To that end, it is important that courts, policymakers, attorneys, and scholars focus on what is achievable in the short term. The quest for high-minded reforms is, of course, always valuable. But achieving such reforms almost always requires rare moments of political consensus, heightened civic engagement, tide-turning historical events, or even a combination of those elements. Accordingly, it is equally important that those concerned by discriminatory lending not shrink from embracing incremental and admittedly less glamorous solutions. The harmful effects of lending discrimination continue apace and will not

203 *See* Jeanne C. Fromer, *Machines as the New Oompa-Loompas: Trade Secrecy, the Cloud, Machine Learning, and Automation*, 94 N.Y.U. L. REV. 706, 733 (2019).

204 Request for Information on the Equal Credit Opportunity Act and Regulation B, 85 Fed. Reg. 46600, 46600 (Aug. 3, 2020).

cease while Congress struggles to reach a comprehensive legislative solution.

It is with a spirit of decided practicality, then, that this Comment offers up an expanded transparency requirement that fits within the disparate-impact framework currently embraced by the Supreme Court. By embedding an expanded transparency requirement into the defendant's business-necessity defense, the federal courts could make a quick and meaningful change without imposing immoderate burdens on creditor defendants. Importantly, such an approach would be amenable to alterations that will almost surely be necessary for dealing with future developments in lending and credit-scoring technology. Finally, a judicially enforced requirement like the one set forth in this Comment is also more likely to avoid the vulnerabilities and rigidities that would plague a one-size-fits-all regulatory scheme, while still providing adequate notice to creditors. Given the increasing prevalence of algorithms in many sectors of the economy, the solution identified in this comment might be modified to address other areas in which disparate-impact discrimination may arise.