FALSE DREAMS OF ALGORITHMIC FAIRNESS: 
THE CASE OF CREDIT PRICING

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Abstract

The pricing of credit is changing. Traditionally, lenders priced consumer credit by using a small set of borrower and loan characteristics, sometimes with the assistance of loan officers. Today, lenders increasingly use big data and advanced prediction technologies, such as machine-learning, to set the terms of credit. These modern underwriting practices could increase prices for protected groups, potentially giving rise to violations of anti-discrimination laws.

What is not new, however, is the concern that personalized credit pricing relies on characteristics or inputs that reflect preexisting discrimination or disparities. Fair lending law has traditionally addressed this concern through input scrutiny, either by limiting the consideration of protected characteristics or by attempting to isolate inputs that cause disparities.

Using data on past mortgages, I simulate algorithmic credit pricing to demonstrate how input scrutiny is no longer appropriate. The ubiquity of correlations in big data combined with the flexibility and complexity of machine-learning means that one cannot rule out the consideration of a protected characteristic even when formally excluded. Similarly, in the machine-learning context, it may be impossible to determine which inputs drive disparate outcomes.

Despite these fundamental changes, prominent approaches in applying discrimination law to the algorithmic age continue to embrace the input-centered approach of traditional law. These approaches suggest that we exclude protected characteristics and their proxies, limit algorithms to pre-approved inputs, or use statistical methods to neutralize the effect of protected characteristics. Using my simulation exercise, I demonstrate that these approaches fail on their own terms, are likely to be unfeasible, and overlook the benefits of accurate prediction.

I argue that the shortcomings of current approaches mean that fair lending law must make the necessary, yet uncomfortable, shift to outcome-focused analysis. When it is no longer possible to scrutinize inputs, outcome analysis provides a way to evaluate whether a pricing method leads to impermissible disparities. This is true not only for the legal doctrine of disparate impact, which has always cared about outcomes even when it did so by scrutinizing inputs. Surprisingly, even disparate treatment, a doctrine that historically has been quite detached from disparate outcomes, can no longer rely on input scrutiny and must be considered through the lens of outcomes. I propose a new framework that regulatory agencies, such as the Consumer Financial Protection Bureau, can adopt to measure the disparities created when moving to an algorithmic world, allowing an explicit analysis of the tradeoff between prediction accuracy and other policy goals.
INTRODUCTION.......................................................................................................................... 4

I. PRICING CREDIT BASED ON BIASED INPUTS ......................................................... 14
   1.1 THE CREDIT PRICING DECISION ........................................................................ 15
   1.2 THE PROBLEM OF BIASED INPUTS ................................................................. 17
      1.2.1 Biased world .............................................................................................. 18
      1.2.2 Biased measurement .................................................................................. 20
   1.3 WHY WE CARE ABOUT ACCURATE PREDICTION ..................................... 23
   1.4 TRADITIONAL FAIR LENDING LAW .............................................................. 24

II. THE CHANGING WORLD OF CREDIT LENDING ................................................... 31
   2.1 WHAT IS CHANGING? ....................................................................................... 32
      2.1.1 Nontraditional data .................................................................................. 34
      2.1.2 Advance prediction technologies .............................................................. 36
      2.1.3 Automation .............................................................................................. 37
   2.2 SIMULATION EXERCISE – HYPOTHETICAL “NEW WORLD” CREDIT LENDER ... 38
   2.3 WHAT ARE THE CHALLENGES IN THE ALGORITHMIC CONTEXT? ............... 41
      2.3.1 Biased world inputs in algorithmic pricing ............................................. 41
      2.3.2 Biased measurement inputs in algorithmic pricing ................................... 44

III. APPROACHES TO ALGORITHMIC DISCRIMINATION ....................................... 45
    3.1 EXCLUDING PROTECTED CHARACTERISTICS .............................................. 48
       3.1.1 Ineffective exclusion ................................................................................ 49
       3.1.2 Disparities may increase with exclusion .................................................. 54
    3.2 EXCLUDING PROXIES FOR PROTECTED CHARACTERISTICS ................. 57
       3.2.1 Correlated inputs as “proxies” ............................................................... 59
       3.2.2 Inputs with no additional informational value ....................................... 62
    3.3 RESTRICTING ALGORITHM TO PREDETERMINED SET OF VARIABLES .... 63
       3.3.1 Entrenching disadvantage ...................................................................... 64
       3.3.2 High cost to prediction accuracy ............................................................. 66
    3.4 ORTHOGONALIZING INPUTS ........................................................................ 68
       3.4.1 Instability of machine learning selection .............................................. 70
       3.4.2 Why machine learning is different ......................................................... 73
    3.5 REQUIRED SHIFT FROM CAUSATION TO CORRELATION ......................... 74

IV. TOWARD A SOLUTION ................................................................................................. 76
    4.1 TESTING OUTCOMES IN THREE STEPS ...................................................... 78
       4.1.1 Can the test compare borrowers who are similarly situated? ............... 81
       4.1.2 Can the test consider incremental change? ............................................. 83
    4.2 REGTECH RESPONSE TO FINTECH .............................................................. 85

CONCLUSION ......................................................................................................................... 86

APPENDICES ........................................................................................................................ 89
INTRODUCTION

Many important decisions made primarily by humans in the past are now being automated using advance prediction technologies and big data. Algorithms are being used in a wide range of domains, from screening resumes\(^1\) to determining criminal justice outcomes.\(^2\) In consumer credit, there is a move towards reliance on algorithms to predict creditworthiness and price credit accordingly. Credit pricing increasingly uses nontraditional data\(^3\) and machine learning algorithms,\(^4\) while decreasing its reliance on human decision-makers and a small set of creditworthiness indicators, such as FICO scores.\(^5\)

Despite the efficiency and accuracy gained via these technologies, there has been increasing concern that machine learning algorithms may be biased or lead to unfair outcomes.\(^6\) Bias, a general term loosely used to describe conduct or an outcome that is unfair to a vulnerable population or legally


\(^3\) See infra Section 2.1.1. See also Bureau of Consumer Financial Protection, Fair Lending Report of the Bureau of Consumer Financial Protection, June 2019, 84 C.F.R. 32420 (July 8, 2019) (describing the recent CFPB Report from June 28, 2019 on a symposium the Bureau held in which they “discussed the role of alternative data and modeling techniques can play in expanding access to traditional credit”).

\(^4\) See infra Section 2.1.3.

\(^5\) FICO, previously known as Fair, Isaac & Co., “has developed a sophisticated algorithms for generating credit scores that characterized consumer financial creditworthiness” to predict whether consumers would default on their debt. FICO’s credit score is based on information in the consumer credit report received from credit bureaus. See Fair Isaac Corp. v. Experian Information Solutions, Inc., 650 F.3d 1139 (8th Cir. 2011).

protected group, can occur in algorithms for several reasons. An algorithm could be trained with nonrepresentative data, it could be set up to predict a human decision that is biased, or it could have imperfect measures of the outcome of interest. One type of concern, particularly important in the credit context and therefore the focus of this paper, is the use of characteristics or “inputs” that are biased because they reflect some preexisting disadvantage or because they are a noisy or biased measurement of borrower characteristics.

On August 19, 2019, the Department of Housing and Urban Development (HUD) published its proposal to replace its rule on the implementation of the Fair Housing Act from 2013. HUD’s Proposed Rule on the Implementation

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7 See Mayson, supra note 7, at 2231 (discussing the ambiguity of the term “bias”). Often the language used to define “bias” is quite circular. See, e.g., Kim, supra note 7, at 887 (“Similarly, data mining models built using biased, error-ridden, or unrepresentative data may be statistically biased”).

8 See Hurley & Adebayo, supra note 7, at 178 (“If credit scorers rely on non-neutral data collection tools that fail to capture a representative sample of all groups, some groups could ultimately be treated less favorably or ignored by the scorers final model”). It could also be that the dataset is simply flawed. For example, the Federal Trade Commission found that 21% of its sample of consumers had a confirmed error on at least one of three credit bureau reports. See Fed. Trade Comm’n, Report on Big Data: A Tool for Inclusion or Exclusion? (Jan. 2016), https://www.ftc.gov/system/files/documents/reports/big-data-tool-inclusion-or-exclusion-understanding-issues/160106big-data-rpt.pdf. This is of particular concern if certain groups, such as racial minorities, are more likely to have errors in their files. This is likely what happened when Amazon used AI to recruit workers, given that past hiring was predominantly male. See Jeffrey Dastin, Amazon Scraps Secret AI Recruiting Tool That Showed Bias Against Women (Oct. 9, 2018), https://www.reuters.com/article/us-amazon-com-jobs-automation-insight/amazon-scrap-secret-ai-recruiting-tool-that-showed-bias-again-women-idUSKCN1MK08G.

9 See, e.g., Bruckner, supra note 7, at 26 (discussing an example in which an algorithm was set up to predict admissions decision using a training set that was created by biased admission officers).

10 This type of concern could arise when the outcome, or “label,” is a noisy measurement of the true outcome of interest. See, e.g., Mayson, supra note 7, at 2227 (arguing that past crime data is distorted relative to actual crime rates). Another concern arises when outcomes are only observed for a sub-group depending on an earlier decision that might itself be biased. This is often referred to as the “selective labels problem,” and it is of particular concern in the credit context in which borrower default is only observed if they received a loan. See Himabindu Lakkaraju et al., The Selective Labels Problem: Evaluating Algorithmic Predictions in the Presence of Unobservables, PROCEEDINGS OF THE 23RD ACM SIGKDD INTERNATIONAL CONFERENCE ON KNOWLEDGE DISCOVERY AND DATA MINING 275 (KDD ’17, ACM New York, NY, USA 2017) (developing a method to overcome the problem of selective labels).

11 See infra Section 1.2.

of the Fair Housing Act’s Disparate Impact Standard discusses for the first time how to determine whether an algorithm violates fair lending law. In fact, the Proposed Rule is one of the first attempts in the United States and worldwide to articulate discrimination law as applied to an algorithm. A crucial focus of the rule is how to scrutinize and justify the “inputs” into a lender’s algorithm. Despite the Proposed Rule’s attempt to facilitate “practical business choices . . . that sustain a vibrant and dynamic free-enterprise system,” the regulation is confused and contradictory and reflects a lack of basic understanding of the technology at play. These shortcomings suggest that fair lending law is likely to become a central battleground on which practitioners and scholars will argue over the application of discrimination law to algorithmic decision-making.

In this Article, I make three arguments. I begin by contending that despite the recent focus on algorithmic bias, it is not possible to determine at the outset whether the use of biased inputs is worse in the algorithmic context than in traditional pricing. Rather than considering algorithmic bias vaguely or anecdotally, as is typical of most of the legal literature, I precisely define different types of biased inputs into a credit decision to highlight what changes in the algorithmic setting. Second, I consider the leading solutions and demonstrate that they are inadequate, even on their own terms. These solutions hold onto the input-centric view of traditional fair lending even as machine learning pricing makes this view obsolete and irrelevant. Finally, I argue that future regulation must focus on the effects of algorithmic credit pricing through empirical testing of algorithmic outcomes.

Throughout the Article I use a simulation exercise in which a hypothetical lender analyzes past loans to make predictions about future borrowers. For this exercise, I combine the Boston Fed Home Mortgage Disclosure Act (HMDA) dataset, which contains information on mortgage applications, with simulated default rates disciplined by information on the loans. My


15 See infra Section 3.5.

16 As explained in Section 2.2 and Appendix A, I fit a model that predicts whether an application is denied or rejected and then calibrate the rejection rates to publicly available statistics on default. Therefore, to the extent that there is some relation between a lending
A hypothetical lender uses a machine learning algorithm to predict default probability, which is then used to price credit for future borrowers. In this simulation exercise, the loan and borrower characteristics serve as the “inputs” to the credit decisions, while the predicted default probability is the “outcome.”

Beginning with the question of why we might be concerned with algorithmic pricing and how it differs from traditional credit pricing, I provide structure and clarity to the discussion on algorithmic bias by distinguishing among different types of input biases. The current focus on algorithms and biases overlooks the fact that even traditional credit pricing relied on borrower characteristics that reflected preexisting disadvantage (“biased world” inputs) or were inaccurately measured (“biased measurement” inputs). In the algorithmic context, the use of biased inputs could increase disparities in some instances while decreasing them in others. On the one hand, differences in inputs could translate into greater variance in outcomes when using machine learning to predict default. This means that the use of machine learning could further entrench pre-existing disparities to a larger extent than was likely under more basic statistical methods. On the other hand, the use of machine learning and big data could also mitigate some of the harm of “biased measurement” inputs if more information is available decision and borrower default, these simulated default rates may capture some of the relation between real-world default and borrower characteristics.

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17 See infra Section 1.2.1. Credit pricing has always considered borrower characteristics such as income and debt-to-income ratios, even though they likely partially reflect pre-existing disadvantage or discrimination. For example, if racial minorities and women suffer discrimination in the labor market or are more often targets of predatory lending practices, then their income and debt-to-income ratios are “biased-world” inputs.

18 See infra Section 1.2.1 If, for example, credit scores only consider certain types of creditworthiness indicators, such as timely loan payments but do not consider timely rent payments, and those indicators are less likely to be available for racial minority borrowers, then credit scores are a “biased measurement” input of creditworthiness. See Board of Governors of the Fed. Reserve Sys., Report to the Congress on Credit Scoring and Its Effects on the Availability and Affordability of Credit (2007) (finding that recent immigrants have lower credit scores than implied by loan performance and recommending that the type of information supplied to credit-reporting agencies to include routine payments such as rent be expanded).

19 See infra Section 2.3. One way to consider the change in the machine-learning setting is by comparing a linear regression to a machine-learning algorithm. As will be discussed further, the flexibility of machine-learning algorithms allows for a greater ability to differentiate among people based on their characteristics than on less flexible methods, such as an OLS regression. I demonstrate this using the Boston Fed HMDA dataset. See also Andreas Fuster et al., Predictably Unequal? The Effects of Machine Learning on Credit Markets 10 (2018), available at https://papers.ssrn.com/abstract=3072038 (presenting a useful demonstration of how a non-linear prediction allows for greater flexibility in differentiating between people based on their characteristics).
Fair lending law is the primary lens whereby to determine whether disparities created by biased inputs amount to discrimination in traditional credit pricing. Fair lending covers both the doctrine of disparate treatment, dealing with intentional discrimination, and the doctrine of disparate impact, dealing with a facially neutral rule that creates impermissible disparities. Despite the ongoing disagreements over the boundaries and philosophical foundations of fair lending law, discussed but not resolved in this Article, the focus has been on scrutinizing decision inputs to determine whether lender pricing amounts to discrimination. This has also been true of disparate impact, which, despite its name, has primarily focused on identifying and justifying inputs and policies that drive disparities. Given that fair lending developed in the traditional credit pricing setting, in which pricing was based on few inputs and involved human discretion, there is a need to adapt the law to the algorithmic context. This is also true of other areas of discrimination law.

The second focus of this Article is to challenge some of the leading approaches in applying discrimination law to the algorithmic context. These approaches are inadequate primarily on their own terms, meaning that they are unable to satisfy their own approach to fairness. They are also undesirable for several other reasons. First, they often fail to recognize that it is not possible ex ante to determine the effects of biased inputs, and so the approaches often fail to capture the benefit or promise of algorithmic pricing to reduce disparities, such as mitigating “bias measurement” through the use

\[\text{See infra Section 2.3.2. One of the examples discussed in that Section is when a lender has information about a borrower’s timely rent payments, it may not matter whether the borrower’s FICO score does not take this information into account.}\]

\[\text{See infra Section 1.4.}\]

\[\text{See infra Section 1.4 and Section 3.5. For disparate treatment, the legal doctrine concerned with intentional discrimination, the central question is whether a borrower’s protected characteristic played a role in setting the price and thereby served as an “input” in the decision. The legal doctrine of disparate impact, which is concerned with facially neutral policies that have an impermissible effect, also focuses on analyzing decision inputs after an initial demonstration of the outcome disparities. Disparate impact requires isolating the input that caused the disparity, and such an input is nevertheless permissible if it is related to a legitimate business justification. Therefore, as discussed in further detail below, although the prima facie case of disparate impact requires a showing of disparities, the analysis revolves around the cause of the disparities.}\]

\[\text{See infra Section 1.4.}\]

\[\text{See Talia B. Gillis & Jann L. Spiess, Big Data and Discrimination, 86 U. Chic. L. Rev. 459 (2019); Hurley & Adebayo, supra note 7, at 183.}\]

\[\text{See Kim, supra note 7. See generally Barocas & Selbst, supra note 7, at 694.}\]

\[\text{Many of these proposals are not only intended to apply to fair lending, but also have a direct bearing on how discrimination law would apply in algorithmic credit pricing.}\]

\[\text{See Kim, supra note 7. See generally Barocas & Selbst, supra note 7, at 694.}\]
of nontraditional data.\textsuperscript{27} Second, the approaches do not provide an adequate framework thought which to consider the potential tradeoffs between fairness and prediction accuracy. Finally, some of the approaches are simply inappropriate for the machine learning context.

I will discuss and criticize four leading approaches. The first approach is the exclusion of protected characteristics, primarily as a method for negating a claim of intentional discrimination under the “disparate treatment” doctrine. Information about a person’s protected characteristic is embedded in other information about the individual, so that a protected characteristic can be “known” to an algorithm even when it is formally excluded. I demonstrate this by predicting “age” and “marital status,” two protected characteristics under fair lending law,\textsuperscript{28} from the other variables within the HMDA dataset.\textsuperscript{29}

Consider an algorithmic lender who is required to comply with the Equal Credit Opportunity Act (ECOA) and cannot discriminate against borrowers based on their age.\textsuperscript{30} ECOA covers both the disparate treatment and the disparate impact doctrines so that the lender cannot directly or intentionally discriminate against an older borrower, nor can the lender use a neutral rule that has a disproportionate effect on older borrowers. The lender is aware,

\textsuperscript{27} See infra Section 2.3.2.
\textsuperscript{28} See 15 U.S.C. §1691(a) (“It shall be unlawful for any creditor to discriminate against any applicant, with respect to any aspect of a credit transaction – on the basis of … marital status, or age (provided the applicant has the capacity to contract).”).
\textsuperscript{29} The ability to predict “marital status” and “age” using the Boston Fed HMDA dataset is likely to be the lower bound on the ability to predict protected characteristics in the algorithmic context. This is because HMDA primarily contains traditional credit pricing variables, unlike “nontraditional” data discussed in Section 2.1.1.
\textsuperscript{30} The requirement to not consider “age” under ECOA is more complex than would seem based on the text of ECOA alone. Regulation B contains specific provisions related to age. See The Consumer Financial Protection Bureau, Regulation B, 12 C.F.R. §1002.6(b)(2)). Whether and how a creditor can use age in a credit decision depends on the system used. According to §1002.6(b)(2)(ii), when using “an empirically derived, demonstrably and statistically sound, credit scoring system, a creditor may use an applicant’s age as a predictive variable, provided that the age of an elderly applicant is not assigned a negative factor or value.” Assuming algorithmic credit pricing meets the criteria of a “demonstrably and statistically sound” scoring system as defined in §1002.2(p), it is unclear how a lender using an algorithm will ever be able to show that they have met the requirement that “applicants age 62 years or older must be treated at least as favorably as applicants who are under age 62.” (see Supplement I to Part 1002- Official Interpretation). This is because with algorithmic pricing, unlike expert based scoring, the weights are not pre-assigned to different characteristics. Similarly, as discussed in more detail in Section 3.4, one must be wary of interpreting the weight on “age” as the true and stable contribution of that variable to a prediction. See Kathryn P. Taylor, Equal Credit for All – An Analysis of the 1976 Amendments to the Equal Credit Opportunity Act, 22 ST. LOUIS U. L.J. 326, 338 (1978–1979) (“The Amendments set limits on the use of age in credit scoring systems, and prohibit the assignment of a negative value to the age of an elderly applicant”). I therefore conclude that it is unlikely that algorithmic credit pricing can consider age under current regulations.
however, that older borrowers are different from other borrowers. They often have less documented credit history and tend to use cash more frequently.\[31\] There is also a mechanical effect of age on default. An older person is less likely to live long enough to repay their loan before dying. The lender does not directly consider age but instead applies a machine learning algorithm to predict borrower default risk. Given the close relationship between age and default risk, an algorithm may be particularly motivated to recover a borrower’s age even when it is excluded from the algorithm. Even a basic machine learning algorithm would be able to ultimately consider a borrower’s age, rendering this exclusion meaningless.

We should also be wary of excluding protected characteristics if we care about outcome disparities.\[32\] As I demonstrate through a simulated example, price disparities could decrease when algorithms are “race aware.” In my example, “ability” is equally distributed across racial groups and is predictive of default. However, “ability” is not observed directly, rather “education” which correlates with “ability” is observed by the lender. In my example, racial minorities have less years of education. In reality this could be true if minorities face discrimination or other kind of disadvantage that made them less likely to attend college. When predicting default using education only, price disparities are significant. However, when the algorithm is able to distinguish white and non-white borrowers, price disparities decrease.

The second approach I discuss expands the exclusion of inputs to proxies for protected characteristics. This approach recognizes that other inputs may act as “proxies” for protected characteristics and therefore should be excluded too. The approach, however, is not feasible when there is no agreed-upon definition of a proxy, and when complex interactions between variables are unidentifiable to the human eye. Even inputs that have traditionally been thought of as proxies for race, such as zip codes, may be less concerning than other ways in which a borrower’s race can be recovered. Using the HMDA data, I demonstrate that there is a greater ability to predict “race” from the traditional credit pricing inputs in HMDA than from zip codes. Similarly, although it may be possible for example to require lenders to exclude clear proxies for age from datasets, borrower age can still be revealed by the


\[32\] As discussed further in Part III, the exclusion of protected characteristics may be considered a fair procedure, regardless on its impact on disparities. This question closely relates to the more general debate on procedural versus substantive justice. See generally Lawrence B. Solum, *Procedural Justice*, 78 S. CAL. L. REV. 181 (2004–2005). What is particularly striking about this context is the extent to which the formal exclusion of the characteristic is unlikely to mean the characteristic was not considered, regardless of the raw disparities among groups.
combination of many consumer behaviors.

Despite the shortcomings of this approach, the Trump administration is promoting this very interpretation of disparate impact. In HUD’s circulated draft of its Proposed Rule from August 2019, a lender can defend an algorithm by demonstrating that it does “not rely in any material part on factors that are substitutes or close proxies for protected classes under the Fair Housing Act.” The proposed rule does not provide any guidance on how to identify a “proxy” or “substitute.” This Article is the first to consider the implications of HUD’s proposed rule, arguing that this type of vague standard deems this approach impractical and unlikely to address the concern that an algorithm creates impermissible distinctions.

The third approach I discuss takes the reverse perspective of restricting algorithm inputs to pre-approved inputs, unlike the first two approaches, which allow all inputs other than certain forbidden inputs. Although this approach may allow for greater control over exactly what algorithms use to price credit, the approach could ultimately restrict access to credit. This is because limiting an algorithm to traditional credit pricing inputs further perpetuates the exclusion of consumers lacking formal credit histories and could thus entrench disadvantage without the ability of big data to undo or mitigate the harm from “biased measurement” inputs. Moreover, using my simulation exercise, I demonstrate that the prediction of default based on fewer inputs decreases prediction accuracy. When lenders have less ability to differentiate among borrowers based on their risk, lenders are limited in their ability to price the lending risk.

The last approach I discuss, the orthogonalization approach, is based on a statistical method meant to prevent inputs that correlate with protected characteristics from serving as proxies. This is achieved by a statistical method, described in greater detail below, in which a protected characteristic is used to estimate a prediction function but not to apply the prediction. I argue that this framework is inappropriate for the machine learning context. I show this technically by demonstrating that by adding little noise to my training dataset, I get vastly different weights on the “race” variable. The deeper purpose of this technical exercise is to demonstrate that an algorithm is set up to optimize a prediction and not to estimate a model. This means that there are limits to analyzing a machine learning prediction to truly uncover the impact of protected characteristics on a prediction.

These four approaches are inadequate because they continue to scrutinize

33 See supra note 14, at page 33.
34 See infra Section 3.4.
35 See Jon Kleinberg et al., Discrimination in the Age of Algorithms, 10 J. L. ANALYSIS (2018), for a discussion of the difference between the training of an algorithm and the application of the prediction (or the “screener”).
decision inputs, similar to traditional fair lending, when this strategy is no longer feasible or effective in the algorithmic context. Approaches to discrimination law in the algorithmic age continue to rely on an outdated paradigm of causality. Fair lending law has traditionally been concerned with two causal questions. The first is whether a protected characteristic had a causal effect on the credit decision (disparate treatment), and the second is whether the inputs into credit decisions caused impermissible disparities (disparate impact).³⁶ Despite its name, the disparate impact doctrine has paid more attention to identifying the cause of disparities than to defining and analyzing disparities.³⁷ Machine learning is a world of correlation and not causation. When using a machine learning algorithm to predict an outcome, the focus is on the accuracy of the prediction. Accuracy is the metric by which we judge the success of the algorithm.

I argue that the shortcomings of current approaches mean that fair lending law must make the necessary, yet uncomfortable, shift to outcome-focused analysis.³⁸ When it is no longer possible to scrutinize inputs, outcome analysis provides a way to evaluate whether a pricing method leads to impermissible disparities. This is true not only for the legal doctrine of disparate impact, which has always cared about outcomes even when it did so by scrutinizing inputs. Surprisingly, even disparate treatment, a doctrine that historically has been quite detached from disparate outcomes, can no longer rely on input scrutiny and must be considered through the lens of outcomes.

I end the Article by discussing possible paths forward. I argue that regulators should develop a framework for an ex ante consideration of the effects of an algorithmic pricing rule. This can be achieved by applying a credit pricing rule, before it is used by a lender, to a dataset of hypothetical lenders. The regulator can then examine the outcomes of the pricing rule to determine whether the pricing rule discriminates. This type of outcome-focused testing brings to the forefront the demonstration of disparities, which is formally part of the first stage of a disparate impact complaint in traditional fair lending law. My proposed testing framework develops this type of analysis and adapts it to the machine learning context.

³⁶ See e.g., Sheila R. Foster, Causation in Antidiscrimination Law: Beyond Intent versus Impact, HOU.S. L. REV. 1469, 1472 (2004–2005) ("By definition, all discrimination claims require plaintiffs to demonstrate a causal connection between the challenged decision or outcome and a protected status characteristic"). This is further developed in Section 3.5.
³⁷ See infra Section 1.4 and 3.5.
³⁸ Some previous writing on discrimination and artificial intelligence has suggested that greater focus should be placed on outcomes. See e.g., Anupam Chander, The Racist Algorithm?, 115 Mich. L. Rev. 24 ("The focus on outcomes rather than how an algorithm operates seems especially useful as algorithms become increasingly complicated, even able to modify themselves.").
The criteria to determine when disparities amount to discrimination depend heavily on the boundaries and interpretation of the doctrine of antidiscrimination, which continues to be disputed. Therefore, I do not provide an exact test, but argue that algorithmic outcomes can be used to answer meaningful questions. The first question that my outcome analysis can answer is whether the pricing rule treats borrowers who are “similarly situated” equally. The second question is whether the pricing rule increases or decreases disparities relative to some baseline, such as the non-algorithmic credit pricing method. In the final Section, I describe how outcome analysis can be used to answer these two questions, and I highlight challenges to the implementation of outcome-based testing for future work.

My outcome-based approach to discrimination testing reflects the need to adopt an empirical and experimental approach to discrimination. In the algorithmic world we can no longer determine a priori how inputs relate to outcomes. We do not know whether an algorithm is using a protected characteristic from observing the algorithm’s inputs. Similarly, we cannot determine whether an algorithmic method will increase or decrease disparities based only on whether it uses nontraditional inputs. Approaches that solely focuses on input scrutiny either fail to achieve their goal or run the risk of further entrenching disadvantage. Therefore, an outcome-based approach seeks to test the actual effects of a credit pricing method providing an appropriate Regtech response to the Fintech industry.

The significance of how to implement discrimination law to the algorithmic context transcends fair lending. My analysis speaks directly to other legal settings in which there are ongoing debates on how to define and implement discrimination to algorithms, from employment to criminal justice. In these domains, like fair lending, there is a misplaced focus on input scrutiny. The Article also contributes to discussions in the computer science and statistical literature on algorithmic fairness, by demonstrating how evaluation of algorithmic decisions should be informed by legal doctrine, and regulatory and institutional realities.

The Article proceeds in four parts. Part I focuses on the traditional world of credit lending and presents the distinction between “biased world” inputs and “biased measurement” inputs. Part II turns to the new world of algorithmic credit pricing, describing the main changes and their meaning for the problem of biased inputs. Part III discusses the main approaches to

discrimination law in the algorithmic context and shows that they are inadequate on their own terms and also otherwise undesirable. Part IV argues that the move to algorithmic pricing requires more fundamental shifts in fair lending law from input scrutiny to outcome analysis and develops an appropriate framework.

I. PRICING CREDIT BASED ON BIASED INPUTS

When pricing credit, lenders often offer people different loan terms based on their individual predicted default probability using borrower characteristics and the loan specifics. In this Part, I discuss how there is commercial and social value in accurately predicting default risk, which underlies differential pricing. However, when characteristics vary by group because they reflect bias, their use to price credit differentially may entrench bias. As I elaborate on in this Part, traditional discrimination law addresses this tension by either prohibiting the direct use of a protected characteristic or by limiting pricing policies that could further bias.

In this Part, I focus on traditional credit lending, before discussing algorithmic credit pricing, to highlight what is likely to change. This is important because current concerns over the fairness of credit pricing algorithms overlook the fact that even traditional credit pricing relied on borrower characteristics that reflected pre-existing disadvantage (“biased world” inputs) or were inaccurately measured (“biased measurement” inputs). Credit pricing has always considered borrower characteristics such as income and debt-to-income ratios, even though they are likely to partially reflect pre-existing disadvantage or discrimination. If racial minorities and women face discrimination in the labor market, or are more often the target of predatory lending practices, their income and debt-to-income ratios are “biased world” inputs. If credit scores only consider certain types of creditworthiness indicators, such as timely loan payments but not timely rental payments, and those indicators are less likely to be available for racial minority borrowers, then credit scores are a “biased measurement” input of creditworthiness. The use of these type of inputs creates disparities in pricing for different groups.

Fair lending law has been the primary lens through which to determine whether the disparities created by biased inputs amount to discrimination in traditional credit pricing. For the legal doctrine concerned with intentional discrimination, disparate treatment, the central question is whether a borrower’s protected characteristic played a role in setting the price, meaning it was an “input” in the decision. For the legal doctrine of disparate impact, concerned with facially neutral policies that have an impermissible effect, the focus has been on analyzing decision inputs after an initial demonstration of
the outcome disparities. Disparate impact requires isolating the input that caused the disparity, and such an input is nevertheless permissible if it is related to a legitimate business justification. Despite the ongoing disagreements over the boundaries and philosophical foundations of fair lending law, which are discussed but not resolved in this Article, the focus of these doctrines is on scrutinizing decision inputs in order to determine whether lender pricing amounts to discrimination.

I begin this Part by providing an overview of a credit pricing decision that presents the terminology I will use throughout the Article. I then discuss the distinction between “biased world” and “biased measurement” inputs and how they effect a pricing decision. As this analysis may raise the question of why we would personalize credit prices at all, I briefly discuss how accurate predictions of default may be beneficial in allowing greater access to credit. I end the Part by discussing how traditional fair lending law has dealt with the tension between personalized pricing that relies on biased inputs and the benefits of accurate default prediction.

My focus in this Section is on the problem of biased inputs. There are, however, other concerns that can arise in the context of credit pricing that I do not fully address. For example, a lender could intentionally deny credit to a member of a protected group, motivated by animus. 40 I focus on the problem of biased inputs for two reasons. First, because of how prevalent biased inputs are in lending decisions, and second, because the use of biased inputs create an opportunity and challenge for algorithmic pricing, as will be discussed in Section 2.3.

1.1 The credit pricing decision

Credit contracts are often personalized, 41 meaning that lenders will determine the specific terms of the contract based on the characteristics of the borrower and the specific loan. We can therefore articulate the pricing decision as one in which inputs, \( x \), are used to determine the outcome, \( y \). The

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40 This is what economists typically refer to as “taste-based discrimination”. See GARY S. BECKER, THE ECONOMICS OF DISCRIMINATION (2010).

41 Not all credit is personalized and not all credit is personalized to the same extent. The personalization of credit contracts can be costly so that the degree of personalization may depend on the magnitude of the credit contract. Personalizing credit contracts could require collecting and verifying a lot of information about consumers, and also using this information to assess risk. Therefore, although default risk can exist with any credit contract, this assessment might only be worthwhile with larger credit contracts. For mortgages, which are typically large loan contracts, there is likely to be a degree of personalization. But this can also be true of smaller loans and other types of debt. For example, many people rely on financing for auto purchases, and there are many forms of non-securitized debt such as personal loans and credit card debt.
inputs, $x$, are all the variables or characteristics that the lender uses to determine the outcome. These inputs could include borrower characteristics, such as the borrower’s income or years of education, as well as the characteristics of the loan application, such as the loan amount or the property value, in an application for a mortgage. The outcome, $y$, could be the interest rate of the loan or the fees associated with the loan, for example. The outcome could also be a binary decision, such as whether to approve the loan application or not.

In traditional credit pricing in general, and mortgage lending in particular, personalization of the credit contract was typically based on a set of borrower and loan characteristics. Borrower’s creditworthiness was assessed based on past loan behavior, often with the assistance of a credit bureau, such as Experian or Equifax, or relied on a borrower FICO score. Borrower income and future income is also used to determine borrower liquidity. Lenders also used the specific characteristics of the loan, and the securitized property, to determine the terms of the loan. The use of these characteristic meant that the exact terms of the loan could vary greatly between borrowers, and so there was a degree of personalization of the prices paid by borrowers.

Credit terms were also personalized because they were partially determined by lender employees or brokers (jointly “loan officers”) with discretion. In traditional mortgage lending the originator would provide the “par rate” which was based on a limited number of characteristics and was often considered the lowest priced at which an originator was willing to extend a loan. Borrowers met with loan officers with discretion in setting the exact terms of the loan who were often incentivized to provide a more expensive loan than the “par rate.” It is likely that loan officers made loan

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42 In this Article I focus on interest rates, but this is only one element of the cost of a mortgage. The overall cost of a mortgage is determined by other costs such as “discount points” and the compensation to the loan officer and broker. See generally Neil Bhutta et al., Paying Too Much? Price Dispersion in the US Mortgage Market (2019), available at https://papers.ssrn.com/abstract=3422904.

43 The difference between the “par rate” and the final rate was known as the “yield spread premium” and was used to compensate loan officers. In the wake of the financial crisis, new regulations from 2010 prohibited loan officer compensation from directly being related to the interest rate. See Board of Governors of the Federal Reserve System, Truth in Lending, Regulation Z, 75 Fed. Reg. 185,58508 (Sep. 24, 2010). Even though loan officers are limited in their ability to be directly compensated for higher interest rates, more expensive loans are clearly more profitable for lenders and could ultimately affect loan officer compensation, albeit less directly. See Howell E. Jackson & Laurie Burlingame, Kickbacks or Compensation: The Case of Yield Spread Premiums, 12 STAN. J.L. BUS. & FIN. 289 (2006–2007), for a discussion on why yield spread premiums were problematic for consumers and for the argument that yield spread premiums lead to higher mortgage prices for consumers, which may fall disproportionately on the least sophisticated borrowers.
more personalized than the originator’s par rates.\textsuperscript{44}

Throughout this Article I focus on credit pricing that results from the prediction of default probability of the borrower. The lender predicts the default probability and then uses this default probability to directly set the price of the loan, such as the interest rate of the loan. I therefore refer to the outcome $y$ as the predicted default probability and the loan price interchangeably.\textsuperscript{45}

Despite my focus on default probability, in reality default prediction is rarely the only metric used to personalize credit contracts. Personalization could depend on whether the loan is securitized or not or the purpose of the loan, as well the creditworthiness of the borrower or the costs of administering the loan to the particular borrower. The personalized terms could also reflect the lender’s assessment of the borrower’s willingness to pay for the loan.\textsuperscript{46} My focus on default prediction allows me to simplify the credit pricing decision while highlighting many conceptual challenges. I also focus on default prediction personalization since this is arguably the least controversial basis for personalization.\textsuperscript{47}

\subsection{The problem of biased inputs}

Most inputs into a credit pricing decision in the traditional context reflect bias; however, the origin of that bias can vary greatly for different inputs. In this Section, I distinguish between a biased input that results from some historic or existing discrimination external to the lender itself (“biased world”) and an input that is biased because of the way it defines and estimates

\textsuperscript{44}This is because mortgage lenders often created borrower “bins” based on a limited set of characteristics in determining par rates. These bins were likely not based on sophisticated risk predictions but rather reflected more coarse divisions between lenders. As I have discussed elsewhere, it is not clear how exactly loan officers decided the final terms of the loan. For example, we do not know whether loan officers were concerned with assessing credit worthiness or tried to learn borrower willingness-to-pay. See Gillis & Spiess, supra note 26.

\textsuperscript{45}One can in theory separate the “prediction problem” from the “decision.” See e.g., Sam Corbett-Davies et al., Algorithmic Decision Making and the Cost of Fairness, PROCEEDINGS OF THE 23RD ACM SIGKDD INTERNATIONAL CONFERENCE ON KNOWLEDGE DISCOVERY AND DATA MINING 797 (KDD ’17, ACM New York, NY, USA 2017).

\textsuperscript{46}A recent study suggests that there is a high degree of dispersion in the prices of mortgages. This suggests that many borrowers overpay for mortgages because they likely do not shop around or negotiate for a better rate. See Bhutta et al., supra note 44.

\textsuperscript{47}See e.g., Robert Bartlett et al., Consumer Lending Discrimination in the FinTech Era 50, https://www.nber.org/papers/w25943. A continuation paper will discuss the different types of personalized pricing. This is particularly relevant to the “business justification” of disparate impact and whether the personalization of prices based on willingness-to-pay can qualify for this defense.
a characteristic (“biased measurement”). Although analytically distinguishable, the difference between the two is often empirically indistinguishable.

A primary concern with personalized prices for credit is that it creates or further increases disparities among groups. Here I focus on bias that affects “protected groups,” meaning the categories of people that discrimination law seeks to protect. We therefore might be concerned that the way in which we predict default, and price credit accordingly, creates disparities among legally protected groups. As will be discussed further in Section 1.4 fair lending prohibits discrimination on the basis of race, religion, sex, marital status and age, among other grounds.

1.2.1 Biased world

A key problem facing lenders who wish to personalize prices of credit to borrowers based on their individual risk is that many of the factors used to determine this risk may be themselves a product of pre-existing disadvantage or discrimination. Although this may not be the fault of the lender, credit pricing using these inputs leads to the further impact of existing discrimination in a new domain. While according to some theories of discrimination, the use of “biased world” inputs does not give rise to a claim of discrimination, according to other theories, a situation of “compounding injustice” could trigger discrimination law, as will be discussed in Section 1.4.

A central factor for determining the repayment risk is a borrower’s income. Past research has suggested that there is a significant racial and gender pay gap in the US. Importantly, the black-white wage gap has

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48 The two Act’s that determine the protected groups for fair lending are the Equal Credit Opportunity Act (ECOA), (15 U.S.C. § 1691 (a)(1)-(2)), and the Fair Housing Act, (42 U.S.C. 3601).

49 I use the term “discrimination” here to describe a reality in which a group was unfairly treated without considering whether those circumstances give formal rise to a claim of legal discrimination. This is sometimes referred to as “structural disadvantage.” See Barocas & Selbst, supra note 7, at 691. I implicitly focus on biased inputs resulting from the protected characteristics itself, such as racial discrimination determining job opportunities. A full discussion of biased inputs would need to encompass a more nuanced categorization, such as distinguishing between biased inputs that are a result of discrimination and inputs that correlate with protected characteristic because of some other type of injustice.

50 Deborah Hellman coined this term to describe a decision that “exacerbates the harm caused by the prior injustice because it entrenches the harm or carries it into another domain.” See Deborah Hellman, Indirect Discrimination and the Duty to Avoid Compounding Injustice, in FOUNDATIONS OF INDIRECT DISCRIMINATION LAW (Hugh Collins & Tarunabh Khaitan eds., 2017).

51 See Kayla Fontenot et al. Income and Poverty in the United States: 2017 United States
increased as wage inequality has risen from 1979 to 2015. These gaps may reflect labor market disparities, meaning that black workers with the same ability and education earn less than comparable white workers or face less employment opportunities. However, it is important to note that even factors that “explain” wage gaps might themselves be a product of discrimination. For example, different levels of education may result from lower access to higher education in minority communities, what is typically referred to as “pre-market factors.”

The higher rate of incarceration of racial minorities could also impact the inputs into a credit decision. A recent paper documented the negative impact...

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53 While the racial wage gap in the labor market is well documented, interpreting this gap and the extent to which it reflects either taste-based or statistical discrimination has proven difficult. See Dan Black et al., Why Do Minority Men Earn Less? A Study of Wage Differentials among the Highly Educated, 88 REV. ECON. & STAT. 300 (2006) (finding substantial unadjusted wage gaps between college-educated minority men - black, Hispanic, and Asian - and non-Hispanic white men. The authors emphasize that they cannot rule out the possibility that this is a consequence of cultural or class prejudice.) See also Eric Grodsky & Devah Pager, The Structure of Disadvantage: Individual and Occupational Determinants of Black-White Wage Gap, 66 AM. SOC. REV. 542, 563 (2001) (find that although black men have gradually gained entry to highly compensated occupational positions, they have simultaneously become subject to more extreme racial disadvantages in respect to earning power). See also Roland G. Jr. Fryer, Devah Pager & Jorg L. Spenkuch, Racial Disparities in Job Finding and Offered Wages, 56 J.L. & ECON. 633, 690 (2013) (estimating that differential treatment accounts for at least one third of the black-white wage gap). Other studies have identified racial disparities in access to the labor market. See e.g., Marianne Bertrand & Sendhil Mullainathan, Are Emily and Greg More Employable than Lakisha and Jamal? A Field Experiment on Labor Market Discrimination, 94 AM. ECON. REV. 991 (2004) (finding that white names triggered a callback rate that was 50% higher than that of equally qualified applicants with black names). See also John M Nunley et al., Racial Discrimination in the Labor Market for Recent College Graduates: Evidence from a Field Experiment, 15 B.E. J. OF ECON. ANALYSIS & POL’Y 1097 (2015).

54 Another important example is when lenders consider whether a borrower is self employed, which may be used to determine that their future income is less stable. See Alicia H. Munnell et al., Mortgage Lending in Boston: Interpreting HMDA Data, 86 AM. ECON. REV. 25 (1996) (finding that the probability that a loan request made by someone who is self-employed will be denied is roughly one third greater than the average denial rate, page 29); Todd J. Zywicki & Joseph D. Adamson, The Law and Economics of Subprime Lending, U. COLO. L. REV. 1, 9 (2009) (“Generally, lenders charge higher interest rates to borrowers with lower credit scores. Lenders may also charge higher interest rates where mortgages have peculiar characteristics, such as loans with high loan-to-value ratio, loans without prepayment penalties, or loans to some self-employed borrowers with less-predictable income”)
of incarceration on credit scores and income. If black defendants are more likely to be incarcerated then the use of credit scores and income presents another way in which credit decisions rely on pre-existing disadvantage.

Another key characteristic that is used to price credit is a borrower’s debt-to-income which measures the level of a person’s debt (including the loan they are requesting) to their level of income. The “debt” component of the ratio may reflect pre-existing disadvantage in addition to the “income” component. For example, high interest lenders, such as payday lenders, often target minorities, leading to the accumulation of higher levels of debt. There is also evidence that credit card lenders may also screen for minority consumers.

When a lender who uses variables that reflect pre-existing disadvantage, or a biased world, that disadvantage is compounded and affects and new domain of lending. The bias input is then used to price credit that is more expensive for the disadvantaged group or even to deny credit altogether. Because credit is a way of potentially creating wealth this essentially could reinforce wealth gaps in the US.

1.2.2 Biased measurement

Many inputs into a pricing decision partially reflect bias measurement, meaning that the way in which an input is defined or estimated is biased rather than the underlying characteristic being biased. In this Section I provide some examples of biased measurement and argue that while the lender may have more control over estimation that causes “biased measurement” inputs than


57 See Andrea Freeman, Payback: A Structural Analysis of the Credit Card Problem Financial Reform During the Great Recession: Dodd-Frank, Executive Compensation, and the Card Act, ARIZ. L. REV. 151, 181 (2013) (“[S]tatistics reflect industry practices that exploit and exacerbate existing inequalities. Credit card companies confine low-income individuals to a subprime market and attempt to steer many middle-class African American and Latinos into subprime loans.”)
“biased world” inputs, practically, these two types of biases are often indistinguishable.

The general reference to “borrower characteristics” masks the fact that any characteristic requires some sort of definition, measurement and estimation. For example, if we want to use a borrower’s income we have to define what income is and how to determine a borrower’s income. For example, we will need to determine whether certain transfers, such as gifts from relatives are considered income, or whether to consider public assistance income. It might also require a determination of the documentation needed to consider a transfer “income.”

Naturally, any way a characteristic is defined or measured will disadvantage certain borrowers, however, when a definition systematically disadvantages a protected group then it could be a case of a “measurement bias” input. This type of bias is separate from the concern that characteristics reflect existing disparity. Even if there was no disparity in the underlying characteristics, the imperfect measurement of the characteristic may be biased. If, for example, minorities are more likely to work in a number of jobs rather than one job, a lender that only includes data from one employer could introduce measurement bias.

Another type of “biased measurement” concern could arise when a substitute or a proxy is used in lieu of the characteristic that is of true interest. Often the variable that is of true interest is unobserved and so a lender might instead rely on a close substitute. Bias might be introduced when the substitute characteristic is not reflective of the underlying characteristic to the same extent for a protected group.

In Section 3.1.1 I provide an example in which a borrower’s “education” is used as a substitute for the borrower’s “ability,” which is relevant in determining future income. A lender may need to determine the extent to

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58 In fact, ECOA directly addresses this issue by prohibiting discrimination on the basis of whether an applicant is a recipient of public assistance income. The motivation behind adding this protected group was the conduct of lenders who refused to consider such income for the purpose of extending a loan. See Taylor, supra note 32, at 339.

59 See e.g., Kleinberg et al., supra note 37. (“The problem can arise not only when the firm collects information that is more favorable to one group than another, but also when the firm simply collects too little information overall.”) The type of measurement bias I discuss here is “feature bias,” which is bias in the right-hand variables, or the predictors x. There is a second type of measurement bias called “label bias,” which is bias in the left-hand variable, y. Label bias could arise, for example, when a recorded late payment is a noisy measurement of a true late payment. If whites are better at avoiding a late payment being formally recorded, then there is label bias. See Chander, supra note 40, at 17 (arguing that label bias is the more severe bias).

60 In the context of employment, this issue often arises when characteristics such as job performance are measured using information such as supervisor’s evaluations, which may be biased. See Kim, supra note 7, at 876.
which a borrower’s future income is stable or will increase and therefore may want to know a borrower’s “ability.” As “ability” is not observed by the lender, they could use borrower education as a proxy. If racial minorities are less likely to go to college for any given level of ability, this proxy will cause measurement bias. In this example, the problem I have highlighted is not necessarily created by pre-existing discrimination but by the imperfect measurement of the underlying variable of interest.

One central characteristic used to price credit, a borrower’s credit score, may suffer from measurement bias. The exact inputs and models used to determine a credit score, such as a FICO score, is proprietary information so that it is hard to know for certain how these scores may be biased. However, we do know that credit scores have traditionally only considered certain measures of creditworthiness like lending from large financial institutions and mortgage payments. Other measures of creditworthiness, such as timely rental payments or lending from smaller and more local financial institutions may be predictive of default.61

Although the theoretical distinction between “biased world” and “biased measurement” is clear, in many cases a variable might combine the two types of biases. For example, a borrower’s income could reflect both pre-existing discrimination in labor markets as well as some kind of measurement bias. This is problematic for the view that the use of variables that reflect a “biased world” are permissible while variables that reflect “biased measurement” are impermissible, discussed in more detail in Section 1.4.62

Moreover, it is unclear whether as an empirical matter it is possible to distinguish between these two types of biases. We can learn whether a certain variable correlates with race, but we might not be able to determine the origin of the correlation. Above I presented intuitive explanations for the reasons a

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61 The fact that only certain types of behaviors are measured by credit scores could mean that some borrowers are not scored at all. Variables that are “traditionally” used to generate a credit score are based on information in consumers’ credit files (history of payment of past obligations, amount owed, length of credit history and types of credit held). As a result, low-income consumers have low credit scores “simply because they have either a ‘thin file’ or ‘no file’. This means that they have very little reported credit history— often because low-income consumers are less likely to access the types of financial services that report to the traditional credit bureaus. A denial of credit to these consumers is based on the absence of credit history rather than anything negative in their credit histories. See Persis Yu et al., Big Data, a Big Disappointment for Scoring Consumer Creditworthiness, NAT’L CONSUMER L. CENTER page 12 Mar. 6, 2013. According to the CFPB, African-Americans and Latinos are more likely to be credit invisible, at rates of around 15% in comparison to 9% for whites. See The Consumer Financial Protection Bureau Office of Research, Data Point: Credit Invisibles, at 24-25 (May 2015), https://files.consumerfinance.gov/f/201505_cfpb_data-point-credit-invisibles.pdf.

62 See Kleinberg et al., supra note 37, for the distinction between “group differences in the raw data” and biases for the “choice of predictors.”
variable might correlate with race, but this is a far cry from establishing the source and explanation for the correlation, or whether it stems from pre-existing discrimination or measurement bias.

1.3 Why we care about accurate prediction

After considering the many ways in which credit decisions use biased inputs, a natural question is why personalize credit decisions at all. Lenders could set a flat price for credit, regardless of the particular characteristics of the borrower. This surely would avoid any issues of bias since the decision whether to extend a loan and at what terms would no longer use biased inputs. It is therefore important to consider whether there is value in credit decisions relying on accurate predictions of default that could potentially justify the use of biased inputs. My purpose is not to argue that all types of personalization of credit are beneficial, or that extending credit even at high interest rates is beneficial. Rather I wish to demonstrate that we should not reject price personalization at the outset.

There are several reasons that accurate default prediction is beneficial for both lenders and borrowers, and provide reasons we would want to personalize credit pricing despite the problem of biased inputs. The first reason is that default causes a loss for lenders. Therefore, when a lender can accurately predict default they can determine a cutoff for extending a loan or price risk accordingly. Inaccurate default prediction could also hurt consumers. The accurate prediction of default may mean that certain customers do not receive loans, however, this may be beneficial to consumers if we consider that default and foreclosure are very costly for consumers.

The accurate pricing of credit could also mean the ultimate expansion of access to credit. When lenders cannot distinguish between the risk of different borrowers, they may avoid lending to larger groups of applicants. The more

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63 A similar pricing method referred to as “average-cost pricing” was sometimes used in traditional credit pricing. See Patricia A. McCoy, Rethinking Disclosure in a World of Risk-Based Pricing, 44 HARV. J. ON LEGIS. 123, 126 (2007), (“a lender aggregates individual credit risks and computes one price for all of its prime borrowers based on the average. As a result, for any given loan product, such as a thirty-year fixed-rate mortgage with no points, a lender will charge all of its prime borrowers an identical price.”)

64 This is often referred to as Risk Based Pricing. See Robert Phillips, Optimizing Prices for Consumer Credit, 12 J. REVENUE PRICING MGMT 360 (2013), (“a riskier customer should pay a higher price in order to compensate for the higher probability of default and the associated cost to the lender”). See also Michael Staten, Risk-Based Pricing in Consumer Lending, J.L. ECON. & POL’Y 33 (2015).

65 See John Gathergood et al., How Do Payday Loans Affect Borrowers? Evidence from the U.K. Market, 32 REV. FIN. STUD. 496 (2019) (showing that at the credit score discontinuity for payday loans, consumers who received a loan were more likely to default and exceed bank overdraft limits).
accurate a lender’s prediction, the more they are able to distinguish borrowers with different levels of risk. This may mean that some borrowers are less risky than previously believed which will expand access to credit, or than even riskier borrowers can receive a loan at a certain cost.\textsuperscript{66} This is particularly likely to be the case in the tails of default prediction, meaning people with higher probability of default.

The use of biased inputs, both “biased world” and “biased measurement,” could increase prediction accuracy. This suggests that there may be a tradeoff between accuracy predictions and price disparities. However, it is important to note that variables that suffer from biased measurement could also cause a decrease in prediction accuracy. For example, if income is a good predictor of default, then a noisy measurement in income could also lead to a less accurate prediction of default. The question with “biased measurement” inputs is therefore the degree to which the noise undermines the benefits of accuracy, and whether there is a better alternative available.

1.4 Traditional fair lending law

Fair lending law is the primary lens through which to consider the personalization of credit pricing. Therefore, in this Section I provide an overview of fair lending law, which covers both the doctrine of disparate treatment, dealing with intentional discrimination, as well as disparate impact, dealing with facially neutral rules that have an impermissible impact. Given that there are ongoing disputes with respect to the foundations and scope of the disparate impact doctrine, I discuss how the different positions view the problem of biased inputs, but I do not adopt a particular interpretation. I end by highlighting how the disagreements over the boundaries of the doctrine have come to the forefront with a new proposed rule by the Department of Housing and Urban Development (HUD).

The two laws that form the core of credit pricing discrimination are the Fair Housing Act (FHA) of 1968 and the Equal Credit Opportunity Act (ECOA) of 1974. The FHA, also known as Title VIII of the Civil Rights Act of 1968, protects renters and buyers from discrimination by sellers or landlords and covers a range of housing related conduct including the setting of credit terms.\textsuperscript{67} The FHA prohibits discrimination in the terms of credit

\textsuperscript{66} See Liran Einav at al., \textit{The impact of credit scoring on consumer lending}, 44 RAND J. ECON. 249 (2013) (showing that the adoption of an automated credit scoring at a large auto finance company improved the pricing process of the loans and led to a large increase in profitability. This led to “[l]ending to the highest-risk applicants contracted due to more stringent down payment requirements, and lending to lower-risk borrowers expanded, driven by more generous financing for higher-quality, and more expensive cars.”)

\textsuperscript{67} In 1988 the Fair Housing Amendments Act was passed, strengthening the mortgage lending provisions of the FHA.
based on race, color, religion, sex, disability, familial status and national origins. In 1974, Congress passed the Equal Credit Opportunity Act (ECOA), banning discrimination in all types of credit transactions. ECOA therefore complements FHA by expanding discrimination provisions to other credit contexts beyond housing related credit. Initially ECOA only covered sex and marital status discrimination but was then amended in 1976 to also cover race, color, religion and other grounds of discrimination.

ECOA and FHA cover both discrimination doctrines of “disparate treatment,” dealing with the direct condition of a decision on a protected characteristic, often with intent to discriminate, and “disparate impact,” which typically involves a facially neutral rule that has a disparate effect on protected groups. ECOA and FHA do not explicitly recognize the two discrimination doctrines in the language of the law itself, however, the disparate impact doctrine has been recognized in the case of credit pricing by courts and agencies in charge of enforcing the laws. The Supreme Court recently affirmed that disparate impact claims could be made under the FHA in Inclusive Communities, confirming the position of eleven appellate courts and various federal agencies including the HUD primarily responsible for enforcing the FHA. Although there is not an equivalent Supreme Court

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69 In this article, I do not focus on other laws that have additional provisions that relating to credit pricing discrimination that are not my focus in this Article. The Community Reinvestment Act (CRA) of 1977, encourages banks and other lenders to address the needs of low-income households within the areas they operate, which often overlaps with serving racial minority areas. The CRA does not give a right to private action but rather instructs the relevant supervisory agency on how to oversee that institutions are serving the lending needs of their community. Another federal law related to credit pricing discrimination is the Home Mortgage Disclosure Act (HMDA) (12 U.S.C. § 2801) (1989), which requires that certain financial institutions make regular disclosures to the public on mortgage applications and lending. Although HMDA does not contain any explicit discrimination provisions, one of its purposes is to allow the public and regulators to consider whether lenders are treating certain borrowers in certain areas differently. HMDA was expanded in 1989 to require a wider number of variables to be reported by mortgage lenders. See The Financial Institutions Reform, Recovery, and Enforcement Act (FIRREA) (12 U.S.C. §1811) (1989). The empirical sections of this Article rely on HMDA data.
71 See Robert G. Schwemm, Fair Housing Litigation after Inclusive Communities: What’s New and What’s Not, COLUM. L. REV. SIDEBAR 106, 106 (2015). (“The Court's 5-4 decision in the ICP case endorsed forty years of practice under the FHA, during which the impact theory of liability had been adopted by all eleven federal appellate courts to consider the matter. This theory had also been adopted by various federal agencies, including the Department of Housing and Urban Development (HUD), the agency primarily responsible for enforcing the FHA.”)
case with respect to ECOA, the Consumer Financial Protection Bureau and courts have found that the statute allows for a claim of disparate impact.72

Disparate treatment involves the direct conditioning of the decision on a protected characteristic and therefore focuses on the causal connection between a protected characteristic and a credit decision. The doctrine could be triggered by directly considering a protected characteristic, such as race, in a specific credit decision73 or when a protected characteristic is used in setting general lending policy, such as in the case of “redlining.”74 Disparate treatment identifies cases in which a protected characteristic directly influenced and a credit decision, it therefore is concerned with the causal relationship between protected characteristics and decisions.

Disparate impact, the second discrimination doctrine under FHA and ECOA, covers cases in which a facially neutral rule has an impermissible disparate effect. A disparate impact case typically follows the burden-shifting framework that was developed primarily in the Title VII employment

72 See e.g., Ramirez v. GreenPoint Mortgage Funding, Inc, 633 F. Supp. 2d 922, 926–27 (N.D. Cal. 2008). The CFPB has recently proposed abandoning disparate impact liability under the ECOA. Compare Consumer Financial Protection Bureau, Consumer Laws and Regulations: Equal Credit Opportunity Act (June, 2013) (“The ECOA has two principal theories of liability: disparate impact and disparate theory.”) with Mick Mulvaney, Statement of the Bureau of Consumer Financial Protection on Enactment of SJ Res 57 (Consumer Financial Protection Bureau, May 21, 2018) (stating that the CFPB will reexamine its guidance on disparate impact liability under the ECOA in light of “recent Supreme Court decisions distinguishing between antidiscrimination statutes that refer to the consequences of action and those that refer only to the intent of the actor”). For a skeptical view of whether the statutory language of ECOA supports disparate impact see Peter N. Cubita & Michelle Hartmann, The ECOA Discrimination Proscription and Disparate Impact - Interpreting the Meaning of the Words That Actually Are There Survey - Consumer Financial Services Law, BUS. LAW 829 (2005–2006).

73 Few FHA cases have dealt with overtly discriminatory lenders. One exception is an early FHA case from 1977 in which a loan officer made several explicitly racist statements. See Harrison v. Otto G. Heinzeroth Mortgage Company, 430 F. Supp. 893 (N.D. Ohio 1977). In general, the FHA initially did not lead to many mortgage discrimination cases. See ROBERT G. SCHWEMM, HOUSING DISCRIMINATION: LAW AND LITIGATION (1990). See also Id. at 318, (discussing overlapping coverage of FHA and ECOA).

74 Redlining is the practice of denying credit to borrowers from predominantly minority neighborhoods and is typically considered a case of disparate treatment. Some early trial cases established the disparate treatment claim under the theory of “redlining”. See Laufman v. Oakley Building & Loan Company, 408 F. Supp. 489 (S.D. Ohio 1976). At first blush it may seem surprising that complaints that attack geographical lending criteria are litigated under the disparate treatment, given the facially neutral nature of the criteria which would seem more appropriate for the disparate impact doctrine. However, even if the race of the borrower is not directly considered, the racial composition of an area was used to make a loan decision and therefore the decision depended directly on a protected characteristic. Moreover, for many years geographical lines were so strongly associated with racial divisions that it seemed natural for litigants to consider geographical criteria as being close to racial criteria.
discrimination context. The first step of the framework is a *prima facie* showing of a disparate outcome for a protected group by the plaintiff. This requires the plaintiff to identify the specific conduct or policy that led to the disparate outcomes. Once a plaintiff has established the disparate outcome and the cause of the outcome, the burden shifts to the defendant to demonstrate that there was a business justification for the conduct or policy that led to disparity. The burden then shifts back to the plaintiff to demonstrate whether there was a less discriminatory way to achieve that same goal.

In spite of the formally coherent structure of a disparate impact claim, there is significant disagreement over the philosophical foundations of the doctrine and whether case law and regulatory action are consistent with those foundations. One of the most important disagreements is over the extent to which disparate impact is meant to address cases that are more about effect than intent. According to one theory, which I call the “intent-based” theory, disparate impact treats unjustified discriminatory effects as a proxy for the true concern of interest which is the discriminatory intent.

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75 Disparate impact first entered US law in the 1971 breakthrough case Griggs v. Duke Power Company, 401 U.S. 424 (1971), in which hiring requirements of a high school diploma and an aptitude test were challenged. A formal burden shifting framework was articulated in the subsequent employment decision Albermarle Paper Co. v. Moody, 422 U.S. 405 (1975), and this was articulated into the three-step burden-shifting approach that is applied today. This burden-shifting framework was formalized into the language of Title VII in §703(k), added by the Civil Rights Act of 1991. A similar language exists in Implementation of the Fair Housing Act’s Discriminatory Effects Standard, 78 Fed. Reg. 30, 11460 (Feb. 15, 2013) (codified at 24 C.F.R. § 100.500) [hereinafter HUD 2013 Disparate Impact Rule]. See Regulation B, §202.6, footnote 2 (discussing the relevance of Title VII for interpreting fair lending disparate impact). See also Equal Credit Opportunity, 41 Fed. Reg. 29870, 29874 (July 20, 1976) (“Congress intended certain judicial decisions enunciating this “effects test” from the employment area to be applied in the credit area.”)

76 A central question in this context is what type of business justification can be considered legitimate. See Louis Kaplow, Balancing Versus Structured Decision Procedures: Antitrust, Title VII Disparate Impact, and Constitutional Law Strict Scrutiny (forthcoming), for a detailed discussion of this burden shifting framework in the context of employment discrimination.

77 For an articulation of these disagreements see Richard A. Primus, *Equal Protection and Disparate Impact: Round Three*, HARV. L. REV. 494, 520 (2003–2004). Another way of articulating this dispute is by asking whether and how disparate treatment and disparate impact are different. This is far from the only topic of debate around disparate impact, or “indirect discrimination,” a similar doctrine in the Europe and many other countries. For example, one important question is the extent to which disparate impact and indirect discrimination represents a moral wrong, or whether there is some other policy justification for the doctrine. A related question is whether disparate impact should in fact be considered discrimination at all. See generally Mark MacCarthy, *Standards of Fairness for Disparate Impact Assessment of Big Data Algorithms*, 48 CUMB. L. REV. 67 (2017–2018).

78 See Nicholas O. Stephanopoulos, *Disparate Impact, Unified Law*, 128 YALE L. J. 1566
emphasizes disparate impact’s ability to unearth cases in which there is a discriminatory motive that is hard to prove.\footnote{79}

A second theory of disparate impact is that disparate outcomes are a concern in of themselves and so the purpose of the disparate impact doctrine is to improve the position of minorities by “preventing their existing disadvantages from spreading into new areas, and ultimately to undermine the entrenched racial hierarchies of American society.”\footnote{80} This second theory has also characterized disparate impact as “disturbing in itself, in the sense that a practice that produces such an impact helps entrench something like a caste system.”\footnote{81} This theory of disparate impact, which I call the “effect-based” theory of disparate impact, views intent as irrelevant and not only for evidentiary reasons but because even lack of intention could lead to disparate impact.\footnote{82}

\footnote{79} Another distinction that is often made, primarily in the context of the Equal Protect Clause, is between legal scholars who argue that discrimination law is meant to target arbitrary misclassification of individuals (“anticlassification”) and scholars who assert that discrimination law targets practices that disadvantage groups or perpetuate disadvantage (“antisubordination”). See e.g., Jack M. Balkin & Reva B. Siegel, *American Civil Rights Tradition: Anticlassification or Antisubordination Fiss’s Way: The Scholarship of Owen Fiss: I. Equality*, U. MIAMI L. REV. 9 (2003–2004). Balkin and Siegel’s primary focus is focus on the Equal Protection Clause, however, they point out that an anticlassification reading of Title VII disparate impact would view the doctrine as primarily concerned with implicit disparate treatment. *Id.* at 22.

\footnote{80} Stephanopoulos, supra note 80, at 1604. See also Samuel R. Bagenstos, *Disparate Impact and the Role of Classification and Motivation in Equal Protection Law after Inclusive Communities*, CORNELL L. REV. 1115, 1132 (2015–2016).


\footnote{82} Despite the large conceptual difference between intent-based and effect-based theories of disparate impact, many cases are somewhat consistent with both understandings of the doctrine. Bagenstos argues that Griggs is consistent with both understandings of disparate impact. See Bagenstos, supra note 82, at 1132.. In the context of fair lending, this is because the cases in which disparate impact is applied are somewhat vague, such as the cases which challenge the practice of mortgage originators to allow loan officers discretion in setting loan terms. These cases argue that the loan officer discretion leads to higher rates for minority borrowers. See Ian Ayres et al., *The Rise and (Potential) Fall of Disparate Impact Lending Litigation*, in EVIDENCE AND INNOVATION IN HOUSING LAW AND POLICY 231 (2017).) The central question is how the loan officers were exercising their discretion, and whether they were intentionally discriminating against racial minorities. Based on this ambiguity, Schwemm and Taren argue that these cases may be considered a hybrid impact/intention case. This is because the conduct being scrutinized is the discretion provided to brokers that resulted in a disparate impact on minorities. However, it is this discretion that may have allowed brokers to intentionally discriminate against minorities. See Robert G. Schwemm & Jeffrey L. Taren, *Discretionary Pricing, Mortgage Discrimination, and the Fair Housing Act*, HARV. C.R.-C.L. L. REV. 375, 406 (2010). Proponents of the intent-based theory would emphasize the fact that underlying these cases is the concern that mortgage brokers were directly considering race in setting terms condition. On the other
Under both theories, the need to establish causal connections between “policies” and “outcomes” is at the heart of disparate impact. Firstly, it is important to establish the causal link between a policy and a disparate outcome for a prima facie claim of disparate impact, so that the plaintiff is required to identify a specific policy that caused disparity. The stringency of this requirement will determine how broad or limited a disparate impact claim can be.

In the second stage of the burden shifting framework, a defendant must demonstrate the causal link between the policy that caused disparity and a business justification to rely on the defense. The legitimate business justification, particularly in cases in which a biased input lead to biased outcomes, relies on the argument that biased input is causally relevant for the outcome of interest, such as the creditworthiness of the borrowers. The burden on the defendant in establishing this causal link, as well as the types of justifications that are legitimate will also help determine how broad or narrow a disparate impact claim can be.

The emphasis on establishing these causal connections reflects the centrality of input scrutiny for both disparate treatment and disparate impact. Disparate treatment is concerned with the direct conditioning on a protected characteristic and therefore is clearly concerned with scrutinizing whether a protected characteristic was an input to the decision. Disparate impact, despite its name, is also concerned with the inputs into a decision. Although the prima facie case requires an outcome-focused analysis, after this initial showing the focus becomes on what inputs created this disparate and whether they related to a legitimate business justification.

hand, proponents of the effect-based theory can point to the fact that the cases do not claim any intent on the part of the mortgage originators who are the target of the discrimination claim

83 This requirement is part of the first stage of the burden shifting framework, which initiates a disparate impact claim. According to the HUD Joint Policy statement, the plaintiff needs to “identify the specific practice that cause the alleged discriminatory effect”. See Policy Statement on Discrimination in Lending, 59 Fed. Reg. 18266(Apr. 15, 1994). But there is a caveat that should be looked into more carefully, namely that “it may be appropriate to challenge the decision-making process as a whole”. See HUD 2013 Disparate Impact Rule, at 11469. The Supreme Court in Inclusive Communities, emphasized the requirement that a plaintiff identify a specific practice and establish the causal connection between the practice and disparate outcome: “a disparate-impact claim that relies on a statistical disparity must fail if the plaintiff cannot point to a defendant’s policy or policies causing that disparity… A plaintiff who fails to allege facts at the pleading stage or produce statistical evidence demonstrating a causal connection cannot make out a prima facie case of disparate impact.” Texas Dep’t of Hous. and Cmty. Affairs v. Inclusive Cmty. Project, Inc., 135 S. Ct. 2507 (U.S. 2015). For a discussion of whether and how Inclusive Communities differs from the HUD joint policy, see: Schwemm, supra note 73. See also supra note 14.

84 This returns to the question of whether profitability, beyond creditworthiness, can be a legitimate business justification.
To return to the two categories of biased inputs, does the use of “biased world” or “biased measurement” inputs trigger discrimination law? On one account the use of bias inputs should not trigger the doctrine of disparate treatment since there is no direct conditioning on a protected characteristic. Similarly, the use of bias inputs should not give rise to a claim of disparate impact since “biased world” inputs are not a result of any actions on the part of the mortgage originator and will continue to exist regardless of the actions of the mortgage originator.\(^85\) However, the effect-based theory of disparate impact may be wary of the use of “biased world” inputs if they entrench and compound existing disadvantage. Under either approach we may be concerned when a biased input highly correlates with a protect characteristic that it becomes a “proxy” for the characteristic.\(^86\)

The use of “biased measurement” inputs arguably gives rise to more liability on the part of the lender. This is because the lender may have a choice how to measure an underlying characteristic or may be able to exert effort to avoid biased measurement. For example, a lender could create a procedure for verifying income from multiple employers and sources, and measure income that is less consistent or formal. A decision to continue to rely on employment income only, which may be a noisy estimate of income, could arguably be a policy choice that triggers a disparate impact claim.\(^87\)

However, the degree of choice for a lender in using “biased measurement” inputs versus “biased world” inputs may be overstated. Firstly, as discussed above, in most cases a characteristic may by a hybrid of both a biased world and biased measurement, such as in a case of income. Second, as an empirical matter, a lender might know whether a characteristic is correlated with race but not whether this is because of biased world or biased measurement. A further issue relates to what is reasonable to expect from a lender in avoiding measurement bias inputs. As mentioned above, credit

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\(^85\) This may depend on the interpretation of the business justification. If a lender used biased inputs to predict willingness-to-pay, and this type of prediction is not a legitimate business justification, then the conduct could trigger discrimination law. Typically, the prediction of default as the basis for pricing is the least controversial of the business justifications a lender can provide.

\(^86\) This is discussed in detail in Part III.

\(^87\) The use of a “biased measurement” input may also reflect discriminatory intent. Once a lender faces a choice in the way they define and measure a variable, a lender’s intention may come into play. Once we can scrutinize a lender’s intention, the intent-based theory of disparate impact may have issue with a lender’s choices. This Article does not fully address the issue of a lender who disguises their discriminatory intent through algorithmic decision-making. For further discussion of this type of discrimination see Kleinberg et al., supra note 37, at 29. (“The human algorithm builder might also choose to collect candidate predictors that are human judgments, rather than objective measures of reality, and these can lead to difficulties in much the same way that using human judgments as outcome variables can cause problems.”)
scores are likely to be a biased measurement of credit worthiness because they focus on certain behaviors that signal creditworthiness and not others, such as timely rental payments. It seems unreasonable to expect a lender to collect all the information a credit bureau would collect along with other consumer payment behaviors in order to address the issue of biased measurement.

In Part III, I discuss current positions on how to apply discrimination law to an algorithmic context given the challenge of biased inputs. I analyze four positions that represent a range of views on how to understand the role and definition of discrimination law. I begin by discussing the approach of excluding protected characteristics. This approach has been argued as sufficient to negate a discrimination claim, both disparate treatment and disparate impact, according to the intent-based theory of disparate impact. I then discuss approaches that further exclude inputs that correlate with protected characteristics, more in line with the effects-based theory of disparate impact. I end my discussion with a statistical approach to orthogonalizing inputs to an algorithm.

In conclusion, although there is general agreement that fair lending law covers both the disparate treatment and disparate impact doctrines, there is disagreement on the theoretical basis and the boundaries of disparate impact. These disagreements have implications for the legality of using biased inputs, an issue that will become more pronounced in the algorithmic context, as discussed in the next part.

In any event, under both discrimination doctrine—disparate treatment and disparate impact—and either theory of disparate impact—intent-based or effects-based, the focus is on input scrutiny. Disparate treatment centers around the question of whether a protected characteristic was used to make a lending decision. Disparate impact, after an initial demonstration of outcome disparities for the prima facie case, primarily focuses on whether a particular input is driving disparities. This focus on inputs also plays a central role in the second stage of the burden-shifting framework, as defendants are called upon to demonstrate that the inputs that are challenged serve a legitimate business necessity.

II. THE CHANGING WORLD OF CREDIT LENDING

In this Part, I discuss how the way we price credit is moving away from pricing that relies on few variables and involves human discretion in setting the final terms to a world in which big data and machine learning are instead

88 See infra Section 3.1.
89 See infra Section 3.2 and 3.3.
90 See infra Section 3.4.
used to price credit. This is likely to change the ways in which we determine whether a pricing method amounts to “disparate treatment” or whether it causes “disparate impact.”

I begin this Part by describing the changes taking place in the context of credit pricing on which I focus in this Article. I then present the central methodology of my Article, which is a simulation exercise in which a hypothetical lender uses machine learning to price credit. Building on the simulation exercise, the Part ends with a discussion of the meaning of the changes for pricing using biased inputs and the application of fair lending law. My conclusion is that algorithmic pricing could in some cases exacerbate the problem of biased inputs but in other cases mitigate the harm.

In analyzing the changes in credit pricing and their implications, a central question that arises concerns the baseline for the comparison. One can consider a range of credit pricing, from human decision-making to machine learning. At one end of the spectrum lies pricing that relies solely on the human discretion of loan officers. A second type of pricing uses defined variables, but human experts determined the weights assigned to the variables. A third option is that credit pricing relies on an empirical method, such as a linear regression, to determine the weights assigned to the variable. Finally, at the other end of the spectrum, credit pricing can rely on big data and advance prediction technologies. For some of my analysis, the focus is on the move from linear regression pricing to machine learning pricing. When discussing changes in human discretion in setting the terms, I primarily focus on the change from the first and second type of pricing to machine-learning pricing.

2.1 What is changing?

The ways in which people receive credit and how the terms of credit are determined is rapidly evolving. These changes form part of the larger revolution brought on by the Fintech industry, a term used to describe the segment of financial services characterized by digital innovations and technology-enabled business model innovations. In this Article, I focus on

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91 “Fintech” covers a large range of financial activity, including payment and trading systems, meaning that credit pricing is merely one sector of Fintech. Technology has also changed credit markets in ways not directly related to the use of big data and prediction methods. For example, in mortgage markets, one of the biggest changes in recent years has been the increase in online platforms that offer mortgages, such as “Rocket Mortgage” (https://www.rocketmortgage.com), which allows consumers to conduct the full process of mortgage origination online. Other Fintech mortgage lenders have developed a complete end-to-end online mortgage application and approval process. This creates automation not only with respect to determining the price of credit but also related to the bureaucratic aspects of a mortgage.
the technological change in the pricing of credit and the role of artificial intelligence.\textsuperscript{92} I focus on three aspects that are reshaping the personalization of credit pricing, namely the use of non-traditional data and advance prediction technologies, and the automation of lending decisions.

There are an increasing number of companies that provide alternatives to traditional lenders, like banks and mortgage originators, which includes the way in which these companies approve and price loans.\textsuperscript{93} In addition, many traditional lenders are using the services of third parties that engage in alternative ways of predicting creditworthiness and pricing credit.\textsuperscript{94} These changes are occurring in many domains of lending, including mortgages, auto loans,\textsuperscript{95} credit card lending, and personal loans.

Many lenders, particularly in the Fintech and non-bank sector, have incorporated a version of all three trends. However, some lenders have only partially adopted some of these changes. For example, some lenders may be using machine learning in forming predictions that are then used by the loan officer making the financial decisions. Therefore, the move to the new world of credit should be considered as a continuum at which on one end there is traditional lending that determines the price of credit with a limited set of variables and human discretion, and at the other end, there are lenders who uses big data and machine learning to make automated credit decisions.

The Fintech market share in borrowing services is significant and increasing. According to one estimate, 82\% of lenders report using

\textsuperscript{92} There are many ways in which artificial intelligence can assist with the process of lending in ways that are separate from their prediction of credit worthiness. For example, AI can help with organizing and reading paperwork, which is especially onerous in the case of mortgage. AI can also allow for information to be gathered in a more efficient way than with a loan officer who asks questions and records answers.

\textsuperscript{93} For example, Upstart (https://www.upstart.com), uses education and other academic variables to set the price of credit, based on the idea that these variables measure propensity to pay that may not be reflected in characteristics like FICO scores. Another company, Lendbuzz (https://lendbuzz.com), targets populations that may not have easy access to credit, such as foreign students who are less likely to have US credit histories.

\textsuperscript{94} For example, ZestFinance (https://www.zestfinance.com), uses machine-learning to predict creditworthiness by providing modeling services that utilize the data already held by lenders. In approving personal loans it helps lenders use information from the loan application process to identify individuals who are likely not to pay back the loan. See AnnaMaria Andriotis, \textit{Shopping at Discount Stores Could Help Get You a Loan}, \textit{Wall Street J.} (Mar. 4, 2019), https://www.wsj.com/articles/use-a-landline-that-could-help-you-get-a-loan-from-discover-11551695400. See also https://www.underwrite.ai; Lenddo, SAS, Equifax, and Kreditech

\textsuperscript{95} See Becky Yerak, \textit{AI Helps Auto-loan Company Handle Industry’s Trickiest Turn}, \textit{Wall Street J} (Jan. 3, 2019), https://www.wsj.com/articles/ai-helps-auto-loan-company-handle-industrys-trickiest-turn-11546516801 (using 2,700 characteristics instead of the few it was using before). Other companies that have embraced this type of lending. For example, Synchrony Financial and Ford Motor Credit Co.
nontraditional and alternative data in lending decisions. The segment of the lending sector that relies on machine learning and big data is also likely to increase over time. A recent survey by Fannie Mae found that 27% of mortgage originators currently use machine learning and artificial intelligence in their origination process whereas 58% of mortgage originators expect to adopt the technology within two years.

2.1.1 Nontraditional data

The first change taking place in the world of credit is the expansion of credit decision “inputs” to nontraditional data. Data such as payment and consumer behavior, social media behavior, and digital footprints are being increasingly used to price credit, unlike traditional lending, which relied on relatively few defined characteristics.

Lenders are increasingly using borrower characteristics that although intuitively seem relevant to creditworthiness, were not traditionally used to


97 See Fannie Mae, Mortgage Lender Sentiment Survey: How Will Artificial Intelligence Shape Mortgage Lending (Oct. 4, 2018), http://www.fanniemae.com/resources/file/research/mlss/pdf/mlss-artificial-intelligence-100418.pdf. It is important to keep in mind that this is the utilization of AI in all aspects of the process, not only risk assessment. For example, use of AI to enhance consumer experience.

98 See Request for Information Regarding Use of Alternative Data and Modeling Techniques in the Credit Process, 82 Fed. Reg. 11183 (Feb. 21, 2017), for a definition of traditional data (“data assembled and managed in the core credit files of the nationwide consumer reporting agencies, which includes tradeline information (including certain loan or credit limit information, debt repayment history, and account status), and credit inquiries, as well as information from public records relating to civil judgments, tax liens, and bankruptcies. It also refers to data customarily provided by consumers as part of applications for credit, such as income or length of time in residence.”) See Hurley & Adebayo, supra note 7, at 162, for a useful overview of some of the non-traditional data sources. The use of non-traditional data is also taking place in other domains in which algorithms are used to make decisions. In the context of employment decisions see Kim, supra note 7, at 861 (“…data models do not rely on traditional indicia like formal education or on-the-job experience. Instead, they exploit the information in large datasets containing thousands of bits of information about individual attributes and behaviors.”)
price credit. For example, information on education, such as the school attended and degree attained,\textsuperscript{99} along GPA and SAT scores,\textsuperscript{100} intuitively relate to a borrower’s future income and are therefore relevant to default risk. This type of information is particularly valuable for young borrowers who have yet to build up a credit history and therefore have had difficulty obtaining certain types of loans.\textsuperscript{101}

In addition, other types of consumer payment behaviors, those that have traditionally been excluded from credit score models, are being used to predict creditworthiness. Credit scores have traditionally only used loan payments to large and established financial institutions to determine creditworthiness. Lenders are therefore increasingly using information on timely payment of utility bills and rent payments as indicators of creditworthiness for people without credit history.\textsuperscript{102} Similarly, data on phone bills and short-term loans, which were often not included in credit files, are now used by Fintech lenders. Companies with rich information on consumer behavior, such as Alibaba, are using this information to create alternative credit scores.\textsuperscript{103}

Consumer behaviors specifically at the time the loan is requested are also being used in pricing credit. For example, a recent paper looks at the use of “digital footprint” data, such as the device and operating system used by the consumer when using a furniture purchasing website, to determine creditworthiness.\textsuperscript{104} These digital footprints predicted default slightly better than did traditional credit bureau scores, suggesting that the digital footprints hold information that is not contained in credit scores.\textsuperscript{105} The use of these types of data may be particularly valuable for lenders who focus on short-term lending that is attached to a consumer purchase. For example, an

\textsuperscript{99} \textit{supra} note 98., page 10.
\textsuperscript{100} \textit{See} for example Upstart (https://www.upstart.com). This is information that was is typically not considered in credit scoring, such as FICO scores. \textit{See} Hurley & Adebayo, \textit{supra} note 7, at 9.
\textsuperscript{101} In some cases, traditional credit rating agencies, recognizing the problem that many people do not have adequate credit histories, have begun to develop their own alternative credit files. FICO Expansion, for example, considers debit data and utility data among other types of data
\textsuperscript{102} \textit{supra} note 98.Aite, page 7. Credit bureaus are becoming increasingly aware of this problem and so solutions, such as Experian’s RentBureau, allow consumers to incorporate information about rent payment history into their credit file. This indicates that non-traditional data may over time be incorporated into traditional metrics.
\textsuperscript{103} For example, Sesame Credit.
\textsuperscript{105} \textit{See} Id. The combination of the digital footprints with traditional bureau scores provided the most accurate prediction. This suggests that digital footprints and traditional scores are complements rather than substitutes.
increasing number of consumer websites are using a ship-first pay-later methods in which goods are shipped before they are paid for, creating a quasi short-term loan.

Fintech lenders are also using social media to price credit and to verify borrower information. Although social media data might not intuitively seem related to credit worthiness, third parties are using this information to provide lenders with alternative or additional data on borrowers. In addition, social media data can be used to verify borrower information.

2.1.2 Advance prediction technologies

Traditional credit pricing used simple models for differentiating among people in terms of their default risk, as discussed in Part I. In recent years, credit pricing is increasingly using more complex prediction methods, such as machine learning, that allow for more accurate default prediction. These advance prediction technologies can be differentiated from more traditional types of credit scoring in which the weight that various variables receive is determined at the outset. In the case of machine learning, the algorithm itself determines which inputs to use and what weights to assign them in reaching an accurate prediction. This means not only that there is less control ex ante on the model the algorithm produces but also that the prediction is potentially much more accurate.

The increased use of nontraditional data and machine learning are closely related to one another. This is because the use of nontraditional data increases the number of characteristics used to predict creditworthiness, and neither

106 See discussion in Chris Brummer & Yesha Yadav, Fintech and the Innovation Trilemma, 107 GEO. L.J. 235, 265 (2018–2019) (“Importantly, unlike in earlier decades, when information on underlying loans or mortgage-backed securities was sourced through central nodes of information—such as credit rating agencies or conventional news organizations—today the production of digital data is often decentralized. Specifically, data emerges from a diffuse proliferation of websites, social media, and various genres of news sources and databases”). See also Rose Eveleth, Credit Scores Could Soon Get Even Creepier and More Biased, VICE (Jun. 13, 2019), https://www.vice.com/en_us/article/zmpgp9/credit-scores-could-soon-get-even-creepier-and-more-biased.

107 Throughout this Article I focus on lender’s attempts to predict default. However, verification of data may be more important than the accurate pricing for mortgage lenders who sell their mortgages on the secondary market. This is because after the sale of the loan, lenders only face the risk of unverified information and not default risk.

108 See Hurley & Adebayo, supra note 7, at 162. (“The basic FICO score, for instance, considers an individual's payment history, outstanding debt, length of credit history, pursuit of new credit, and debt-to-credit ratio in determining a credit score. The model assigns a numeric value for each of these five variables, and then applies a pre-determined weight (in percentage terms) to each of these input values and averages them to arrive at a final credit score.”)
traditional prediction techniques nor human decision-makers are well-suited for high-dimensional data, a term used to describe data that contain many characteristics. Moreover, when characteristics do not bear an immediate and intuitive relation to the outcome of interest, it is difficult to determine which model to use in relating inputs to outcomes. Machine learning is optimal for this setting because it is designed to overcome difficulties in high-dimensional data and uses nonintuitive correlations to form accurate predictions.

The increase in prediction accuracy comes at a price of lower interpretability. Because machine learning algorithms are set up to optimize prediction accuracy, and not to produce a meaningful model of how inputs relate to outcomes, the algorithm outputs are not always easy to interpret. This issue that has received considerable attention in both academic and policy circles and has been the motivation behind legislation that attempts to mitigate the harms that stem from uninterpretable algorithms.109

2.1.3 Automation

An additional important trend in credit lending is the automation of credit pricing, meaning the reduction of human involvement and discretion is setting prices. In an automated context, once the characteristics of the borrower and loan are set, the price of lending is automatically determined by some function or algorithm. This is a significant departure from some categories of traditional lending, particularly larger loans such as mortgages, which typically involved a broker and employee who would meet face-to-face with borrowers to determine the exact terms of the loan. Although these loans included a formulaic or automated aspect,110 the ultimate loan terms could not be known unless a borrower was to complete the application process.

Automation can offer several benefits. First, it may allow for a more efficient process of pricing and approving loans and a greater ability to adjust to changes in lending markets.111 In addition, it may avoid errors in human

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110 For example, credit scores typically use some sort of algorithm to determine creditworthiness. Credit scores can either be used as a dimension used to price credit or the only determinant of credit price. In addition, Fannie Mae and Freddie Mac have typically used some type of algorithm to determine the price at which they purchase mortgages.

111 See Andreas Fuster et al., The Role of Technology in Mortgage Lending, 32 REV. FIN. STUD. 1854 (2019).
judgment with respect to evaluating credit worthiness.\textsuperscript{112}

The reason I focus on the trend towards automation, even in highly personalized credit decisions such as mortgages, is that fair lending law has longed focused on the human decision-making context. Automation on the one hand provides an important opportunity for increased transparency, because in the human context it is difficult to determine which factors were used in making a decision, which can more easily be determined in the automated context. On the other hand, the automated context forces the development of a clear legal definition of which factors are permissible in making a credit decision.

\section*{2.2 Simulation exercise – hypothetical “new world” credit lender}

To consider the implications of the change on credit pricing, I use a hypothetical “new world” lender. This lender takes data on past loans and their performance to predict the default risk of new borrowers. The lender then uses the predicted default risk to price credit. For example, the lender may determine that people above a certain risk of default will pay a higher interest rate on the loan. This hypothetical lender is a “new world” lender because it uses past loan information to form predictions using machine learning.

New world credit lenders are likely to rely on data from past loans or data collected by third parties when predicting credit worthiness. Some lenders have been providing loans for years and even decades and could use information on their past loans to predict the creditworthiness of future borrowers. Similarly, some financial institutions may have other information about consumers, which they can then use to form predictions, such as a retail bank that also provides loans. Because machine learning requires training data, new lenders or lenders seeking to improve predictions might rely on third parties that collect information on consumer and payment behaviors, which is then used to train algorithms.\textsuperscript{113}

My hypothetical lender uses loan information reported by mortgage lenders under the Home Mortgage Disclosure Act (HMDA)\textsuperscript{114} to predict credit worthiness. Specifically, I use the Boston Fed HMDA dataset to which I add simulated default rates. Details on the Boston Fed HMDA dataset and the model I use to simulate default rates can be found in Appendix A. Although these default rates are based on real-world data, because they are

\textsuperscript{112} A recent paper demonstrates how loan officers that have discretion may make worse decisions when busy, for example. See Dennis Campbell et al., \textit{Making Sense of Soft Information: Interpretation Bias and Loan Quality}, J. ACCT. & ECON. 101240 (2019).

\textsuperscript{113} See for examples companies like ZestFinance and underwrite.ai.

\textsuperscript{114} Home Mortgage Disclosure Act (HMDA) (12 U.S.C. \textsection 2801))
simulated, any figures and numerical examples in this Article that show default rates should not be seen as reflecting real-world observations.

The prediction of loan default as a function of individual characteristics of the loan applicant from the training sample is made either by using a “random forest,” in which the machine learning algorithm makes the prediction using decision trees, or a “lasso regression,” another common machine learning algorithm in which the algorithm selects the variables it deems most important for the prediction. The algorithm is trained on a sample with 2000 clients, with more than 40 variables each (many of which are categorical). This function can then be applied to new borrowers, which is a subset of borrowers from the HMDA dataset not used to train the algorithm. One thing to note is that unfortunately, due to data limitations, this lender does not include many of the types of the nontraditional discussed in Section II.2.1.1.

The purpose of this exercise is to demonstrate what changes in the algorithmic context and whether current approaches to discrimination law in the new context are likely to be effective. This methodology, first developed in “Big Data and Discrimination,” allows for a meaningful analysis of the legal and methodological challenges in analyzing algorithmic decision rules in a stylized setting.

Figure 1: Distribution of predicted risk. The graph shows the distribution risk for all borrowers in the holdout set of 2,000 borrowers. The graph is cutoff at 10%, meaning that only borrowers with a default risk of less than 10% are plotted. The vertical line is the median borrower (of the full sample, not just the borrowers with a risk below 10%).

115 The objective of the lasso is to minimize the sum of squares between the true outcome and predicted outcome (like a linear regression), subject to regularization that restricts the magnitude of coefficients.

In Figure 1, the prediction function is applied to a holdout set, meaning a subset of 2,000 borrowers that is drawn from the same distribution but was not used to train the prediction function. In the real world, this is likely to be a group of new applicants for which the lender is deciding whether to extend a loan and at what price. Borrowers who are to the left of the distribution have a lower probability of default, meaning they are less likely to default. When credit pricing is based on default probability, these borrowers will pay a lower interest rate for a loan because they are less likely to default. Borrowers who fall on the right side of the distribution are more likely to default and therefore will pay a higher interest rate.\(^{117}\)

The algorithm used to plot Figure 1 was race blind in the sense that it did not use the variable “race” to form its prediction.\(^{118}\) However, the holdout dataset to which the prediction is applied does contain a “race” variable. We can therefore separately plot the default distribution for white and non-white and Hispanic applicants (“minority applicants”). Figure 2 shows the default distribution for white applicants (on the left) and minority applicants.

![Figure 2: Distribution of default risk for white (W) and minority (M) applicants. Both graphs are cut off at 10% default risk. The vertical line plots the median default risk for the full sample.](image)

Figure 2 shows that the default distribution is further to the left for white

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\(^{117}\) I emphasize the use of default risk as a way to set the price of the loan. But the default risk could also be used to decide who to approve for a loan altogether. A lender might have a cutoff for lending altogether so that applicants who are predicted to default above a threshold default probability will be denied a loan altogether.

\(^{118}\) Throughout most of this Article I consider a lender who does not use the variable “race” in forming a prediction. This is simply because a lender who does not have a clear intention to discriminate is unlikely to use this variable. In Section 3.1 I discuss the exclusion of a protected characteristic in more detail.
borrowers, reflecting there being a higher proportion of white borrowers who are low risk. This can also be seen by the vertical line, signifying the median applicant, which is further to the left for the white applicants than for the minority applicants.

2.3 What are the challenges in the algorithmic context?

As credit pricing is undergoing a transformation, so is the problem of biased inputs. Although the problem of biased inputs is not new to algorithmic context, its consequences may be different in the traditional and algorithmic setting.

On the one hand algorithmic pricing could exacerbate the problem of “biased world” because it increases the variance in predictions and may expand the number of “biased world” inputs due to its use of nontraditional data. Algorithmic pricing also allows for a greater ability to recover protected characteristics.119 On the other hand, the algorithmic context could mitigate the harms of “biased measurement” by providing an increased amount of information on individuals.

2.3.1 Biased world inputs in algorithmic pricing

The first way in which the move to the new world of credit pricing could increase the disparities between protected groups is by broadening input variables to include additional “biased world” inputs. This is the change that receives the most attention in the media and in legal writing. If algorithmic credit pricing differentiates between people along dimensions that correlate with race, then clearly the outcome disparities will increase.120

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119 This has nearly been the sole focus of scholarly and policy attention. See, e.g., Hurley & Adebayo, supra note 7. The argument is typically that disparities and bias will increase in the algorithmic context because algorithms will have greater access to information about the way people differ and can better use this information to distinguish among people. One such example is when an algorithm can learn of a person’s protected characteristic from other available information.

120 Another concern is that as the number of inputs increases, so will the number of inaccurate inputs. In general, the accuracy of the data used to price credit (and score consumers) is highly regulated. The Fair Credit Reporting Act stresses the crucialness of accurate data by obligating all "consumer reporting agencies" to ensure that credit histories are accurate (15 U.S.C. § 1681e(b) and see also the amendments to this act enacted as the Fair and Accurate Credit Transaction Act); See Yu et al., supra note 63, at 29 (expressing concerns about the use of big data in the lending process since “Expanding the number of data points also introduces the risk that inaccuracies will play a greater role in determining creditworthiness”); See also Robert B. Avery et al., Credit Report Accuracy and Access to Credit, Fed. Res. Bull. 297 (2004) (a “follow up” research that examines the possible effects of data limitations in consumer credit report, including inaccuracies, on consumers).
Another way in which machine learning pricing could increase the disparities of credit prices is due to the greater ability of machine learning to personalize prices. The flexibility of the machine learning regression means that in forming predictions, the algorithm can better distinguish between individuals creating more granular predictions. This could mean that differences among individuals are more likely to translate into greater differences in predicted outcomes than would be true with other less flexible prediction technologies, such as a linear regression.\textsuperscript{121} Even small differences between individuals could translate into greater gaps between the price for credit paid by white and non-white borrowers. One way to describe the increase in price personalization is through the variance of the distribution. A higher variance in the default probability means that people are more spread out in terms of the price they pay for credit, creating a greater range of predictions.

To consider how machine learning can increase the price variance, I compare a simple function using just a few variables with a machine learning algorithm that uses many variables. For the simple prediction function, I use an OLS (ordinary least squares) regression to predict default with a small subset of the variables available in HMDA.\textsuperscript{122} For the machine learning prediction, I use a random forest with the full set of HMDA variables, other than “race.” Therefore, the comparison between the simple function and the machine learning function differ along two dimensions. They differ with respect to the number of variables they are using to form the prediction along with the prediction “technology,” meaning the statistical method used to form the prediction.

\textsuperscript{121} It is not clear that an OLS regression is the right comparison here since the typical “old world” pricing method relied on human discretion and perhaps human discretion is a more flexible prediction than some machine-learning regressions. However, the par-rate set by the mortgage originator is likely to rely on a function closer to an OLS regression if not more basic (such as default means within bins). On the one hand, it could

\textsuperscript{122} The four variables used for this example are – “housingdti,” “totaldti,” “fixedadjustable,” “loanterm”
For the graph on the left, an OLS regression was used to predict default with the independent variables - "housingdti," "totaldti," "fixedadjustable," "loanterm." The prediction function was then applied to a "hold out" set. The graphs show the distribution of predicted default probabilities. For the graphs on the right, a random forest algorithm was used to predict default using all variables in the Boston Fed HMDA dataset, other than race. The prediction function was then applied to the same holdout set as the OLS prediction. The graph on the right shows the distribution of predicted default probabilities. The vertical lines are the mean default predictions, and the horizontal bars are the standard errors.

Comparing the two distributions in Figure 3 demonstrates how the use of machine learning algorithm leads to borrowers being more spread out. This reflects there being a higher variance in the default predictions and, accordingly, the price of credit or the extent to which pricing is "personalized." The greater variance of the random forest prediction, represented by the wider horizontal bar, is the combined effect of the use of more inputs and a more flexible prediction technology. In reality, these two effects are also likely to be combined, as with big data, classic regression analysis will lead to overfitting. Therefore, big data and machine learning often go hand in hand.

The increased variance of the random forest prediction has implications for racial disparities even though Figure 3 does not directly measure these disparities. When new credit pricing uses new data sources in which there are large differences between people who belong and do not belong to protected groups, the use of machine learning could translate the differences in inputs into larger outcome disparities. For example, if male and female borrowers are different with respect to inputs that predict default, a more flexible prediction technology can increase the differences in predicted default for men and women.

The ultimate welfare implications of increased personalization are
unclear in the real world. As will be discussed in further detail below, the more accurate prediction may allow for certain groups previously denied credit altogether to now receive credit. Because of the ability to estimate their risk more accurately, a lender may agree to extend credit to this group at a higher interest rate than would be available to safer borrowers. This means that groups previously completely excluded from credit markets might be able to receive credit, albeit at a higher price than that made available to more creditworthy borrowers.

2.3.2. Biased measurement inputs in algorithmic pricing

Many of the concerns of the effects of big data and machine learning credit pricing discussed in the context of “biased world” also apply to variables that reflect “biased measurement.” The added variables and the increased flexibility that follows from the use of machine learning could increase the credit pricing disparities.

However, the extent to which a prediction will create disparities based on biased measurement can change over time and with the introduction of additional variables and characteristics. One way in which this could happen is through the decreased reliance on a biased proxy. For example, FICO scores may be biased because they reflect creditworthiness as measured by past mortgage payments but not timely rental payments, which are more prevalent for minorities. If big data provides lenders with the opportunity to use rental payment data in addition to FICO scores, this could reduce the differences in predicted default. In this example, the use of algorithmic credit pricing could decrease disparity rather than increase disparity.

There is empirical evidence that the use of nontraditional data leads to decreased reliance on FICO scores. A recent paper written by researchers at the Philadelphia Fed found that the correlation between the credit ratings of LendingClub, a Fintech lender, and FICO scores has decreased over time, indicated by the increased usage of nontraditional data. This evidence is consistent with the story that the impact of the measurement bias of FICO scores is reduced via the use of nontraditional data. The Consumer Financial Protection Bureau recently discussed the potential benefit of alternative data and machine learning in expanding credit. Based on the finding than an algorithmic lender’s model “approves 27% more applicants

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123 Andreas Fuster et al., Predictably Unequal? (Rochester, NY Nov. 6, 2018).
124 These ratings are called “rating grades” and are determined by LendingClub.
126 See id.
than the traditional model, and yields 16% lower average APRs for approved loans,” it concluded that “some consumers who now cannot obtain favorably priced credit may see increased credit access or lower borrowing costs” as a result of the use of non-traditional data.\textsuperscript{127}

The conclusion is that it is difficult to assess at the outset the exact consequences of the widespread changes occurring in the world of credit pricing. On the one hand, the use of advance prediction technologies means that only inputs that contribute to prediction accuracy are considered in pricing. However, the use of biased inputs might further increase disparities when algorithms are better able to differentiate among people. On the other hand, the expansion of input data could undo some of the harm of measurement bias. Thus, the fact that the use of algorithmic pricing could either increase or decrease disparities relative to classic credit pricing suggests that only experimentation or empirical investigation can determine the direction of the effect. This will be further explored in Part IV.

III. APPROACHES TO ALGORITHMIC DISCRIMINATION

The changes taking place in the landscape of credit pricing could have far-reaching implications for how fair lending law applies to the algorithmic setting. In this Part, I focus on the principal approaches of how to apply discrimination law to the algorithmic context, including approaches of legal academics and policy makers, along with proposed regulation. Some of these approaches have not developed primarily with credit pricing in mind but are highly relevant to fair lending.

Disagreements over the scope and boundaries of discrimination law in the non-algorithmic context, discussed in Section 1.4, carry into the new world. For the intent-based theory of disparate impact, the focus is primarily on whether a lender uses a protected characteristic in pricing, even when this occurs in a facially neutral way. For the effect-based theory of disparate impact, the concern will be whether algorithmic credit pricing exacerbates or entrenches disadvantage. The specific interpretation of the burden-shifting framework may be informed by these theories, such as the stringency applied to the initial burden on the plaintiff and how narrowly to construe the “business justification.”

Although I cover a wide range of approaches that are based on different interpretations of the doctrine, a common thread is their outdated focus on

input scrutiny. These approaches follow the logic of traditional
discrimination law by focusing chiefly on what goes into the algorithm
(“inputs”). These approaches are inadequate for three reasons. First, they
often fail on their own terms by not fulfilling their own loose definition of
fairness. Second, they sometimes cannot be practically implemented and are
unsuitable for the machine learning setting. Finally, at times these approaches
could restrict access to credit for vulnerable populations and further entrench
disadvantage.

I cover four approaches, summarized in Table 1. The first approach I
discuss is the exclusion of protected characteristics, primarily as a method for
negating a claim of intentional discrimination under the “disparate treatment”
doctrine. Information about a person’s protected characteristic is
embedded in other information about the individual, meaning that a protected
characteristic can be “known” to an algorithm even when formally excluded.
I demonstrate this by showing that “age” and “marital status” can be predicted
fairly accurately from the HMDA data. Moreover, we should be wary of
excluding protected characteristics if we care about outcome disparities. As I
demonstrate through a simulated example, price disparities could in fact
decrease when algorithms are “race aware.”

The second approach I discuss expands the exclusion of inputs to proxies
for protected characteristics. This approach recognizes that other inputs
may act as “proxies” for protected characteristics and therefore should be
excluded too. The approach, however, is not feasible when there is no agreed-
upon definition of a proxy and when complex interactions between variables
are unidentifiable to the human eye. Even inputs that have traditionally been
thought of as proxies for race, such as zip codes, may be less concerning than
other ways in which a borrower’s race can be recovered. Using HMDA data,
I demonstrate that there is a greater ability to predict “race” from traditional
credit pricing inputs in HMDA than from ZCTAs, the Census Bureau
 equivalent of zip codes.

The third approach I discuss takes the opposite perspective of restricting
algorithm inputs to only preapproved inputs. This is unlike the first two
approaches that allow all inputs other than certain forbidden inputs. I argue
that if algorithms are restricted to traditional credit pricing inputs, such as
income and credit scores, this approach risks entrenching disadvantage
without the ability of big data to undo or mitigate the harm from “biased
measurement” inputs. More generally, I argue that this approach could
ultimately restrict access to credit. Using HMDA data, I demonstrate that risk
prediction using fewer inputs decreases prediction accuracy. When lenders

128 See infra Section 3.1.
129 See infra Section 3.2.
130 See infra Section 3.3.
are less able to differentiate among borrowers based on their risk, the lenders are limited in their ability to price the lending risk accurately.

The last approach I discuss, the orthogonalization approach, is based on a statistical method to prevent inputs that correlate with protected characteristics from serving as proxies. Variables that are correlated with protected characteristics can both provide information relevant to the prediction and function as proxies for protected characteristics. This approach therefore seeks to isolate the component of these variables that serves as a proxy for protected characteristics. I argue that this framework is inappropriate for the machine learning context. I provide a technical demonstration of how the approach does not work in the machine learning context because variable selection is unstable. Building on this demonstration, I argue that the machine learning algorithm’s variable selection should not be interpreted as reflecting some true model of how the characteristic impacts the prediction.

The primary source of the shortcomings of these approaches is that they continue to scrutinize decision inputs, similar to traditional fair lending, when this strategy is no longer effective in the algorithmic context. Approaches to discrimination law in the algorithmic age continue to rely on an outdated paradigm of causality. Fair lending law has traditionally been concerned with causal questions. Disparate treatment centered on the question of whether a protected characteristic had a causal effect on the credit decision. Disparate impact required plaintiffs to show a causal connection between disparities and a policy. A defendant could then negate a claim of discrimination by showing that a policy had a causal relationship to a legitimate business interest. Machine learning is a world of correlation and not causation. When using a machine learning algorithm to predict an outcome, the focus is on the accuracy of the prediction, and this is the metric by which the success of the algorithm is judged. Therefore, effective approaches to discrimination law in the algorithmic setting cannot rely on traditional causal analysis.

Table 1: Summary of approaches

<table>
<thead>
<tr>
<th>Approach</th>
<th>What the approach is trying to achieve?</th>
<th>Can the approach be implemented?</th>
<th>Is the approach effective?</th>
<th>Is the approach otherwise undesirable?</th>
</tr>
</thead>
<tbody>
<tr>
<td>Excluding protected characteristic (Section 3.1)</td>
<td>No direct consideration of race</td>
<td>Yes</td>
<td>Algorithm can use protected characteristics regardless (recovery of protected characteristics)</td>
<td>Exclusion of protected characteristic can increase disparities</td>
</tr>
<tr>
<td>Excluding proxies for protected characteristic (Section 3.2)</td>
<td>No consideration of race through proxies</td>
<td>Difficulty in defining and identifying proxies</td>
<td>Algorithm can recover protected characteristics better than classic proxies (like zip codes)</td>
<td>—</td>
</tr>
<tr>
<td>Restricting inputs to pre-approved characteristics</td>
<td>No consideration or race through proxies (and)</td>
<td>Challenging to determine which inputs are</td>
<td>Classic inputs can continue to serve as</td>
<td>The selection of pre-approved variables could</td>
</tr>
</tbody>
</table>

131 See infra Section 3.4.
3.1 Excluding protect characteristics

One approach to addressing the concerns highlighted in Part I is to require that algorithms not consider a protected characteristic directly by excluding the characteristics as an input. This means that prior to running the algorithm on the training set, a lender would exclude any protected characteristics from the inputs of the algorithm, even if they were available to the lender. Formally, the prediction is blind to a borrower’s protected characteristic because any two people who are identical except for the input “race,” for example, would have the same predicted default probability.\(^{132}\)

The requirement to exclude protected characteristics is mainly discussed in the context of the disparate treatment doctrine. Disparate treatment focuses on the intentional discrimination or the direct classification on the basis of a protected characteristic. Therefore, the requirement that an algorithm exclude a protected characteristic is seen akin to avoiding the classification on the basis of a protected characteristic.\(^{133}\)

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\(^{132}\) See Kleinberg et al., supra note 37, at 27 for an articulation of this approach (“the algorithm might be engaging in disparate treatment – as, for example, if it considers race or gender and disadvantaged protected groups (perhaps because racial or gender characteristics turned out to be relevant to the prediction problem it is attempting to solve).”) See also Sunstein, supra note 83, at 7 (“Importantly, the algorithm is made blind to race. Whether a defendant is African-American or Hispanic is not one of the factors that it considers in assessing flight risk.”). In the context of employment discrimination, see Sullivan, supra note 7, at 405. In Sullivan’s motivating example, “Arti” is an algorithm who determines whom to employ: “Arti doesn’t have any “motives” which seems to mean that its using a prohibited criterion to select good employees can’t be said to violate Title VII’s disparate treatment prohibition”. Ultimately Sullivan argues that Title VII is primarily concerned with the causal connection between a protected characteristic and a decision, and “motivation” is one way to establish causality.

\(^{133}\) This assumed translation between inclusions of a protected characteristic and “discriminatory intent” is not obvious. See Aziz Z. Huq, What Is Discriminatory Intent, CORNELL L. REV. 1211, 1242 (2017–2018) for a discussion of the various interpretation of discriminatory intent in context of the Equal Protection Doctrine. Discriminatory intent has been interpreted as “motivation” and “animus,” which are human attributes and seem irrelevant when considering an algorithm. The basis for attributing discriminatory intent to an algorithm seems to derive primarily from discriminatory intent as an impermissible proxy or anticlassification understanding of intent, articulated by Huq. In the algorithmic setting the mainstream position seems to be that disparate treatment would require the exclusions of protected characteristics. For a related discussion of whether statistical discrimination violates the Equal Protection doctrine, see Will Dobbie & Crystal Yang, Equal Protection
What is particularly appealing about the exclusion approach is that in the automated setting, protected characteristics can formally be excluded, which is often not possible in the human context. In the human decision-making context, very often the protected characteristic, such as race, is observed. This has been a major challenge for discrimination law, as it is difficult to plausibly show that an observed characteristic was not taken into account.\(^\text{134}\) In the context of algorithmic decision-making, companies can guarantee the formal exclusion of these characteristics when they define or delineate the features used by an algorithm. Enforcement of the prohibition is also more feasible as long as there is some documentation of the inputs used by the algorithm.

Despite the intuitive appeal of this approach, as I will argue below, it is ineffective in guaranteeing that a protected characteristic is not used to form a decision. Moreover, this approach might lead to undesirable outcomes, particularly if we also care about the disparities created by a pricing rule.

3.1.1 Ineffective exclusion

In this section, I argue that it is unlikely that the formal exclusion of the protected characteristic as an input guarantees that a characteristic was not used in forming a decision. This is because information about a person’s protected characteristic is embedded in other information about the individual, meaning that a protected characteristic can be “known” to an algorithm even when formally excluded. I distinguish between protected characteristics that are of interest because they correlate with some other unobservable characteristic (“correlates”), such as race,\(^\text{135}\) and protected characteristics that are of direct interest because they have a causal relationship with the predicted outcome (“causal” characteristics), such as age. An algorithm may be particularly motivated to recover a protected

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\(^{134}\) See Kleinberg et al., supra note 37, at 16 (arguing that a major challenge for discrimination law has always been detecting and establishing illicit motivations.). The problem is deeper than a mere evidentiary barrier in establishing discriminatory intent, given that people might suffer for implicit bias and are unaware of how a protected characteristic shapes their decision. See Samuel R. Bagenstos, *Implicit Bias’s Failure*, BERKELEY J. EMP. & LAB. L. 37 (2018).

\(^{135}\) As I note later on, it is not possible to perfectly establish whether a characteristic is causal or not of an outcome. However, a common intuition is that race, to the extent that it is predictive of default, is not causal in of itself but because it serves as a proxy for another characteristic. However, race might be causal of some other characteristic that is causal of default. For example, animus could cause minority workers to be excluded from the labor force, and employment was causal of default. Nonetheless it is employment itself that is the object of interest and not race. Intuitively, therefore, an algorithm could use race as a proxy for employment.
characteristic when it is “causal” of the outcome of interest.

The ubiquity of correlations in big data combined with the flexibility of machine learning means it is much likelier that an algorithm can recover protected characteristics. The correlations in big data also mean that it is hard for the human “eye” to disentangle these correlations and interactions between variables to identify when an algorithm is actually using a protected characteristic. Particularly with the use of nontraditional data, much more can be inferred about a person’s protected characteristic, such as their gender, age, and race.

When a characteristic is considered protected, that characteristic is “legally irrelevant” to the outcome of interest. But the fact that a characteristic is considered “legally irrelevant” does not mean it is “empirically irrelevant.” In fact, proposals to exclude protected characteristics imply that an algorithm would possibly use a protected characteristic to form a prediction—if it were provided the characteristic, meaning it would deem the protected characteristic “empirically relevant,” in that it contains information that is relevant to the outcome of interest.

An algorithm could consider a protected characteristic “empirically relevant” if it correlates with some other unobservable characteristic. In such a case, the protected characteristic is not of interest in and of itself, but rather it correlates with other factors that are related to the outcome that are imperfectly observed by the algorithm. I refer to these types of protected characteristics as “correlates.” For example, an algorithm may use “race” in predicting an outcome because it correlates with other characteristics that the algorithm cannot observe directly such as wealth or access to credit, which do affect default risk. If an algorithm is limited in its ability to use the “true” characteristics of interest in its prediction, it may use race instead.136

Economists often describe this situation as “statistical discrimination” because race is used to infer other information.137 Many protected characteristics are of that nature, as intuitively race and ethnicity seem unrelated to default, except to the extent that they might provide information that the algorithm does not directly observe.138

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138 There is more nuance to the types of correlations that an algorithm might want to discover than is presented here. See Prince & Schwarcz, *supra* note 138, for other types of examples. See also Deborah Hellman, *Measuring Algorithmic Fairness* (2019),
It is unclear whether the ability to recover “correlates” is a significant concern. Protected characteristics that are “correlates” were never of interest in and of themselves but were used instead of an unobserved variable. Therefore, the protected characteristic is not of direct interest. Moreover, the recovery of “correlates” could become less important as data scope and accuracy increase. This allows an algorithm to directly observe the variable of interest instead of using the “correlates” as substitutes. If an algorithm uses “race” to infer a borrower’s wealth, for example, then the ability to directly observe wealth, or more accurate indications of wealth, would render the use of “race” unnecessary. One of the promises of big data is that more information on individuals from multiple sources decreases the reliance on noisy substitutes for unknown or unobservable characteristics. As lenders expand the kinds of data they use, an algorithm would gradually put less weight on race (if it could use race in its prediction) until, perhaps, race itself contained no predictive power.

When a protected characteristic is causal or closely related to the outcome of interest, then an algorithm has a direct interest in recovering the characteristic. The protected characteristic is not substituting for an unobservable variable but will continue to be of interest even with the expansion of the data available to algorithms. In fact, changes in data scope and accuracy may only mean that algorithms will have a better ability to know a person’s “causal” protected characteristic, even when formally hidden. This


The question of whether this situation falls under typical understandings of disparate treatment is more complex than the way I deal with it in this Article. On a theoretical level it is difficult to understand why the inclusion of race, for example, reflects discriminatory intent if race is in fact of no underlying interest to the algorithm or decision itself, but is merely using race as a proxy, and how truly different is this than using a classification that is itself highly correlated with race. This is particularly challenging for the view that discriminatory intent is about “animus,” which seems irrelevant in a context in which you predict a legitimate outcome. Huq addresses this theoretical challenge in the case of Constitutional discriminatory intent (Huq, supra note 135.). In our context suppose urban neighborhoods with high levels of foreclosures was highly correlated with the race composition and a lender decided to limit lending in areas in which high levels of foreclosures cause spillover effects. (Assuming that such a policy is found to have a legitimate business justification and therefore would also not be considered disparate impact) Huq asks: “What then is the difference between taking aim directly at a protected class, and taking aim at a classification that substantially and predictably overlaps with that class?” (Id. at 1249.) A distinction between the two policies puts weight on the formal conscious (a concept taken from human psychology) deployment of protected characteristics, but nevertheless the moral quality and outcome of these policies may be identical.

This is closely related to what is often referred to as “rational discrimination” that often comes up in the context of disability insurance. See Samuel R. Bagenstos, Rational Discrimination, Accomodation, and the Politics of (Disability) Civil Rights, VA. L. REV. 825 (2003).
may mean that there is no difference between when an algorithm is provided with a person’s protected characteristic or when it is not, rendering the exclusion strategy meaningless.

Discrimination law often prohibits consideration of a causal characteristic, creating a significant gap between what is “legally irrelevant” and “empirically irrelevant.”141 In the case of ECOA, the Act prohibits discrimination on grounds that are possibly causal of default.142 ECOA prohibits discrimination based on age or whether a borrower receives his or her income from public assistance programs, as discussed above. It is plausible that these two factors affect a borrower’s predicted future income and therefore closely relate to default risk. Yet, ECOA prohibits their consideration. Similarly, ECOA prohibits discrimination based on marital status, although this could affect the likelihood of default when a mortgage is underwater.143

To demonstrate the ability to recover a protected characteristic from other information, I use the Boston Fed HMDA data set to predict two protected characteristic, “age” and “marital status.” Each time I exclude the protected characteristic while predicting this characteristic from the remaining variables.

141 See Prince & Schwarcz, supra note 138, at 4 (discussing the example of life insurance and genetic information). Clearly, genetic information is highly relevant to the cost of insuring an individual, and yet the insurer is forbidden from considering this information.

142 Although not the mainstream view of ECOA, there is an interpretation that ECOA is only really meant to address “arbitrary” consideration of these factors. See Taylor, supra note 32. For an economics perspective on this type of discrimination, see J. Aislinn Bohren et al., Inaccurate Statistical Discrimination, Working Paper 25935 (National Bureau of Economic Research), Jun. 2019 (proposing a new category of discrimination “inaccurate statistical discrimination,” which is a type of statistical discrimination that is based on inaccurate beliefs).

143 There are examples in other domains of discrimination law prohibiting the consideration of causal characteristics. For example, many states prohibit the consideration of gender in setting life and health insurance premiums. See Ronen Avraham et al., Understanding Insurance Antidiscrimination Law, 87 S. CAL. L. REV. 195 (2013–2014). However, gender is clearly empirically relevant to the cost of insuring an individual. Nonetheless, the law in these states prohibits insurers from charging different rates to men and women. In this case, gender is morally irrelevant even when it is empirically relevant. Another important example are laws that prohibit discrimination of costs of annuities based on gender, such as the EU Directive on insurance pricing. See Council Directive 2004/113/EC (Dec. 13, 2004) (covering insurance in general and not only annuities). A person’s gender will highly affect the costs of providing an annuity, given that women often live longer than men.
Figure 4: ROC curve for prediction of borrower “age.” The “age” variable in the Boston Fed HMDA dataset is not a continuous variable of age but rather an indicator of whether the applicant’s age is above or below the median in the Boston Metropolitan Statistical Area. The ROC curve plots the true-positive-rate and false-negative-rate for different cut off rules. The number in the lower right corner is the Area Under Curve (AUC).

Figure 5: ROC curve for prediction of “marital status.” The “marital status” variable is a dummy variable equal to 1 if the applicant is married and 0 if the applicant is unmarried or separated in the Boston Fed HMDA dataset. The ROC curve plots the true-positive-rate and false-negative-rate for different cut off rules. The number in the lower right corner is the Area Under Curve (AUC).

Figure 4 and Figure 5 demonstrate the ability to predict “age” and “marital status” with a high level of accuracy from the other HMDA dataset variables. The two figures are a representation of how accurately I was able to predict a borrower’s age and marital status from the HMDA dataset in the form of a ROC curve. The number on the bottom right corner is the Area(s) Under Curve (AUC), which measures the prediction accuracy. Appendix B
provides more details on exactly how the ROC curve is plotted and how it should be interpreted. Intuitively, because the ROC curves are close to the upper left corner, and the AUC are high (0.84 for age and 0.9 for marital status), we are able to predict these protected characteristics with a high level of accuracy.

The above prediction shows that the formal exclusion of a protected characteristic may be meaningless with respect to the ability of an algorithm to actually use the characteristics. In reality, the results above are a lower bound with what is feasible with big data and machine learning. As discussed above in Section 2.3.1., the variables in the Boston Fed HMDA dataset are primarily more traditional pricing variables and are unlikely to represent the richness of data available to algorithmic lenders. With nontraditional data, lenders can potentially recover protected characteristics with greater accuracy.

Although we might be particularly concerned with an algorithm’s motivation to recover “causal” characteristics, in reality, it is often not possible to draw the line between “correlates” and “causal” characteristics. The ability to establish that a characteristic is truly causal is very difficult when characteristics such as age and marital status are not randomly assigned. Therefore, the distinction between “correlates” and “causal” characteristics is meant to provide intuition on why algorithms can be interested in directly recovering protected characteristics—and not because they are substituting for other variables.

The continued interest of a “blind” algorithm in a protected characteristic, combined with the ability to recover these characteristics, means that the exclusion of protected characteristics cannot negate a claim of disparate treatment. The exclusion of a protected characteristic does not guarantee that an algorithm is not using the characteristic in forming the prediction.

### 3.1.2 Disparities may increase with exclusion

In the previous Section, I argued that the exclusion of a protected characteristic may be insufficient to negate a claim of disparate treatment in algorithmic pricing. There is an additional reason to be wary of the exclusion of protected characteristics as a way to apply discrimination law. This is because if we care about price disparities, the inclusion of a protected characteristic, rather than the exclusion, could decrease disparities.\(^{144}\)

When a characteristic should be interpreted differently for various racial groups, excluding “race” could increase disparities. This is because by

\(^{144}\) The extent to which disparate impact is concerned in directly reducing outcome disparities is discussed above in Section 1.4, and may depend on what type of reason is driving the disparities created by exclusion.
excluding the race variable, we are imposing a similar interpretation of a characteristic for both white and non-white applicants. For example, even if the borrower’s number of children is predictive of default only for white applicants and not non-white applicants, the algorithm will give the characteristic the same weight for all racial groups when “race” is excluded. This critique is consistent with the growing skepticism among scholars about the usefulness of the wholesale approach of excluding protected characteristics.145

The inclusion of protected characteristics may also be important in mitigating the harms of “biased measurement” variables. The inclusion of a protected characteristic allows the algorithm to distinguish between its treatment of the biasedly measured input for certain groups. For example, if disposable income is measured in a way that disadvantages minorities, because it does not give sufficient weight to part-time jobs, we may want the algorithm to put less weight on disposable income for minorities if they are more likely to hold part-time jobs. However, we inhibit the ability of an algorithm to do so when we exclude “race,” particularly when there are many more whites in a training dataset, which is likely to be the case even in a representative dataset.146 Then the prediction will be formed according to the weight attributed to the characteristics for whites.

Consider a hypothetical lender that predicts default from an input that suffers from measurement bias. In this example, “ability” is equally distributed across the population (meaning that whites and non-whites have the same ability) and that higher “ability” people default less.147 The characteristic “ability” is not observed by the lender. Instead the lender has information about college attendance, which is correlated with “ability.” Assume that racial minorities face discrimination in college applications and are therefore less likely to attend college. In this example, the input “college

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146 In the 2000 HMDA dataset, for example, black applicants are less that 10% of all applications reported. See Federal Financial Institutions Examination Council (FFIEC), Reports – Nationwide Summary Statistics for 2000 HMDA Data, Factsheet (July 2001), Table 2, https://www.ffiec.gov/hmcrpr/hm00table2.pdf. It’s important to note that the Boston HMDA is skewed to overrepresent minorities relative to their share amongst mortgage applicants.

147 This could be because higher ability borrowers are likely to have higher future earnings, and therefore have a lower risk prediction.
attendance” suffers from measurement bias because it is a noisier measurement of “ability” for racial minorities.

Figure 6 shows that in my simulated example, predicting default risk from college attendance only means that non-white borrowers have a higher default probability.\textsuperscript{148} This can be seen in the graph to the left in which the distribution for non-white and Hispanic borrowers (“M”) is shifted to the right, meaning there are more borrowers with a higher default risk. When default prediction includes the race variable (graph on the right), the default risk of white and non-white is more similar. This is because a race-aware algorithm knows to treat “college attendance” differently for white versus non-white borrowers.

The conclusion of this discussion is not that including protected characteristics always reduces disparity. In fact, this is unlikely to be true when a protected characteristic is causal of the outcome of interest.\textsuperscript{149} Rather, the argument is that it is difficult to determine \textit{a priori} what effect the inclusion of a protected characteristic might have. Therefore, we should be wary of treating the exclusion of protected characteristics as a means to reduce disparity.

A separate question is whether the inclusion of a protected characteristic, when used to reduce disparities or treat groups more fairly, is legal. As

\textsuperscript{148} This example uses an OLS regression and not a machine learning algorithm. For the purposes of this highly stylized example, the OLS regression is sufficient.

\textsuperscript{149} In Section 3.4, I present a case in which the lasso regression puts weight on the input “race,” meaning that it predicts that white borrowers are less likely to default.
discussed above, many approaches to discrimination and algorithms assume that protected characteristics must be excluded. 150 Recently, however, several scholars have suggested that discrimination law’s position on the consideration of a protected characteristic may be more nuanced. Deborah Hellman argues that separately considering which inputs are predictive of future criminal activity may not in fact constitute disparate treatment.151

### 3.2 Excluding proxies for protected characteristics

A second approach to applying discrimination law to algorithmic pricing is expanding the prohibited inputs to also include “proxies” for protected characteristics. The discussion in the previous part demonstrates that exclusion of the protected characteristic may not eliminate disparate outcomes and alone may be meaningless if an algorithm can use proxies for those characteristics. If it is the proxies that are causing a protected characteristic to be considered, a natural response is to exclude these proxies as well. This second strategy can therefore be thought of as an expansion of the first strategy. It requires that we not only exclude protected characteristics themselves but also exclude their proxies. In traditional fair lending, this strategy is sometimes adopted by excluding salient examples of proxies, such as zip codes. The use of a zip code in credit pricing could also trigger a claim of “redlining,” in which a lender avoids extending credit to borrowers who live in neighborhoods with higher minority populations.152

150 See MacCarthy, supra note 79, at 72 (“these cases do suggest that the use of group variables in algorithms would be subject to strict scrutiny, even if their purpose is to reduce group disparities.”)

151 See Hellman, supra note 140, at 38 for a discussion of the possibility of separately considering which inputs are predictive for different racial groups. Although Hellman discusses this proposal in the context of Constitutional discrimination, it is closely related to fair lending disparate impact. Hellman discusses a case in which “an algorithm might use race within the algorithm to determine what other traits would be used to predict the target variable” and suggests that perhaps strict scrutiny may not apply because a separate algorithm is treating the groups equally in the sense that “only relevant information is utilized” (Id. at 40). As a technical matter it is unlikely that the proposition is functionally different from including race in an algorithm, even if it might be treated differently legally.

In general, the fact that the explicit consideration of a protected characteristic can reduce disparities suggests a possible tension between disparate treatment and disparate impact. The tension between the requirement to ignore forbidden characteristics, yet assure that policies do not create a disparate impact, thereby requiring a consideration of people’s forbidden characteristics, has recently been debated in the context of Ricci v. DeStefano, 557 U.S. 557 (2009) (in which a promotion test was invalidated by an employer because of the concern that promotion based on the test would trigger disparate impact). See Richard Primus, The Future of Disparate Impact, MICH. L. REV. 1341 (2009–2010). See also Hellman, supra note 140, at 47; Kim, supra note 7, at 925.

152 See Alex Gano, Disparate Impact and Mortgage Lending: A Beginner’s Guide, U.
This approach in the algorithmic context was recently articulated by the Department of Housing and Urban Development (HUD) in a proposed rule from August 19, 2019. The Proposed Rule revises §100.500 of HUD’s 2013 Rule\textsuperscript{153} with respect to its interpretation of the disparate impact doctrine. Section (c)(2) relates to a case in which a plaintiff is challenging a defendant’s use of model with a discriminatory effect and lays out the defenses on which a defendant can rely. According to (c)(2)(i), a defendant can rebut a claim of discrimination by showing that “none of the factors used in the algorithm rely in any material part on factors which are substitutes or close proxies for protected classes under the Fair Housing Act.”\textsuperscript{154} Therefore a defendant can negate a claim’s disparate impact by showing that a risk assessment algorithm excludes proxies for protected characteristics.

Several scholars have also proposed preventing algorithms from using variables that highly are correlated with a protected characteristic. For example, Hurley and Adebayo propose a model bill — the Fairness and Transparency in Credit Scoring Act – that contains this type of provision.\textsuperscript{155} The model bill requires credit scores “not treat as significant any data points or combinations of data points that are highly correlated to immutable characteristics.”\textsuperscript{156}

The expansion of input exclusion, beyond protected characteristics themselves, requires a clear articulation of the criteria for exclusion. Prior work has suggested that a proxy be defined as an input that is 1) highly correlated with the protected characteristic\textsuperscript{157} and/or 2) does not contain informational value beyond its use as a proxy.\textsuperscript{158} It is not clear whether these

\textsuperscript{153} supra note 14.

\textsuperscript{154} According to (c)(2)(i), the defendant must also show that the model is predictive of credit risk or “other similar valid objective”. Section (c)(2)(i) contains similar language but relates to showing that a third party has established that it does not rely on proxies or close substitutes. This is the third defense available to the defendant in the proposed rule. See Id. at 33.HUD Proposed Rule 2019, at 33.

\textsuperscript{155} Hurley & Adebayo, supra note 7, at 196.

\textsuperscript{156} Id. at 206. The “immutable characteristics” that the provision is referring to are race, color, gender, sexual orientation, national origin, and age. There is a similar provision for marital status, religious beliefs or political affiliations.

\textsuperscript{157} See Charles River Associates, Evaluating the Fair Lending Risk of Credit Scoring Models, 3 (2014), http://www.crai.com/sites/default/files/publications/FE-Insights-Fair-lending-risk-credit-scoring-models-0214.pdf (“Ostensibly neutral variables that predict credit risk may nevertheless present disparate impact risk on a prohibited basis if they are so highly correlated with a legally protected demographic characteristic that they effectively act as a substitute for that characteristic.”)

\textsuperscript{158} See FED. TRADE COMM’N, REPORT ON BIG DATA: A TOOL FOR INCLUSION OR EXCLUSION?, 67 (Jan. 2016). Here I focus on two possible definitions of a proxy, however, this is not the only way to define a proxy we may want to exclude. A somewhat different approach to the expansion of excluded features, looks to other factors beyond correlation to
should be considered alternative criteria or cumulative criteria. Hurley and Adebayo focus on variables that highly correlate with protected characteristics.\textsuperscript{159} Other approaches require something beyond a correlation, such as requiring that the variable not contain much information relevant to the outcome of interest. I first discuss the initial way of defining a proxy, by its correlation to the protected characteristic and then discuss the second definition, wherein the variable does not have independent informational value.

3.2.1 Correlated inputs as “proxies”

Excluding proxies for protected characteristics, defined as inputs that highly correlate with those characteristics, is unlikely to guarantee that protected characteristics are not used by an algorithm. This is because in the big data context, considering how individual inputs correlate with protected characteristics does not fully capture the complex interactions among inputs. Therefore, expanding the excluded characteristics to inputs that correlate with protected characteristic will only have a limited effect in reducing disparities, if any at all.

Figure 7 shows how an algorithm may produce different risk predictions for white and non-white borrowers even when excluding inputs that highly correlate with race.\textsuperscript{160} The graph on the left shows the distribution of default risk for white and non-white borrowers when the algorithm does not use “race,” and the graph on the right shows the default risk when the algorithm a protected characteristic. For example, Sunstein in a recent paper has suggested: “Difficult problems are also presented if an algorithm uses a factor that is in some sense an outgrowth of discrimination”. See Sunstein, \textit{supra} note 83, at 8. In the context of credit pricing this would mean excluding many of the fundamental features used to price credit, even today, such as credit scores and wealth. This approach is likely to be based on the argument that disparate impact grows out of the duty to avoid compounding injustice as argued by Deborah Hellman. See Hellman, \textit{supra} note 52, available at https://papers.ssrn.com/abstract=3033864. While Hellman’s focus is the justification of the disparate impact and indirect discrimination doctrines as a moral wrong, it also suggests guidelines as to what conduct should be prohibited. In our case, if variables used by an algorithm were themselves a result of discrimination, even if this discrimination did not originate in any action on the part of the lender, the active use of these variables in setting the price of credit could be a compounding of the initial injustice towards minority groups.

\textsuperscript{159} See Hurley & Adebayo, \textit{supra} note 7, at 200. (“The FaTCSA addresses the potential problem of proxy-based discrimination by prohibiting the use of models that "treat as significant any data points or combinations of data points that are highly correlated" to sensitive characteristics and affiliations.”)

\textsuperscript{160} This figure is similar to the figure produced in Gillis & Spiess, \textit{supra} note 26, at 469. One important difference is that this figure does not contain a separate distribution for black and non-white Hispanic borrowers but rather collapses them into one category of non-white borrowers.
excludes “race” and the ten variables that correlated most with “race.” One way to consider the disparities between the groups is by the gap between the vertical lines, which are the median predictions for white and non-white borrowers. Although the difference in median risk prediction for white and non-white borrowers is lower in the graph on the right, the disparities between the groups continue to persist. This is because the individual correlations of variables with a protected characteristic do not capture the full range of how variables correlate and interact.\footnote{It is important to note that this demonstration is somewhat of a lower bound of how information on protected characteristics is embedded in other inputs with big data. As already mentioned the number of variables and types of data used in the simulation example are similar to more traditional credit pricing since it does not include non-traditional data such as consumer purchasing and payment behavior. When the amount of data and type of data expands, this problem is likely to be more severe given the complex relationship between different characteristics and the ubiquity of correlations.}

![Figure 7: Distribution of risk predictions across groups for different inputs. The graph on the left shows the risk predictions when using all HMDA inputs other than race, plotted separately for the non-Hispanic white (W) and non-white (M) borrowers in the holdout group. The graph on the right shows the risk predictions when using HMDA inputs other than race and ten variables with the highest correlation to race. Also in this graph, the predictions are plotted separately for white and non-white borrowers. The vertical lines are the median risk prediction for each racial group. The ZCTA populations are reweighted to account for the oversampling of black borrowers in the Boston Fed HMDA dataset.]

Furthermore, classic examples of “proxies,” such as zip codes, may be less indicative of race than other variables used by lenders. To demonstrate this, I consider how accurately I am able to predict whether a borrower is black from the Boston Fed HMDA dataset, which contains mostly classic variables used by lenders. I then compare this to how accurately I am able to predict whether a borrower is black from Zip Code Tabulation Areas.
(ZCTAs), the Census equivalent of zip codes,\textsuperscript{162} for the Boston Metropolitan Statistical Area.\textsuperscript{163}

\begin{figure}[h]
\centering
\includegraphics[width=0.5\textwidth]{ROC_curve.png}
\caption{ROC curve for prediction of "black" using HMDA covariates and using Census ZCTA}
\end{figure}

Figure 8 shows that the prediction of whether a borrower is black is more accurate using the HMDA dataset than ZCTAs. For nearly all the distribution, the curve of the HMDA covariates is above the Census ZCTA curve. This means that for nearly any cut-off rule with respect to predicting whether a borrower is black, the HMDA covariates produce a more accurate prediction (meaning that the “true positive rate” is higher and the “false positive rate” is lower. See Appendix B). This can be also seen by comparing the area under a curve for the Census ZCTA (0.86) and the HMDA covariates (0.79). This example demonstrates how common intuitions about which variables serve as proxies might be misleading. If what we are truly interested in is the ability to recover a person’s protected characteristics, intuitive judgments are insufficient to determine which features to exclude. Features that intuitively feel like proxies might correlate less than might features that do not feel like proxies.

The final reason to be wary of this exclusion approach is that most inputs used to price credit, even in the traditional context, correlate with a protected characteristic.\textsuperscript{164} Restricting the use of variables that correlate with protected

\textsuperscript{162} The reason that the Census uses ZCTAs and not zip codes is that zip codes often cross state, county, census tract, and census block group and therefore could not be used as a defined area in the Census.

\textsuperscript{163} This is the geography that the HMDA dataset is based on. The populations in the ZCTAs have been reweighted to reflect the over sampling of blacks in the Boston Fed HMDA dataset. See the description of who was included in the Boston Fed HMDA dataset in: Munnell et al., supra note 56, at 26.

\textsuperscript{164} See supra Section 1.2.
characteristics reduces lender’s ability to accurately predict default risk and personalize pricing accordingly.\textsuperscript{165} The recent HUD Proposed Rule shows that not appreciating the prevalence of correlations can create confused and incoherent policy. According to the Proposed Rule, a plaintiff can undermine a defense of a model they show “that the defendant’s analysis is somehow flawed, such as by showing that a factor used in the model is correlated with a protected class.”\textsuperscript{166} This would likely mean that a risk model would never be able to rely on the defense laid out in the Proposed Rule.

\subsection*{3.2.2 Inputs with no additional informational value}

The second possible criteria for a proxy, namely that it contains little or no informational value beyond its use as a substitute for a protected characteristic,\textsuperscript{167} is also difficult to implement in practice. This is because there is no credible way to identify variables that do not contain information beyond their value as proxies. As emphasized throughout this paper, we do not have a good understanding of the causal model of default and which variables are causal of default. Even if we knew the “true” model of default, we would not necessarily know how other variables relate to those causal variables.

In some cases, intuition is used to replace empirical understanding of how variables relate to default. Using such intuition, we might be able to tell a plausible story of whether an input that correlates with race does or does not contain information related to default, beyond its use as a proxy for race.\textsuperscript{168} The appeal of this approach depends on one’s faith in the ability of intuitive arguments to identify variables that are causally related to default or that are related to those causal variables. In some cases, an intuitive case can be made in either direction. For example, zip codes are often considered to contain little value beyond their substitute for race. However, zip codes could be used to capture neighborhood effects that are highly relevant to default risk, such

\begin{itemize}
\item \textsuperscript{165} See supra Section 1.3.
\item \textsuperscript{166} supra note 14, at 20-21.
\item \textsuperscript{167} See Prince & Schwarcz, supra note 138, at 4 (defining “proxy discrimination” as the use of an input that not only correlates with a protected characteristic but “that the usefulness to the discriminator of the facially-neutral practice derives, at least in part, from the very fact that it produces a disparate impact”).
\item \textsuperscript{168} See Yu et al., supra note 63, at 29 (providing an example of this type of intuitive argument). According to the NCLC, to rely on a business necessary justification, the lender would need to show the connection between the input and credit risk. For example, “[t]here is an understandable connection between timely repayment of past obligations and the likelihood of timely repayment of future obligations, so a “demonstrable relationship” argument can be easily made.” See Id.
\end{itemize}
as the real estate fluctuations in a particular area.\textsuperscript{169}

A further difficulty is that many variables can both be an indicator of a protected characteristic but also independently contain information relevant to the outcome of interest. In most cases, we are not able to isolate the component of a variable that is merely a proxy for a protected characteristic and the component that contains independent information. In Section 3.4, I discuss a statistical approach that seeks to isolate the proxy component from variables that correlate with protected characteristics. I argue, however, that this method is inappropriate for the machine learning context.

In summary, while the attempt to exclude proxies in addition to protected characteristics is intuitively appealing, there are practical challenges endemic to defining and detecting proxies. Correlation to a protected characteristic does not fully capture the extent to which variables can be used as a substitute for a protected characteristic. Moreover, variables that correlate with race form the core of even traditional credit pricing. Finally, input exclusion comes at the price of prediction accuracy, which may hurt vulnerable populations.

3.3 Restricting algorithm to predetermined set of variables

A third approach of restricting the inputs of an algorithm to inputs that are pre-approved. This approach was recently proposed by Prince and Schwarcz in the context of insurance: “Instead of allowing use of any variable not barred, as in the traditional antidiscrimination model, actors can only use pre-approved variables.”\textsuperscript{170} This approach is similar to the first two in that it limits the inputs into an algorithm. However, instead of focusing on excluding variables that are impermissible, this approach seeks to define what variables are permissible. Therefore, this approach shifts the default from treating all variables as permissible unless determined otherwise to treating all variables as impermissible unless determined otherwise.

Predetermining permissible variables could either be implemented by a regulator or by an internal screening process by the lender to decide which variables can be used. Approaches that require that lenders show that inputs are “relevant” or “causal” to the outcome are likely to amount to a form of predetermining permissible inputs.\textsuperscript{171} If lenders must show that a lending

\textsuperscript{169} See Erik Hurst et al., \textit{Regional Redistribution through the US Mortgage Market}, 106 AM. ECON. REV. 2982 (2016) (documenting large regional variation in default risk, despite the uniform pricing of Government Sponsored Enterprises (GSEs) across regions.)

\textsuperscript{170} See Prince & Schwarcz, \textit{supra} note 138, at 54.

\textsuperscript{171} This is another one of the proposals in \textit{Id.} at 59 (“One possible solution is to require those employing algorithms to establish the potential causal connections between the variables utilized and the desired outcome.”)
decision relies on inputs that are logically related to outcome, they will need to exclude other variables. Predetermining which variables are related to the outcome will allow lenders to meet this burden.172

3.3.1 Entrenching disadvantage

The main challenge with this approach is defining which variables are permissible. This depends on what the restriction is meant to achieve. If the goal was simply to only use inputs relevant to default in that they predict default, there is no reason to restrict input at all. The algorithm, rather than a human, is likely to be the best judge of whether an input predicts default. Therefore, to the extent that what we are trying to achieve is a more accurate prediction, restricting inputs to a predetermined list is a misguided strategy.

Limiting the algorithm to characteristics that are used in traditional credit pricing, such as FICO scores or a borrower’s income, undermines the benefits of big data and machine learning in extending access to credit. The use of nontraditional data can expand credit to people without sufficient credit history, so excluding this data maintains their status as “credit invisibles.”173 Moreover, when FICO scores, for example, only measure certain indicators of the likelihood of meeting obligations on time, big data can mitigate this “bias measurement” by expanding the data used to predict default. By restricting algorithms to classic characteristics, these benefits cannot be captured, potentially entrenching disadvantage for certain populations.

An alternative approach is to allow for the use of characteristics that are not classic credit pricing variables but to restrict inputs to variables that are closely related to models of repayment. This is the approach advanced by Bartlett et al. who argue that in determining what variables are legitimate, “one can write down a life-cycle model in which cash flow for repayments emerge from the current borrowing position (debt), cost of borrowing (credit score), income (in levels, growth, and risk), wealth, and regular expense levels (cost of living measures).”174 When a variable correlates with a

172 See Grimmelmann & Westreich, supra note 41, at 176 (“Where a model has a disparate impact, our test in effect requires an employer to explain why its model is not just a mathematically sophisticated proxy for a protected characteristic.”) See also Kim, supra note 7, at 921 (“The existence of a statistical correlation should not be sufficient. Instead, because the employer’s justification for using an algorithm amounts to a claim that it actually predicts something relevant to the job, the employer should carry the burden of demonstrating that statistical bias does not plague the underlying model.”)


protected characteristic, it can only be used to the extent that it relates to the life-cycle structural model of debt repayment. Similar to the approach in Section 3.2.2., the position advanced by Bartlett et al. seeks to prevent an algorithm from using proxies for protected characteristics.

The success of this approach relies on human intuitions to accurately determine how inputs relate to the “life-cycle” model of repayment. In reality, we do not always directly observe the variables of the structural model of repayment and rely instead on noisy substitutes for the variables of the model. With high-dimensional data wherein correlations are ubiquitous, we can lose any direct sense of how inputs relate to the structural model.\footnote{\textsuperscript{175} Bartlett et al., avoid this problem by focusing on a context in which mortgage lenders do not face default risk so that differential pricing cannot be explained by default prediction altogether. \textit{See} Bartlett et al., \textit{supra} note 49.} For example, a person’s wealth is typically unknown, and so in order to infer wealth, we may need to rely on proxies or correlates of wealth. As the complexity of the structural model and the list of inputs that can be used to infer the variables in the structural model increase, we will ultimately depend on human intuition in determining when a variable “feels” related to a characteristic in the model, such as wealth, and not a proxy for a protected characteristic.

Furthermore, there is little reason to believe that we know the true structural model of repayment. Structural models are useful when engaging in empirical research and need to estimate the effect of different changes on an outcome of interest. They also provide discipline in interpreting empirical results. However, they are a far cry from a true reflection of the actual causal relationships that exist in the world. For example, the literature on micro-financing in development economics points to a number of factors that might affect default rates, not captured by Bartlett et al.’s “life-cycle” model. For example, public repayment of loans may lead to lower default rates due to reputation concern.\footnote{\textsuperscript{176} \textit{See, e.g.,} Abhijit Vinayak Banerjee, \textit{Microcredit Under the Microscope: What Have We Learned in the Past Two Decades, and What Do We Need to Know?}, 5 \textsc{Ann. Rev. Econ.} 487 (2013) (discussion of the various theories and empirical evidence on microlending).} If we rely on a structural model to dictate what can and cannot be used as an input, it is a problem when the structural model is incomplete. This is particularly worrisome if the mode is more incomplete for protected groups.\footnote{\textsuperscript{177} For example, suppose creditworthiness is affected by social attitudes to foreclosure, but that these social norms were not part of the structural model of repayment. If minorities are more likely to belong to such communities you could be excluding measures of creditworthiness more reflective of minority communities, creating a bias against minorities. Essentially in trying to restrict the bias concerns of big data, this type of restriction may in fact increase bias.}
3.3.2 High cost to prediction accuracy

More generally, limiting the inputs an algorithm can use to form a prediction of default could lead to less accurate predictions, the main benefit of machine learning pricing. This increase in accuracy can stem from the various changes machine learning pricing brings about. First, the focus on an automated system of prediction versus human prediction could add accuracy to the prediction.\(^\text{178}\) Second, machine learning versus other statistical methods, such as linear regressions, allows for greater flexibility in forming a prediction versus a linear regression, for example, and also increases accuracy.\(^\text{179}\) Finally, the expansion of the type and number of inputs considered by an algorithm could increase the accuracy.

To demonstrate how accuracy can change when reducing the inputs of an algorithm, I return to my hypothetical lender. I compare two algorithms, one that uses the full set of inputs (other than race) and another that is only limited to a small subset of variables.\(^\text{180}\)

![Figure 9: Distribution of risk predictions. The graph on the left shows the risk predictions using a random forest with the full set of inputs (other than race). The graph on the right shows the risk predictions using a random forest with a small set of more traditional credit inputs. Both graphs...](image)


\(^{179}\) See supra Section 2.3.

\(^{180}\) I use one possible subset, which includes some variables that are typically used to price credit today – income, debt-to-income ratio and characteristics of the loan.
separate the risk prediction for non-Hispanic white borrowers (W) and non-white borrowers (M). The vertical lines are the median for each group of borrowers.

Figure 9 shows that when using a smaller set of inputs, the risk distribution changes, and differences between white and non-white borrowers go down. The risk distribution becomes more condensed when predicting from a smaller set of inputs (graph on the right). This is because using fewer variables means that the there are less variables to distinguish between people so that the distribution is more concentrated around the mean. The vertical lines, signifying the median risk prediction for white and non-white borrowers, are also closer to one another in the graph on the right, showing that raw disparities decrease when fewer variables are used.

To demonstrate the change in prediction accuracy, I plot the receiving operator characteristic (ROC) curve corresponding to the two distributions in Figure 9. \[181\]

\[Figure 10: ROC curves corresponding to risk distributions in Figure 9. The ROC curve on the left shows the accuracy of the risk predictions using a random forest with the full set of inputs (other than race). The graph on the right shows the accuracy of the risk predictions using a random forest with a small set of more traditional credit inputs. The number on the bottom right corner is the Area Under Curve (AUC).\]

Figure 10 shows that the prediction based on the larger set of inputs is more accurate. This can be seen from the curve in the left graph being closer to the upper left corner and from the AUC in the lower right corner being higher for the prediction using the full set of inputs.

The potential tradeoff between different notions of fairness and accuracy has been previously noted and is also relevant when trying to limit the inputs into an algorithm.\[182\] However, as argued in the previous sections, the

\[181\] See Appendix B on ROC curves.

\[182\] See Corbett-Davies et al., supra note 47. Also see: Geoff Pleiss et al., On Fairness
proposal to limit an algorithm to inputs that seem intuitively relevant to the outcome of interest face further challenges, as the decision could be arbitrary and even undermine the benefits of big data in mitigating the harm of measurement bias. Therefore, the restriction of inputs may not even be a case of trading off accuracy for fairness but could in fact reduce accuracy and fairness. Moreover, as discussed in Section 1.3, reduced accuracy could hurt vulnerable borrowers who are excluded altogether from credit markets when the lender cannot accurately price risk.183

3.4 Orthogonalizing inputs

A fourth approach to applying discrimination law to the algorithmic context focuses on statistical methods of “orthogonalizing” inputs. Orthogonalization in this context means that inputs that correlate with a protected characteristic do not serve as proxies for protected characteristics. This approach, recently proposed by Prince & Schwarcz184 and fully developed by Dobbie & Yang185 attempts to transform the inputs into an algorithm in a way that reduces or eliminates bias. Although neither of these proposals deals directly with fair lending, each one’s analysis is highly relevant for fair lending.

This approach is meant to address problems that arise when a variable that correlates with a protected characteristic plays a dual role. On the one hand, a variable that correlates with race, for example, may provide important information for the outcome of interest, such as when default is predicted using a borrower’s income. On the other hand, a variable that correlates with

\[ \text{and Calibration, ArXiv:1709.02012 [cs, stat]} \ (2017). \text{ See also Prince & Schwarcz, supra note 138, at } 53 \text{ (“Given that the goal of algorithms is to ferret out the most efficient predictors of a specified outcome, any changes to this system will naturally introduce inefficiencies. However, society cannot just put blinders on and argue that algorithms should be allowed to be as efficient as possible without intervention; the absence of intervention will result in proxy discrimination. If, for efficiency’s sake, no solution is adopted, it must be acknowledged that this comes at the expense of the goals of anti-discrimination laws.””)}

\[ 183 \text{ The need to be sensitive on who bears the burden of more or less accurate predictions has been discussed by Huq in the context of criminal justice. Huq argues that racial equity requires to consider who bears the cost of algorithmic errors in determining how to apply notions of fairness. See Aziz Z. Huq, Racial Equity in Algorithmic Criminal Justice, 68 Duke L.J. 1043 (2018–2019).} \]

\[ 184 \text{ See Prince & Schwarcz, supra note 138, at 57. They propose this method in the context of insurance.} \]

\[ 185 \text{ See Dobbie & Yang, supra note 135. Dobbie & Yang discuss their proposal in the context of the Equal Protection. This paper, as well as Prince and Schwarcz’s paper, base their proposals on an economics paper from 2011. See Devin G. Pope & Justin R. Sydnor, Implementing Anti-Discrimination Policies in Statistical Profiling Models, 3 American Economic Journal 206 (2011).} \]
race could also serve as a proxy for race. Therefore, a principal advantage of this approach is that it highlights the limits of excluding a protected characteristic. Dobbie & Yang demonstrate how when a protected characteristic is excluded, the coefficients of inputs that correlate with the protected characteristic will partially reflect the omitted protected characteristic.\textsuperscript{186} Therefore, the inputs that correlate with the protected characteristics serve as “proxies.”

This statistical approach separates between the “training” and “screening” stages of an algorithm.\textsuperscript{187} Focusing on the example of race, in the training stage, the algorithm is “race aware” in the sense that the algorithm uses “race” as one of its inputs. This produces an estimate of the weight given to race in forming the prediction. However, in the screening stage, meaning the stage in which the prediction is applied to a particular person, the algorithm is unaware of a borrower’s race. This means that even though “race” was used to train the algorithm, formally there is no differential treatment based on race.\textsuperscript{188} Intuitively, this method alleviates concerns over the use of proxies because it is able to subtract the pure effect of “race” on the prediction.

Formally, Dobbie & Yang consider a case in which we are trying to predict outcome $y_i$ for individual $i$, where there are three types of inputs. There is the protected characteristic, such as race, $X_i^{\text{race}}$, inputs that correlate with race $X_i^{\text{corr}}$,\textsuperscript{189} and inputs that do not correlate with race, $X_i^{\text{noncorr}}$. Focusing on a linear regression, at the training stage, the following regression is estimated:

$$y_i = \beta_0 + \beta_1 X_i^{\text{noncorr}} + \beta_2 X_i^{\text{corr}} + \beta_3 X_i^{\text{race}} + \epsilon_i$$

Estimating the model above produces coefficients $\beta_1$, $\beta_2$ and $\beta_3$. Applying this estimated function to predict default for future borrowers is likely to trigger “disparate treatment,” as it treats borrowers differently on the basis of race.\textsuperscript{190} Therefore, when applying this model to future borrowers,

\textsuperscript{186} This is typically considered “omitted variable bias”.
\textsuperscript{187} See discussion of this separation in Kleinberg et al., supra note 37, at 20–21.
\textsuperscript{188} In spirit, this method is similar to an approach in the computer science and statistics literature known as “disparate learning processes” (DLP). In DLP, protected characteristics are used in the training stage but not during what I call the “screening” stage. The primary purpose of DLP is reduce disparate outcomes across groups without formally treating people differently based on a protected characteristic. For a skeptic view of this approach see: Zachary Lipton et al., Does Mitigating ML’s Impact Disparity Require Treatment Disparity?, ADVANCES IN NEURAL INFORMATION PROCESSING SYSTEMS 31 8125 (S. Bengio et al. eds., Curran Associates, Inc. 2018).
\textsuperscript{189} See Dobbie & Yang, supra note 135, for further discussion of whether the use of $X_i^{\text{corr}}$ could also be illegal.
\textsuperscript{190} This is true for any $\beta_3 \neq 0$. 
race is set to the mean race ($\bar{X}_{race}$) for all individuals, meaning that the model does not formally distinguish between different racial groups. This formally satisfies the requirement of not discriminating on the basis of race while not allowing correlates to serve as proxies for race.

How would this framework apply in the context of machine learning? In their paper, Dobbie & Yang apply this method to an OLS, or linear, regression, and Prince & Schwarcz explicitly discuss the method in the context of artificial intelligence. The machine learning algorithm closest to an OLS regression is a lasso (least absolute shrinkage and selection operator). It is similar to an OLS regression in that it produces a function of variables $x$ and estimators $\beta$. Therefore, we may be able to apply this method, at least in the case of a lasso algorithm, by substituting $\bar{X}_{race}$ if the lasso selects the race variable.

### 3.4.1 Instability of machine learning selection

Applying orthogonalization method to the machine learning context creates practical and conceptual difficulties. Practically, the variable selection of the lasso is unstable, and even small amounts of noise lead to different variable selection. Conceptually, a lasso algorithm is not meant to estimate a model, as with an OLS regression, so that it is incorrect to interpret the weights of different variables as reflecting some underlying model, as the orthogonalization method does.

To demonstrate the practical challenges in applying this method to

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1. Pope & Sydnor also focus on the application to an OLS regression but also expand the analysis to a probit regression. See Pope & Sydnor, supra note 187, at 215.
2. See Prince & Schwarcz, supra note 138, at 57 (“For a model produced by an AI, accomplishing this requires including in the training data information on legally prohibited characteristics, such as the race or health status of individuals in the training population.”)
3. The objective of the lasso is to minimize the sum of squares between the true outcome and predicted outcome (like a linear regression), subject to regularization that restricts the magnitude of coefficients.
4. Pope & Sydnor’s paper also presented results on how accuracy is largely maintained using this method. See Pope & Sydnor, supra note 187. For a discussion of how this analysis may not hold in the machine-learning context, see Kristen M. Altenburger & Daniel E. Ho, *When Algorithms Import Private Bias into Public Enforcement: The Promise and Limitations of Statistical Debiasing Solutions*, 175 *JOURNAL OF INSTITUTIONAL AND THEORETICAL ECONOMICS (JITE)* 98 (2019).
5. Prince and Schwarcz discuss other challenges for this approach, which I do not discuss in detail. For example, they suggest that an insurer might be more inclined to discriminate if they learn from this method that a protected characteristic is predictive. They also suggest that because this approach requires the explicit consideration of protected characteristics, it might trigger discrimination law. It could also give rise to a constitutional challenge because it requires companies to consider protected characteristics. See Prince & Schwarcz, supra note 138, at 57.
machine learning, I show that whether an algorithm selects and puts weight on race is unstable. To create 10 comparable datasets with slightly different noise, I randomly draw 2,000 observations from my full dataset 10 times. Because these 10 datasets are randomly drawn from the same full dataset, they should roughly be the same, although they are unlikely to be identical. I then fit a lasso regression to each of the 10 training datasets: I let the algorithm choose which of the many characteristics to include in the model. As pointed out above, the advantage of using a lasso regression is that its output looks quite similar to an OLS output in that it produces a function with the variables used to form a prediction and the weights of each variable.

Despite being drawn from the same population, it is not the case that the random sampling leads to identical algorithmic decisions. Figure 11 plots the weights on the variable “race.”\textsuperscript{196} Each column represents a different random draw from the data set. We can see that for seven of the draws, the variable “race” is not selected at all. In draw 4 the “race” variable receives a very small and negative weight, and in draw 5 and 9, “race” receives a larger negative weight of around $-0.0059$ and $-0.0082$, respectively. This means that in draw 5 and 9 (and to some extent draw 4), white borrowers are predicted to have a lower default risk.

![Figure 11: Weight on “race” variable. Each of the 10 columns represents a different random draw of 2,000 observations from the full data, on which I fit a lasso regression. The columns plot the weight of the lasso regression on the race variable. There is a non-zero weight on the race variable for only 3 out of 10.](image)

Importantly, despite the different weights put on “race” in draw 5 and 9,

\textsuperscript{196} The “race” variable is a dummy variable. It is 1 when a borrower is white and 0 otherwise.
relative to the other draws, the overall predictions appear qualitatively similar. The top row of Figure 12 shows the distribution of default predictions by group for whites and non-whites for draws 4 and 5. The distribution for whites and non-whites is not identical across the two draws; however, they are qualitatively quite similar with respect to their pricing properties across groups. Therefore, although the prediction functions look very different, the underlying data, and the way in which they were constructed, and the resulting price distributions are all similar.

![Figure 12: The top row shows the distribution of the risk prediction for white (W) and non-white (M) borrowers, from a lasso regression using the all inputs. The graph on the top left corner is the prediction from random draw 4 from the dataset, and the graph on the top right corner is the prediction from random draw 5 from the dataset. The bottom row shows the prediction when “race” is substituted by “mean race” (0.8). The vertical lines represent the median for whites and non-whites.](image)

Applying the orthogonalization method would lead to different results depending on the draw. To see this, I applied the “mean race” to all
borrowers and plotted the default distribution in the bottom row of Figure 12. For draw 4, the left column of Figure 12, the top and bottom row are nearly identical, and the median for white and non-white borrowers does not change. This is because in draw 4, the variable “race” has a weight that is close to 0. For draw 5, on the right, the orthogonalization reduces the disparities between whites and non-whites. This can be seen by the fact that the vertical lines, representing the median for white and non-white borrowers, are closer to one another on the bottom graph relative to the top graph, for draw 5.

The conclusion of this exercise is that even though the training datasets of draws 4 and 5 are very similar, the lasso regression made different choices with respect to the weight on “race.” The orthogonalization method, which uses the coefficient or weight on “race” for the screening stage, will therefore yield different results based on the random draw. Appendix C broadens this example by demonstrating how, more broadly, there is instability with respect to the variables selected by the lasso regression.

3.4.2 Why machine learning is different

The technical exercise in the previous section reveals a more substantive limitation in how to interpret machine learning algorithms. In a standard regression analysis, the coefficients represent some estimation of the impact of the independent variables on the predicted dependent variables. The fact that regression coefficients are often stable, even when slightly adding noise to the dataset, reflects the regression’s estimation of an underlying model.

This is not the case with machine learning. Although the lasso regression output function looks similar to the output of an OLS regression, it should be interpreted differently. Machine learning is constructed to optimize the prediction accuracy. Therefore, the fact that even small amounts of noise in the data can change the variables that are selected by the algorithm in forming the prediction may not matter as long as the prediction accuracy is somewhat stable. When there are many possible characteristics that predictions can depend on, and algorithms choose from a large, expressive class of potential prediction functions, then many rules that look very different have qualitatively similar prediction properties. Which of these rules is chosen in a given draw of the data then may come down to a flip of a coin.

The orthogonalization method goes wrong in the machine learning context because it essentially involves lying to the algorithm. The method asks the algorithm to optimize the prediction when it has access to race, only to restrict this access when applying the prediction function. This may not be

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197 There are many more white borrowers in my dataset than non-white borrowers, so that $\bar{X}_{race} = 0.8$. 
a problem when the prediction was based on estimating the model, therefore isolating the effect of race on the prediction. However, when using a machine learning algorithm, the use of race is instrumental in optimizing the prediction accuracy and is not a substantive evaluation of its contribution to the prediction.

3.5 Required shift from causation to correlation

In this Section, I argue that translating traditional discrimination law to the algorithmic context requires more than small tweaks suggested by approaches that continue to focus on the credit pricing inputs and their causal relationship to the differential treatment on protected groups. Instead we must recognize that in the machine learning context, we cannot identify causal relationships and cannot consider variables selected by an algorithm in forming a prediction as estimating a model.198

Fair lending law has traditionally focused on causal questions. Disparate treatment is concerned with whether a protected characteristic affected a decision and therefore seeks the causal connection between a protected characteristic and a lending decision.199 Disparate impact is also concerned with causal connections. A disparate impact claim is initiated through establishing the causal link between a specific input or policy and a disparate outcome.200 Similarly, a defense to a disparate impact claim must rely on the causal connection between an input and a legitimate business goal.201

198 See Martin J. Katz, The Fundamental Incoherence of Title VII: Making Sense of Causation in Disparate Treatment Law, 94 GEO. L. J. 489, 552 (2006) (discussing the causation requirement in anti-discrimination laws); Sheila R. Foster, Causation in Antidiscrimination Law: Beyond Intent versus Impact, 41 HOUS. L. REV. 1469, 1472 (2005) (“The prohibition against discrimination is a prohibition against making decisions or taking actions on account of, or because of, a status characteristic singled out for protection by our civil rights laws or constitutional traditions (which generally include race, gender, nationality, religion, disability, and age).”)

199 See Sullivan, supra note 7, at 408 (suggesting that in the employment context, one way to read Title VII is that it “embraces ad causal view of what we call disparate treatment.”)

200 See MacCarthy, supra note 79, at 83 (“The law is generally clear that there must be a nexus or causal connection between some element of institutional practices and the disparate outcome for there to be a finding of illegal discrimination.”)

201 See OCC 97 Bulletin 97-24. For the OCC to find that credit score meets can be justified by a business necessity the variable causing the disparity must have “an understandable relationship to an individual applicant’s creditworthiness” (page 11). In the employment context, legal scholars have argued that there needs to be some causal link between job performance and input, and not correlation alone is insufficient. See: Grimmelmann & Westreich, supra note 41, at 170 (“We believe that where a plaintiff has identified a disparate impact, the defendant’s burden to show a business necessity requires it to show not just that its model’s scores are not just correlated with job performance but
In considering discrimination law in the algorithmic context, not only do many scholars continue to apply a causal framework, but also regulators focus on causal relationships. The recently proposed HUD disparate impact rule suggests that defendants can negate a claim of disparate impact if they “break down the model piece-by-piece and demonstrate how each factor considered could not be the cause of the disparate impact.”

HUD’s articulation of the defense relies on the ability to isolate inputs and separately evaluate their causal relationship to a disparate outcome.

These causal relationships break down in a machine learning world. The relationships that an algorithm uses to form a prediction reflect correlations in the data and not a causal connection to the outcome of interest. For example, when an algorithm considers whether a borrower has an android phone to predict his or her creditworthiness, it is not telling us about the causal relationship between phone type and default. A person who buys a new phone is unlikely to change the risk of default. Rather, the basis for an algorithm to use a borrower’s phone type could be its own correlation with a variable that is causally related to default, such as income, or some other type of association.

The shift away from causality means that we cannot distinguish between an input that is used to form a prediction because it is a proxy for race and an input that is innocuous. For example, the time it takes a person to fill in an online application may be predictive of default risk. Is this because the time explain it.”). The extent to which this might be true under fair lending is unclear, given the strict criteria for a “business necessity” defense. See King & Mrkonich, supra note 41, at 571. Law’s causal inquiry should be distinguished from a social science understanding of causality. Legal causal analysis does not rely on presenting rigorous empirical identification of causal relationships. Instead, claims of causality focused on intuitive understanding of how factors and inputs are related to the outcomes of policies or how they related to a legitimate business end and were justified accordingly. For example, see the NCLC’s description of this intuitive type of argumentation (“There is an understandable connection between timely repayment of past obligations and the likelihood of timely repayment of future obligations, so a “demonstrable relationship” argument can be easily made”). Yu et al., supra note 63, at 29. In the context of employment discrimination, Kim argues that in traditional forms of testing for a job, employers determined which skills are related to job performance and then used tests for those attributes. This is consistent with an intuitive model of causality between inputs (attributes) and outputs (job performance). See Kim, supra note 7, at 874. Also see page 881 (“If, however, the variables are merely correlated and not causally related, there is no necessary connection between them, and the correlation may not hold in the future.”)

See HUD Proposed Rule 2019. at 20 (explanation of the proposed rule). It is unclear what exactly HUD means by this defense, especially in light of the following sentence, according to which a plaintiff can undermine the defense if they show that “the defendant’s analysis is somehow flawed, such as by showing that a factor used in the model is correlated with a protected class.” Id., at 20-21.

203 See Berg et al., supra note 106.
it takes to fill out the application is related to a person’s education level that relates to creditworthiness? Is it because it tells us something about how much thought the applicant has dedicated to the application? Or is it an indicator that a person is married with children and has less time for online applications? This last speculation relates the application time to a protected characteristic, marital status, which may be particularly worrying. Ultimately, we do not know why application time is predictive of default. All we know is that it is predictive. The traditional focus on causality is also a problem because in machine learning, the algorithm’s selection of inputs is unstable, as demonstrated in the previous Section.204

These differences between traditional regression analysis and machine learning are not only important for social scientists but also for legal analysis. In considering a claim of disparate impact, we wish to know which inputs are driving disparities; however, with machine learning, we should not interpret the selection of variables as an indication of which input drives disparities.205 If the inputs used to form a prediction are unstable, this will also make it difficult for the human eye to identify when “proxies” are being used for a protected characteristic.

IV. TOWARD A SOLUTION

Given the unsuitability of input-based approaches in the algorithmic setting, there is a need to rethink how to analyze discrimination in the algorithmic setting. This is true for both disparate treatment and disparate impact. For disparate treatment, we have no reliable way to detect proxies for protected characteristics. For disparate impact, we need new tools to evaluate the effects of algorithmic pricing that are appropriate for machine learning, as restricting variables upstream can have a limited or surprising effect on the disparities downstream.

One challenge in developing an outcomes-based test is that there are currently widespread and far-reaching disagreements over the theoretical foundations and boundaries of the discrimination doctrine. The exact details about the implementation of the test rely on a clear definition of what discrimination law aims to achieve. I do not adopt a particular position on these disagreements. Instead I highlight how outcome analysis can be used to answer important questions that often are of interest to discrimination law.

204 In most social sciences the focus is on parameter estimation, meaning to produce functions that produce meaning estimates of the way inputs (independent variables) relate to what is being predicted (dependent variable). For further discussion see: Sendhil Mullainathan & Jann Spiess, Machine Learning: An Applied Econometric Approach, 31 J. ECON. PERSP. 87 (2017).

205 See Gillis & Spiess, supra note 26.
The framework I lay out is flexible enough to accommodate varying views of discrimination law.

The required change from input scrutiny to outcome analysis will be uncomfortable for fair lending law. Discrimination law has always resisted focusing solely on the outcomes or effects of a policy as a way of identifying discrimination. However, the shift in paradigm requires developing tools to consider downstream outcomes given the limitations in upstream analysis. When credibly scrutinizing inputs is not an option, downstream analysis provides important opportunities.\(^\text{206}\)

This section begins with a discussion of how to create an outcome-based framework for discrimination analysis. In this framework, a regulator applies the pricing rule to a designated dataset to analyze the properties of the pricing rules. I highlight two particularly meaningful questions a regulator can

\(^{206}\)One possibility, not fully addressed in this paper, is that discrimination law altogether is no longer the appropriate legal framework to address concerns in the algorithmic context. Several academics and policy makers have argued that the unique challenges of the algorithmic fairness require an alternative framework to discrimination. Some have argued that the way we need to address algorithmic challenges is closer to the framework of affirmative action than discrimination. See Cynthia Dwork et al., *Fairness Through Awareness*, PROCEEDINGS OF THE 3RD INNOVATIONS IN THEORETICAL COMPUTER SCIENCE CONFERENCE 214 (ITCS '12, ACM New York, NY, USA 2012) (proposing “fair affirmative action.”) Chander makes a similar argument with respect to affirmative action as the appropriate framework through which to deal with unfair outcomes as a result of biased inputs is through affirmative action. See Chander, supra note 40, at 1040. Huq’s recent proposal to evaluate algorithmic criminal justice measured based on their effect on racial stratification is also an output-based framework because it looks to the benefits and costs of the criminal justice measures. See Huq, supra note 185, at 1128. Huq discusses the limitations of discrimination law in the context of the Constitutional Equal Protection, and therefore focuses on the disparate treatment doctrine. For broader discussions of the appropriateness of discrimination law, see Anna Lauren Hoffmann, *Where Fairness Fails: Data, Algorithms, and the Limits of Antidiscrimination Discourse*, 22 INFORMATION, COMMUNICATION & SOCIETY 900 (2019). Arguing that discrimination law is an insufficient framework to address the structural concerns that arise as a result of big data and algorithmic decision-making.) My focus here is on how to identify credit pricing that could raise red flags in light of the concerns highlighted in Section 2.3. Whether the correct way to address these concerns is through discrimination law or another legal framework is not an issue wherein I argue for any particular position. However, it is important to keep in mind that the basic challenges of “biased world” and “biased measurement” have always been a challenge for discrimination law, even prior to the algorithmic context.

Others have suggested that the concerns of algorithmic fairness be addressed not through mechanisms that directly regulate conduct but through creating appropriate frameworks that allow further private or public scrutiny. For example, one major approach discussed in the literature is transparency. See for example Frank Pasquale, *The Black Box Society: The Secret Algorithms That Control Money and Information* (2015). For skepticism over whether transparency or privacy can address fairness concerns, see Cynthia Dwork & Deirdre K. Mulligan, *It’s Not Privacy, and It’s Not Fair*, STAN. L. REV. ONLINE 35 (2013–2014).
address using this framework. First, a regulator can ask whether borrowers who are “similarly situated” are treated the same. Second, a regulator can analyze whether the pricing rule increases or decreases disparities relative to some baseline, such as the pricing rule used prior to the utilization of an algorithm. I end the section by discussing how this framework takes advantage of the technological change to enhance its toolkit. This type of outcome-focused testing brings to the forefront the demonstration of disparities, which is formally part of first stage of a disparate impact complaint in traditional fair lending law. My proposed testing framework develops this type of analysis and adapts it to the machine learning context.

A full discussion of the various ways this test can be structured and implemented is beyond the scope of this paper. Future work will consider the various challenges in designing and implementing the test along with the incentives the test could create for lenders. Importantly, it will demonstrate how the test can be adjusted based on different normative theories of discrimination.

4.1 Testing outcomes in three steps

The outcome testing I propose requires regulators to apply a lender’s pricing rule to a dataset of hypothetical borrowers and then examine the properties of the outcome. The framework can therefore be split into three stages. At the first stage, the lender determines what inputs and which algorithm to use to predict default and price accordingly.207 At the second stage, the regulator then takes that prediction or pricing rule and applies it to a dataset of people to see the distribution of prices the rule produces. Finally, the regulator evaluates this outcome to determine whether the disparities created by the pricing rule amount to discriminatory conduct. I will briefly describe the first two stages and then focus on the third stage. I use the example of race as a protected characteristic, but the analysis is generalizable to other protected characteristics.

The first stage of the test is the pricing rule developed by the lender, which does not directly involve a regulator. What is unique about the machine learning context is that a pricing rule exists even before specific borrowers receive loans. In traditional credit pricing, little was known before actual prices were given to real borrowers. In the algorithmic context, regulators can analyze prices in an ex ante manner, before the algorithm is applied to price credit.

In the second stage, the pricing rule is applied to a dataset, containing real

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207 An alternative analysis that the regulator could conduct would be to compare the binary decision of lenders of whether to extend or deny a loan application. In fact, HMDA is primarily focused on understanding whether this lender decision varies by race.
or hypothetical people and their characteristics. Elsewhere I have argued that it is difficult to analyze a prediction function in the abstract. Rather, the prediction function should be applied to a group of borrowers in order to examine its properties. For computer scientists, this is typically the holdout set, meaning a subset of the data on which the algorithm is not trained but is instead used to assess the accuracy of the prediction. A regulator could be strategic in selecting which population to apply a pricing rule to, by not sharing the dataset with the lender in advance.

Figure 13: Distribution of risk predictions. This graph separately plots the distribution of risk predictions for non-Hispanic white (W) and non-white (M) borrowers.

Figure 13 plots an example of what the regulator’s initial analysis would look like. In this example, a regulator takes a lender’s pricing rule and applies it to a dataset held by the regulator. One way to think of the dataset used by the regulator is that it represents a group of hypothetical borrowers for which we want to learn the price this group would be charged for a loan. Figure 13 then plots the distribution of prices separately for white and non-white borrowers. The disparities in the distributions show that even when the prediction does not use the “race” variable, the predicted risk is different for the two groups.

The credit price is not the only outcome metric that is of interest to a regulator. The regulator could use a similar method to analyze a lender’s

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208 See Gillis & Spiess, supra note 26, at 473.
209 Future work will discuss the various factors a regulator should consider in selecting the population used to analyze a lender’s pricing rule.
210 The main outcome metric on which I focus in this paper, namely the prices paid by borrowers, is a type of outcome measure that is often referred to as “demographic parity”.
binary decision of whether to extend a loan. Using the lender’s algorithmic rule in determining whether to reject a loan, the regulator could apply this rule to its hypothetical dataset of lenders. In Appendix D, I discuss a possible alternative for the outcome of interest to analyze in considering disparities, namely error rates and how they vary by race. This outcome has been the focus of computer science and statistics literature\(^\text{211}\) and of some recent legal literature.\(^\text{212}\)

The raw disparities are rarely of interest in and of themselves, so that in the third stage of the test, the regulator needs to determine whether a pricing rule disparity amounts to discrimination.\(^\text{213}\) Unlike traditional fair lending law, the criteria used to determine whether pricing disparities amount to discrimination needs to be formulated without reference to the inputs used. The exact criteria to be used in outcome analysis cannot be defined without a clear definition of what discrimination law, and disparate impact in particular, are meant to achieve. As I have emphasized throughout, this is an issue that is disputed and that I do not resolve.

The focus of this part is to demonstrate how outcome analysis can answer

\(^\text{211}\) A significant portion of the algorithmic fairness literature has focused on fairness definitions that are types of “classification parity” meaning they consider whether a measure of classification error is equal across groups. See Corbett-Davies & Goel, supra note 213, at 5. Corbett-Davies and Goel define this category as any definition that can be calculated from a confusion matrix, which tabulates the joint distributions of a certain decision and outcomes by group. See: Richard Berk et al., Fairness in Criminal Justice Risk Assessments: The State of the Art, SOCIOLOGICAL METHODS & RESEARCH 0049124118782533, 3 (2018). Two of these measures, the “true positive rate” (TPR) and “false positive rate” (FPR), discussed in Appendix B, to provide a way to measure the prediction accuracy. An ancillary literature has focused on the documenting how the various classification errors can often not simultaneously be satisfied. See discussion in Jon Kleinberg et al., Inherent Trade-Offs in the Fair Determination of Risk Scores, arXiv:1609.05807 [cs, stat] (2016); Alexandra Chouldechova, Fair Prediction with Disparate Impact: A Study of Bias in Recidivism Prediction Instruments, 5 BIG DATA 153 (2017); Berk et al., supra.

\(^\text{212}\) See Hellman, supra note 140; MacCarthy, supra note 79, at 88.

\(^\text{213}\) Outcome analysis has always been a part of a disparate impact claim for the purposes of the \emph{prima facie} case, but was rarely the determining factor. A typical disparate impact claim begins with a demonstration of outcome disparities. This showing of disparities is rarely sufficient in of itself even for the first stage of a case, since a plaintiff is also required to isolate the particular policy or input that lead to the disparity. Despite the role outcome analysis plays in a disparate impact case, there is little guidance on how exactly to conduct this analysis.
meaningful questions related to discrimination. I focus on two questions that can be analyzed using outcome-based analysis. The first question is whether borrowers who are “similarly situated” are treated the same. The second question is whether the pricing rule increases or decreases disparities relative to some baseline. The next two sections discuss these two questions. My aim in this part is not to provide a precise definition of when a disparity amounts to discrimination given the widespread disagreement over the boundaries of the doctrine but rather to demonstrate the usefulness of outcome analysis.

4.1.1 Can the test compare borrowers who are similarly situated?

An important question for discrimination law is whether borrowers who are similarly situated are treated the same. In traditional disparate impact case, this is required as part of the prima facie case although there is very little existing analysis on who exactly is similarly situated in credit pricing. Given the need to expand the role of outcome analysis, future regulatory and scholarly attention could be devoted to how we define who is similarly situated and give this a more prominent role.

Discrimination law has long recognized that there are differences that are a legitimate basis on which to distinguish between borrowers. For

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214 This requirement originates in the seminal Title VII case, McDonnell Douglas Corp. v. Green, 411 U.S. 792 (1973). Some courts were willing to extend the "McDonnell Douglas standard" to the credit context. See Robert G. Schwemm, Introduction to Mortgage Lending Discrimination Law A Fair Lending Symposium: Litigating a Mortgage Lending Case, J. MARSHALL L. REV. 317, 329 (1994–1995), (summarizing fair lending cases and the requirement that the plaintiff had to establish that "the defendant approved loans for white applicants with qualifications similar to the plaintiff's"). See also Simms v. First Gibraltar Bank, 83 F.3d 1546, 1558 (5th Cir.1996). See Judge Posner in Latimore v. Citibank, 151 F.3d 712, 713 (7th Cir. 1998), for a more skeptical view of the application of the “similarly situated” requirement to the credit context. In general, the notion of “similarly situated” has been somewhat controversial over the years, including in the context of employment discrimination. For further discussion, see Suzanne B. Goldberg, Discrimination by Comparison, YALE L. J. 728 (2010–2011); Ernest F. III Lidge, The Courts’ Misuse of the Similarly Situated Concept in Employment Discrimination Law, Mo. L. REV. 831 (2002).

215 There is some ambiguity over whether the requirement to demonstrate that a member of a protected group was treated differently to someone “similarly situated” is part of the first or third stage of the burden-shifting framework. See Goldberg, supra note 217, at 746–47 (discussing this ambiguity in demonstrating "comparable"); See also Schwemm, supra note 217, at 328–29. Furthermore it is unclear whether the requirement is part of a disparate treatment case as well as a disparate impact case.

216 According to the Supreme Court in Inclusive Communities, even the prima facie case of the plaintiff cannot rely only a showing of disparities, See Texas Dep’t of Hous. and Cmty. Affairs v. Inclusive Cmty. Project, Inc., 135 S. Ct. 2507 (U.S. 2015). (“In a similar vein, a disparate-impact claim that relies on a statistical disparity must fail if the plaintiff cannot point to a defendant’s policy or policies causing that disparity.”)
example, we may think that it is legitimate to distinguish between people who have different levels of income, even if income correlates with race.\textsuperscript{217} The central question then becomes the extent to which the differences in prices are explained by differences in income. Only the unexplained component of price disparity would then be the basis of discrimination and not the raw disparities alone.

In the algorithmic context, we can consider this as a set of characteristics which determine who are the people who are similarly situated. Any differences that are explained by this set of characteristics are not deemed to be impermissible discrimination.\textsuperscript{218} This set can intuitively be considered like adding control variables into a regression in that they explain differences between people.\textsuperscript{219} The size and scope of the similarly situated set are likely to have a significant effect on whether there is a finding of impermissible disparity. As this set expands, more of the raw differences are accounted for by the preexisting differences of protected groups.

It is important to note that who is similarly situated is essentially a normative question and not an empirical one, as it reflects who we believe should be treated similarly.\textsuperscript{220} The difference between the empirical question of who is the same versus who should be treated the same becomes particularly apparent when considering that fair lending law prohibits discrimination based on protected characteristics, even if they are causal of default. As discussed above, age and marital status may change a borrower’s default risk, yet these characteristics cannot be used to distinguish between people. Despite the significance of the definition of who is “similarly situated”, even under traditional fair lending, there is little guidance on this question.\textsuperscript{221}

\textsuperscript{217} See supra Section 1.2.
\textsuperscript{218} There are some similarities between my framework and the framework proposed by Dwork et al., supra note 209. Their approach is based on a similarity metric between individuals who are treated fairly if the classifier ensures similar outcomes for similar individuals.
\textsuperscript{219} This is similar to the analysis discussed in Ayres et al., supra note 84. The expert report discussed in that paper presented different linear regression models, which included different variables as controls to consider whether there was still a significant coefficient on “race” after adding the controls.
\textsuperscript{220} Note that the similarly situated set is separate from the set of characteristics that is predictive of the outcome. If all the characteristics that are predictive of an outcome were included in the similarly situated set, then by definition, the algorithmic credit pricing does not create impermissible disparity. Adopting such a definition of the similarly situated test puts us back into the world in which once the protected characteristic is excluded, discrimination law is no longer relevant, a position discussed in detail in Part II.
\textsuperscript{221} Despite the role outcome analysis plays in a disparate impact case, particularly in the prima facie case of a claimant or plaintiff, there is little guidance on how exactly to conduct this analysis. See discussion in Giovanna Shay, Similarly Situated, GEO. MASON L. REV.
Testing for disparities among the “similarly situated” may seem as a return to input-based approaches, as it relies on the selection of the legitimate bases for differentiation. If the test requires selecting normatively relevant criteria for distinction then it may seem similar to restricting an algorithm to pre-approved inputs. However, this test differs from restricting an algorithm’s input to the characteristics in the similarly situated set in several ways. Restricting an algorithm’s inputs to the similarly situated set would definitely be sufficient for this test, but it is not necessary to do so. This is because there may be many inputs that increase prediction accuracy while not creating significant disparities. This is especially important in the case of characteristics that would help increase access to credit for protected groups but are unlikely be included in the similarly situated set, such as timely rental payments. Moreover, a regulator may set the tolerance level such that some disparity is permissible.

In general, creating a test that relies on similarly situated characteristics makes the tradeoff between accuracy and other policy goals explicit, rather than the opaqueness of restricting to inputs that intuitively seem relevant to default. It also means that this set can be adjusted and tested rather than the inability to learn and adapt that results from input restriction. Nonetheless, the disadvantage of this approach is its reliance on a normatively determined set, which may be problematic particularly if the set includes characteristics that may themselves be the source of disadvantage, such as credit scores.

4.1.2 Can the test consider incremental change?

Another meaningful way to consider the disparities created by algorithmic pricing is to do so relative to some baseline, such as traditional

581, 583 (2010–2011) (“Although the phrase ‘similarly situated’ is a familiar component of equal protection case law, it has not received much scholarly attention. Constitutional law scholars have focused more on other aspects of the doctrine”)

For an example of what outcome analysis might look like in the, see the expert opinion discussed in Ayres et al., supra note 84, at 238. The effect of race was considered by using a regression with various controls although the paper does not directly discuss which controls are appropriate to include.

Some cases mention who the relevant comparison groups should be, but only in passing. Take a recent decision in which the plaintiff alleged that Well Fargo’s had engaged in reverse redlining against blacks and Hispanics. In considering the defendant’s motion to dismiss, the judge states that “the City uses statistical analysis to allege that, under these policies, African-American and Latino borrowers with FICO credit scores above 660 were more than twice as likely to be issued a high-cost or high-risk loan when compared to a similarly situated white borrower.” This suggests that FICO score alone would be in the set of similarly situated characteristics although this point is not further developed. See City of Philadelphia v. Wells Fargo & Co. United States District Court, E.D. Pennsylvania (Jan. 16, 2018), Civil Action No. 17-2203.
credit pricing. Rather than judging algorithmic pricing by the absolute level of disparities, by comparing the algorithmic pricing to traditional credit pricing, we are able to answer the question of whether disparities increase or decrease as a result of a change in technology. This approach avoids holding algorithms to a standard that is far harsher than current standards of fair lending are, which may end up overlooking the potential of algorithmic pricing to help consumers.

The implementation of the incremental approach to testing is similar to testing whether borrowers who are similarly situated are treated the same. In the case of similarly situated testing, the baseline was the prices using the limited set only whereas in the incremental approach, some other baseline could be selected, such as the prices borrowers were paying under traditional lending. Similarly, a regulator could compare the prices produced under the use of traditional lending variables versus a new data available to a lender, such as consumer and payment behavior.

An incremental approach to disparities recognizes that credit is priced in a “biased world” but also seeks to prevent algorithmic pricing from exacerbating preexisting disadvantage. When personalized pricing relies on biased inputs, it is unlikely to ever produce pricing that is not disparate for protected groups. However, as discussed in Section 2.3, the use of nontraditional datasets could mitigate the harms of biased measurement, which would reduce disparities among groups. Moreover, more accurate pricing could also expand access to credit, which could also benefit vulnerable groups. The conclusion is that there is a need for an empirical test for determining whether there is harm to protected groups stemming from changes in credit pricing rather than from the general use of biased inputs in credit decisions.

This type of incremental analysis is suggested by a recent update published by the Consumer Financial Protection Bureau (CFPB). The background for this update is a No-Action Letter that the CFPB provided an algorithmic lender, Upstart, in 2017. In its update on the No-Action Letter,

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222 See Berk et al., supra note 214, at 29. (“At the same time, the benchmark is current practice. By that standard, even small steps, imperfect as they may be, can in principle lead to meaningful improvements in criminal justice decisions. They just need to be accurately characterized.”)

223 Consumer Financial Protection Bureau, No-Action Letter (Sep. 14, 2017), https://www.consumerfinance.gov/documents/5462/201709_cfpb_upstart-no-action-letter.pdf. This was the first and only No-Action letter that the CFPB has provided. For the general policy, see Bureau of Consumer Financial Protection Policy on No-Action Letters, 81 FR 8686 (Feb. 22, 2016). On August 6, 2019, the CFPB provided an update on the No-Action letter, discussing how Upstart had expanded access to credit. See Patrice Ficklin and Paul Watkins, Consumer Financial Protection Bureau, An Update on Credit Access and the Bureau’s First No-Action Letter (Aug. 6, 2019). In its update, the CFPB suggests that Upstart
from August 6, 2019, the CFPB reported results from Upstart’s analysis “comparing outcomes from its underwriting and pricing model (tested model) against outcomes from a hypothetical model that uses traditional application and credit file variables and does not employ machine learning (traditional model).” The focus of Upstart’s analysis was therefore the incremental change in moving from traditional credit pricing to algorithmic credit pricing. It is this type of analysis that should form the core of fair lending analysis.

HUD’s recent Proposed Rule suggests a similar approach to determining a lender’s defense in a disparate impact case. According to the proposal, when relying on an algorithm, a lender can show that “use of the model is standard in the industry.” The Proposed Rule therefore recognizes that one of the ways to establish that an algorithm is not discriminatory is by reference to some baseline, in this case the “industry standard,” rather than some absolute level of disparity.

In summary, outcome-based testing could provide important information about two questions that are meaningful to discrimination analysis, namely whether similarly situated borrowers are treated the same and whether a change in pricing increases or decreases disparity. Many questions regarding the implementation of the test will be discussed in future work. These issues include how to deal with a case in which a new pricing rule decreases disparities for one category (say, race) but increases disparities for another (say, sex) or how regulators can balance the need to clear rules that allow for certainty with the flexibility of the incremental change approach.

4.2 Regtech response to Fintech

Regulators need to develop tools that will allow them to respond effectively to changes in the credit pricing world. Credit pricing is becoming more complex, both with respect to the decision inputs and how those inputs are used to produce predictions and pricing rules. This environment is becoming increasingly difficult to oversee, as regulators need to supervise an evolving technological environment. The old world of input scrutiny-focused regulators was to a large extent feasible because of the limited complexity of

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225 HUD Proposed Rule 2019, at 42859.
credit pricing decisions.

The move to a more technologically complex environment can create important opportunities for regulators. This is underappreciated by many scholars who focus solely on the challenges for regulators in gaining competency in new domains. However, machine learning pricing brings new types of transparency which can also create new regulatory tools. In the case of credit pricing, the greatest change is that much is known about credit pricing even before a pricing rule is applied to new borrowers. In the traditional credit pricing context, regulators respond to materialized prices, meaning actually prices charged to actual borrowers.

In the machine learning pricing context regulators can analyze pricing rules before they are applied to real borrowers, since the pricing rule exists independently from its implementation. Because the function exists independently from any defined set of borrowers, its properties can be learned by applying it to a population before the lender adopts it. Regulatory testing therefore takes advantage of this added degree of transparency available in the algorithmic context. As argued throughout this Article, the effects of changes in credit markets on disparities between groups is unclear and cannot be adequately studied from a theoretical perspective. This means that only a testing method can provide information on the actual effects of pricing rules.

This approach also provides more certainty to lenders. Lenders who wish to depart from traditional credit pricing face a very uncertain regulatory landscape. Although much of the writing about discrimination and artificial intelligence focuses on preventing intentional discrimination, the reality for many lenders is that they are unsure of how to comply with discrimination law. A testing approach might be especially valuable for lenders who wish to embrace a new technology or use a novel dataset but are concerned with the legal uncertainty that often accompanies technological change. The outcomes-based testing approach provides a method whereby to resolve some of that uncertainty, either by delineating an approach in which lenders can themselves test for the way changes affect protected groups or by allowing lenders to receive more certainty from regulators.

**CONCLUSION**

Risk-based pricing is about differentiating borrowers. Big data and machine learning enhance the ability to differentiate, increasing the tension with fair lending law that limits differentiation of borrowers on protected grounds. Traditional fair lending law sought to constrain pricing practices by scrutinizing inputs. This approach was developed in a world in which pricing relied on few inputs, depended on human expertise and used loan officers to set the final terms of credit contracts. Modern underwriting is increasingly
relying on nontraditional inputs and advanced prediction technologies, challenging existing discrimination doctrine.

How to capture the benefits of algorithmic credit pricing while limiting its potential to hurt protected groups has become a pressing issue for legislators and regulators. In May 2019, the House Financial Services Committee established a task force on financial technology to “examine the current legal framework for fintech, how fintech is used in lending, and how consumers engage with fintech,” along with a second task force on artificial intelligence. The CFPB, in its July 2019 fair lending report, highlighted the Bureau’s interest in “ways that alternative data and modeling may expand access to credit” while also seeking to understand the risks of these models. Finally, the CFPB announcement from August 6, 2019, endorsed the view that big data and machine learning lenders could comply with fair lending if they demonstrate that their lending practices do not increase disparities.

This recent focus on legislators suggests that fair lending is likely to be a central battleground on which the boundaries of algorithmic fairness and discrimination will be fought.

My aim in this Article has been to demonstrate that the direction in which we are going in resolving the tension between old law and new realities is not a promising one. Current approaches are inadequate because they continue to scrutinize decision inputs, similar to traditional fair lending, when this strategy is no longer feasible or effective in the algorithmic context. This input-scrutiny perspective is adopted both by opponents of a broad disparate impact standard, such as the Trump administration’s HUD, and proponents of a broad standard. Algorithmic decision-making, however, requires a fundamental shift from analysis that seeks to reveal causal connections between inputs and outcomes.

I propose that fair lending shift its gaze downstream to the outputs of an algorithm. This means that regulators develop tests for considering when the outcomes an algorithm creates are impermissible, based on regulators defined policy goals. Regulators can begin doing this by asking meaningful questions that can be answered by examining algorithmic outcomes, such as whether similarly situated borrowers are treated differently or whether the move from traditional pricing to algorithmic pricing has increased disparities. This type of test is particularly important when it is not possible to determine at the

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outset whether a change in prediction technology or input variables will increase or decrease disparities. An empirically driven and experimental approach means not only that regulators keep up with the fintech industry but also that they embrace technological advancement to improve regulation.

The conclusions of my analysis go beyond credit pricing. They are important for other domains in which scholars and lawmakers are struggling to apply discrimination law to the algorithmic setting, such as criminal justice and employment. It is time for discrimination law to fully recognize the challenges related to algorithmic decision-making while embracing its opportunities.
APPENDICES

APPENDIX A: SIMULATION DATA

As discussed in the main Article, I demonstrate my main points in a stylized simulation exercise that is calibrated to real data. Specifically, I consider a lender who prices mortgages based on an algorithmic prediction of their default risk, in order to consider the implications of using biased inputs in the algorithmic setting and to evaluate leading approach to the application of discrimination law to algorithmic decision-making. I also use the simulation exercise and to present my regulatory framework.

The simulation demonstration is based on real mortgage application data from the Boston HMDA data set. From this dataset a simulation model relates applicant and mortgage characteristics to the probability of default. Because mortgage defaults are not observed in this dataset, but are an essential aspect of the simulation demonstration, the default probabilities from loan approvals can be imputed and calibrated to overall default rates. As an important restriction of the analysis, I cannot make any statements about actual defaults in this data but rather demonstrate methodological points under this hypothesized model of default.

In general, HMDA requires mortgage lenders to disclose loan-level information on mortgage applications and whether they were granted or denied. A modified version of HMDA data is publicly available and includes basic data on the loan and the applicant, including demographic information such as race. I specifically use the Boston Fed HMDA dataset, which is based on a follow-up survey conducted by the Boston Fed to supplement the data in HMDA on loans made in 1990 with additional information on financial, employment, and property characteristics.

Despite the dataset’s being nearly 30 years old, it is a uniquely rich dataset and therefore useful to consider a lender using machine learning predictions to set loan prices. The dataset contains information on the finances of the borrower, such as total debt-to-income ratio, the applicant’s credit and borrowing history, whether the applicant is self-employed, and whether the borrower was denied private mortgage insurance. The dataset also contains information on the loan, such as whether the property is a multi-family home, whether the loan has a fixed interest rate, and the term of the loan. The most significant advantage of using HMDA data is that they contain

1 (Adapted from “Big Data and Discrimination”)
2 For a description of how the Boston Fed created this unique dataset and a discussion of their findings, see: Munnell et al., supra note 56.
3 HMDA does not contain information about credit histories, debt burdens, loan-to-value ratios among other factors. See: Id. at 25. Other important details about the Boston Fed data. They also used census data on neighborhood characteristics.
demographic characteristics, such as borrower race, gender, age, and marital status along with various neighborhood characteristics.\(^4\) The lender can be considered a “big data” lender because this type of lender uses many variables (around 40) relative to the number of observations (around 3,000). Unfortunately, due to data limitations, this lender does not include many of the types of the nontraditional discussed in Section II.2.1.1; however, the types of variables are slightly broader than what is typically used by mortgage originator in setting the “par-rate” in traditional lending.\(^5\)

The Boston Fed HMDA only contains information available at the time of the loan application and therefore does not contain information on the performance of the loan, such as whether a borrower defaulted on the loan. Based on the HMDA data alone, one could not run a default prediction exercise because the training data need to contain labels, meaning the outcome that the machine learning algorithm is trained to predict. To overcome this difficulty for the purposes of this exercise, I construct a model based on the dataset that links rejection approval rates to loan default.\(^6\)

From this dataset a simulation model relates applicant and mortgage characteristics to the probability of default. Because mortgage defaults are not observed in this dataset, but are an essential aspect of the simulation demonstration, the default probabilities from loan approvals can be imputed and calibrated to overall default rates. As an important restriction of the analysis, I cannot make any statements about actual defaults in this data but rather demonstrate methodological points under this hypothesized model of default.

Specifically, a ridge-penalized logistic regression model of loan approval is fitted on approximately fifty characteristics of the loan and the borrower (including demographics, geographic information, and credit history), excluding race and ethnicity, which is then recalibrated such that the default rate among those approved for the loan matches the rate reported in a recent paper that uses the matched HMDA-McDash dataset.\(^7\) As a result, for every individual in the Boston HMDA dataset, a probability of default is obtained.

The samples are drawn from the simulation population as follows. First, a bootstrap sample is drawn, without replacement, from the full Boston HMDA dataset. Second, for every individual in the bootstrap sample, whether that individual defaults is simulated based on the default probability

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\(^4\) Such as the appreciation of housing properties in the neighborhood.

\(^5\) For a full description of the variables in the Boston Fed HMDA dataset see Munnell et al., supra note 56.

\(^6\) The methodology is similar to the that discussed in the Online Appendix in Gillis & Spiess, supra note 26. Further details are provided in Appendix A.

\(^7\) Fuster et al., supra note 21.
implied by the calibrated simulation model. As a result, default indicators along with individual characteristics for each individual in the sample are obtained.

In the simulation demonstration, the firm constructs a prediction of default based on a training sample of two thousand consumers drawn randomly. The firm utilizes a machine-learning algorithm that uses this data to produce a prediction function that relates available consumer characteristics (potentially including race) to the predicted probability of default. The properties of a given prediction rule on a new sample of two thousand consumers is then assessed.

As an example of an algorithm that produces such a prediction rule, the firm could run a simple logistic regression in their training sample that produces a prediction function of the form:

\[
\text{predicted probability of default} = \text{logistic}(\alpha + \beta_1 \text{characteristic}_1 + \beta_2 \text{characteristic}_2 + \ldots)
\]

where the characteristics could be the applicant’s income or credit score. While the machine-learning algorithms considered in this Article also produce functions that relate characteristics to the probability of default, they typically take more complex forms that allow, among other things, for interactions between two or more characteristics to affect the predicted probability and are thus better suited to represent richer, possibly nonlinear relationships between characteristics and default. Some of these algorithms build on top of another simple prediction function, namely a decision (or regression) tree. The decision tree decides at every node, based on the value of one of the characteristics, whether to go left or right (for example, if income is below some threshold, go left, otherwise right), before arriving at a terminal node that returns a prediction of the probability of default of all individuals with the relevant characteristics. An example of a decision tree is given in Figure 1. Using this decision tree, the firm would predict that an individual who obtained mortgage insurance (top level, go left) but has a debt-to-income ratio of above 75 percent will have an 80 percent probability of default.
In order to analyze default predictions by group—for which the primary focus is on racial/ethnic groups in the simulation demonstration—I consider their distribution in the new (“holdout”) sample of two thousand consumers drawn from the population. For most of the paper I use a rule obtained from a random forest machine-learning algorithm, which is a collection of many decision trees that are averaged.

**APPENDIX B: UNDERSTANDING ROC CURVES**

The Receiver Operating Characteristic (ROC) curve is a way of capturing prediction accuracy, by focusing on the binary classification of borrowers. The algorithm used in the Article produces the default risk for each borrower. The predicted default risk can then be used by the lender to determine whether they believe a borrower is likely to default or not. For example, a lender can determine a cutoff of 30% default risk, so that all borrowers with a risk above 30% are deemed “defaulters” and all those below are “non-defaulters”.

This cutoff will naturally produce some errors. There will be a group of borrowers who were classified as “defaulters” but end up repaying the loan and not defaulting (type I error). Conversely, there will be a group of borrowers that were classified as “non-defaulters” that end up defaulting (type II error). There is a tradeoff between the size of each of these error groups and minimizing the size of one group will increase the size of the other group. For example, raising the cutoff to 60% will decrease the type I error and increase the type II error. The more accurate a prediction, the smaller the tradeoff between these two types errors.

The ROC curve captures the intuition that a more accurate prediction requires less of a tradeoff between different types of errors. On the one hand it considers the True Positive Rate (TPR) which is the number of people who

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8 In reality this is often not observed. This is because the outcome of a loan is only known if an applicant actually receives a loan. I therefore treat these examples as the error rates that are observed in the holdout set.
were correctly classified as “positive” relative to the total number of people classified as “positive”:

\[ TPR = \frac{True\ Positive}{All\ Positive} \]

In our case a “positive” event is when a borrower defaults on the loan, so that the “true positive” is all the borrowers that the algorithm predicted would default on their loan and indeed they did. On the other hand, the ROC curve, considers the False Positive Rate (FPR) which is the number of people falsely classified as “positive” relative to the total number of people classified as “positive”:

\[ FPR = \frac{False\ Positive}{All\ Positive} \]

The ROC curve plots the TPR for every level of FPR. It therefore can be considered as a measure of the accuracy of the prediction. The closer the curve is to the top left corner, the more accurate the prediction. When the curve lies on the diagonal 45° line, it means that the prediction contains no information beyond random assignment.

Figure 2 shows the ROC curve for the risk prediction function that was produced using all variables other than race. The ROC curve is plotted separately for white and non-white borrowers. The Figure shows that the prediction for white borrowers is more accurate for nearly every classification cutoff.
Figure 15: ROC curve for risk prediction using all inputs (other than race), plotted separately for whites (W) and non-whites (M) borrowers.

One common metric used to measure the prediction accuracy is the Area Under Curve (AUC). The AUC is a number from 0.5 (perfectly random prediction) to 1 (perfectly predictive). When comparing two prediction functions, the AUC is an useful metric to describe overall relative accuracy.
APPENDIX C: INSTABILITY OF SELECTED VARIABLE

In this Appendix, I demonstrate how the variables selected by a machine-learning algorithm can be unstable. This instability has several implications. First, it means that we should be wary in putting weight on the fact that a variable was selected, since this selection could be fairly random. It also means we should not put too much weight on the fact that a variable was not selected by the algorithm. Ultimately, this analysis shows that we are unable to easily isolate the effect a variable has on the predicted outcome. I demonstrate this through an example similar to the one discussed in “Big Data and Discrimination”.

In a standard regression analysis, the coefficients obtained represent some estimation of the impact of the independent variables on the predicted dependent variables. Although one must exercise caution in interpreting these coefficients as bearing a causal relationship to the dependent variable, they at least represent the weight they play in the prediction of the dependent variable. In most cases, adding some noise to the dataset used for the regression analysis should not significantly change the estimates. In other words, the estimates obtained are pretty stable and allow for some estimation of the underlying model of how the independent variables relate to the dependent variable.

This is not the case with machine-learning. With machine-learning even slight differences in the training set, or small amounts of noise in the data can vastly change the variables that are selected by the algorithm in forming the prediction. To create two comparable datasets with slightly different noise I randomly draw 2,000 observations from the full dataset (“training dataset 1”) and then again randomly draw 2,000 observations from the full dataset (“training dataset 2”). Because these two datasets are randomly drawn from the same full dataset, they should roughly be the same, although they are unlikely to identical.

I then fit a logistic lasso regression to each of the two training datasets. The algorithm selects which of the many characteristics to include in the model. The advantage of using a logistic lasso regression is that its output looks quite similar to a regression output, in that it produces a function with the variables used to form a prediction and the weights of each variable.

Both training datasets originate from the same population and therefore we may expect that both training datasets produce qualitatively similar prediction functions. Although these samples are not identical, because of the

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9 See Gillis & Spiess, supra note 26. See Mullainathan & Spiess, supra note 206, for further discussion of the difference between estimation and prediction.
random sampling, they are drawn from the same overall population, and we therefore expect that the algorithmic decisions should produce similar outputs.

Despite being drawn from the same population, it is not the case that the random sampling leads to identical algorithmic decisions. The specific representation of the prediction functions and which variables are used in the final decision rule vary considerably between training dataset 1 and training dataset 2. A graphic representation of this instability can be found in Figure 2. This Figure records which characteristics were included in the logistic lasso regressions we ran on the two draws. Each column represents a draw, while the vertical axis enumerates the over eighty dummy-encoded variables in our data set. The black lines in each column reflect the particular variables that were included in the logistic lasso regression for that sample draw. While some characteristics (rows) are consistently included in the model, there are few discernible patterns, and an analysis of these prediction functions based on which variables were included would yield different conclusions from the two draws, despite originating from similar data.

![Figure 16: Representation of the variables selected by the logistic regression in each of the 2 draws. Each column is one of the draws and each row is one of the variables. Black bars represent variables that are selected.](image)

Importantly, despite the two functions looking vastly different, their overall predictions indeed appear qualitatively similar. Figure 3 shows the distribution of default predictions by group for whites and non-whites, documenting that they are qualitatively similar with respect to their pricing properties across groups. So while the prediction functions look very
different, the underlying data, the way in which they were constructed, and the resulting price distributions are all similar.

Figure 17: Distribution of default risk using logistic lasso regression, plotted separately for white borrowers (W) and non-white borrowers (M). The two graphs show the distribution of the function based on two different draws from the full dataset. The vertical lines are the mean prediction by race.

In addition, the accuracy of the prediction is quite similar when using the two training datasets. Figure 5 shows the ROC curves for the prediction using training dataset 1 and training dataset 2. While not identical across all levels of true positive rates and false positive rates, they roughly provide the same prediction accuracy. This makes sense because the predictions are based on the draws from the same underlying population and should provide similar information with respect to the ability to predict out of sample.

Figure 18: ROC curves for risk prediction using training dataset 1 (left graph) and training dataset 2 (right graph).
The conclusion from this exercise is that there is limited expressiveness of the variables an algorithm uses and so we should be wary by putting weight on this selection.

This conclusion is at odds with the orthogonalization approach, which uses the selection of the protected variable and its weight to orthogonalize correlated variables. First, the orthogonalization approach relies on the selection of a protected characteristic to argue that its omission would lead to omitted-variable-bias. The analysis above, however, suggests that an algorithm may or may not select a protected characteristic without this directly relating the underlying model. Second, the orthogonalization approach relies on recovering the “true” effect of a protected characteristic on the prediction in the full model. The analysis, above, however, suggests that the weight the lasso regression puts on a variable should not interpreted as some truth with respect to the significance it plays in the prediction of the outcome.

Finally, it is important to note that even when the prediction and accuracy stay stable across draws, this does not mean that each individual is treated the same. Figure 6 compares the risk prediction under each of the two functions, showing the variation for many borrowers.
APPENDIX D: ERROR RATES AS AN OUTCOME OF INTEREST

In the main Article I assumed that the relevant outcome metric to focus on is the different prices that protected groups pay for credit, inferred from predicted risk, however this is not the only way to consider credit decisions. This is because price disparity is a direct way to consider whether a group is disadvantaged relative to another group. For the position that disparate impact is about preventing the entrenchment of disadvantage or the compounding of injustice, this view is particularly appealing as it directly considers the impact of pricing rules. However, another way to think about the decision of a lender is as a binary to decision of whether to extend a loan or not. A lender might determine a threshold of default risk above which they do not extend the loan. When considered in this light we might ask whether these thresholds accurately classify the risk that white and non-white borrowers will default.

In recent years, the computer science and statistical literature has discussed the various ways to consider whether an algorithm is fair. The majority of these definitions are outcome based, meaning they define what type of outcome is fair. The multiplicity of outcome-based metrics creates an interesting dilemma, since only under relatively narrow circumstances can more than one definition of fairness be satisfied. This has lead lawyers and policy makers to consider which definition of fairness most closely relates to discrimination law.

10 This outcome measure is what is often referred to as “demographic parity”. See Corbett-Davies & Goel, supra note 213, at 6. This is also closely related to what MacCarthy calls “statistical parity”. See MacCarthy, supra note 79, at 93 (“The metric that this notion of fairness attempts to equalize across groups is the percentage of positive predictions relative to all predictions – the fraction of all people being assessed who are selected as having a characteristic”). See Id. at 109 for a defense of this notion of fairness.

11 See Corbett-Davies et al., supra note 47(providing an overview of different criteria of algorithmic fairness); Also see Berk et al., supra note 214.

12 Much of the discussion over the correct statistical test for determining unfairness has taken place in the context of criminal justice risk scores. This is largely due to the public disagreement between one of the companies that produces risk score models, Northpointe, and the authors of an article in ProPublica (see: Julia Angwin et al., Machine Bias: There’s Software Used across the Country to Predict Future Criminals. And It’s Biased against Blacks, PROPUBLICA (May 23, 2016), https://www.propublica.org/article/machine-bias-risk-assessments-in-criminal-sentencing), which argued that those scores were biased against blacks. See for example: Anne L. Washington, How to Argue with an Algorithm: Lessons from the COMPAS-ProPublica Debate, COLO. TECH. L.J. 131, 154 (2018). (proposing a framework to allow defendants to challenge risk assessments at sentencing)

In a recent paper, Aziz Huq argues that we should not adopt the metrics of the algorithmic fairness literature given that they do not adequately address the underlying normative concerns. See Huq, supra note 185, at 1102. Instead he offers a framework which focuses on the costs and benefits of the use of criminal justice tools with respect to the group
“classification parity,” meaning they consider whether a measure of classification error is equal across groups.

Misclassification errors could also be concerning in itself or be an indication of other types of “unfairness.” When false positive rates differ for white and non-white borrowers this could capture some of the intuition of why we are concerned with credit discrimination. Credit plays an important role in creating wealth. Therefore, when minorities borrowers who are creditworthy are denied credit or are required to pay higher prices, this may further entrench disadvantage. On the other hand, different misclassification errors could indicate some other harm. For example, different misclassification errors could indicate that the algorithm was trained on a dataset that under-sampled black borrowers or that there was measurement bias in the “label” or outcome of interest.

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of concern. The primary question is whether the practice increases or decreases racial stratification. See also Hellman, supra note 140.

13 Corbett-Davies & Goel, supra note 213, at 5.

14 Corbett-Davies and Goel define this category as any definition that can be calculated from a confusion matrix, which is tabulates the joint distributions of a certain decision and outcomes by group. See Berk et al., supra note 214, at 3.

15 Hellman argues that the ratio between the FPR and FNR does not alone determine whether an algorithm is fair but may be suggestive of some unfairness. For example, it could be a result of inaccurate data. See Hellman, supra note 140, at 28.

16 See Hellman, supra note 52 (discussing discrimination law’s duty to avoid “compounding injustice.”)

17 See Hellman, supra note 140, at 28. In the credit context an example of a biased label would be if the label “default” captured the notion that a borrower did not repay a loan differently for white and non-white borrowers. This could happen, for example, if white borrowers were better able to renegotiate when they are late on a payments so that it is not documented that they defaulted. See Jean Braucher et al., Race, Attorney Influence, and Bankruptcy Chapter Choice, 9 J. EMPIRICAL LEGAL STUD. 393 (2012) (studying the possibility that white and non-white consumers facing financial difficulties behavior differently (and are advised differently)).
Figure 7, which plots the ROC curve for the risk prediction using all inputs (except race), shows that the misclassification errors are different for white and non-white borrowers. Overall the prediction accuracy for whites is higher. This can be seen from the fact that the solid black line is closer to the upper left corner of the graph. This means that for any decision rule that equalizes the TPR for whites and non-whites, there will be a higher FPR for non-white borrowers.

One implication of this graph is that we cannot equalize both the TPR and FPR for whites and non-whites. This is consistent with the literature that highlights the conditions under which it is impossible to satisfy different classification fairness measures. Similarly, the ratio between the FPR and “false negative rate”, which Hellman considers the correct focus of fairness, cannot be equalized across groups for any lending threshold a lender can adopt.

A second implication is that even equalizing one type of misclassification error may require a race-specific lending threshold. For example, if we would want to achieve the same TPR for the two groups, say a TPR of 0.75, one would have to have a race-specific threshold for lending for whites and for racial minorities. So, the equalizing of this error rate may actually only be achieved by treating groups differently in a much more striking way and

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18 See Hellman, supra note 140, at 24.
potentially more intuitively discriminatory way.

Beyond the practical difficulties, error rates may be a problematic measure of fairness because disparities may be driven by underlying differences between the groups. To be clear, unfair conduct, such as under-sampling minorities, could affect error-rates. However, differences in error-rates could reflect differences in population size when predictors are different for whites and non-whites. In the Boston Fed HMDA sample there are far fewer non-white borrowers (around 700) than white borrowers (around 2,300). This is largely because there were many more white borrowers than non-white borrowers in Boston at the time. Moreover, when the mean and variance of default differ for whites and non-whites differ, then their “base rates” are different which will necessarily be reflect in their different risk distributions. In other words, it is observed difference between the groups which may be driving the differences rather than any fault of the prediction method. This suggests that in some cases collecting more data or better will not solve this problem.

APPENDIX E: IMPLEMENTING A TEST FOR SIMILARLY SITUATED

To implement the similarly situated test, we would need to first define which variables are part of the “similarly situated” set and then measure disparities controlling for this set. One way to do this is to predict default risk from the “similarly situated” set only and then compare this distribution to the distribution from the full set. This would be a comparison between two distributions, so the regulator would need to set the metric used to compare the distributions and the “tolerance level,” meaning how much the two distributions are allowed to differ. Setting this tolerance level is one way a regulator could adjust the test depending on the weight it gives to accuracy versus fairness.

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19 See Corbett-Davies & Goel, supra note 213, at 12.
20 On possible metric is the “Wasserstein distance” metric, which measures the distance between two distributions. It could also be that the regulator wishes to focus only on part of the distribution.
21 See Corbett-Davies et al., supra note 47, at 6 ("satisfying common definitions of fairness means one must in theory sacrifice some degree of public safety"). A full discussion of the question of how to define who is similarly situated is beyond the scope of this Article. However, it is important to note that the decision of what to include in this set is likely to be crucial in whether disparities amount to discrimination. First, the size of this set essentially determines the extent to which observed differences are used to explain raw disparities. Second, even though there is a natural tendency to include classic credit pricing variables in the similarly situated set, their inclusion could lead us to overlook the most significant discrimination.
Figure 8: Disparities controlling for “similarly situated” borrowers. The graph on the left is the risk prediction using all variables other than race, plotted separately for white and non-whites (the same as Figure 13). The graph in the middle is the risk prediction using “similarly situated” variables, plotted separately for white and non-whites. The graph on the right is the residual of the graph on the left and the middle graph, plotted separately for whites and non-whites. The numbers in the lower right corner are the “Wasserstein distances,” meaning the difference between the distribution for whites and non-whites.

Figure 8 shows an example of how a regulator can consider whether similarly situated borrowers are treated the same. The graph on the right shows the residual from the prediction of the full set of inputs (graph on the left) and the prediction from the “similarly situated” set (graph in the middle). Intuitively, the graph on the right is the difference between white and non-whites, controlling for “similarly situated” characteristics.

\[22\] In this example, I defined the similarly situated set to include some variables that are typically used to price credit today – income, debt-to-income ratio, and characteristics of the loan. This is just one example of how the regulator could define this set. How large the set is, and what variables are included, will affect the difference of the residual.