

The Arity of Disparity: Updating Disparate Impact for Modern Fair Lending

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Abstract

Plaintiffs often cannot prevail under a disparate impact (“DI”) claim of discrimination unless they show the defendant failed to implement a less discriminatory alternative (“LDA”) to a practice that yields a disparate output across protected classes. Traditional LDA analysis focuses on a singular notion of fairness: parity, or the equality of screening decisions across protected groups. However, recent scholarship highlights that parity is only one of numerous competing notions of fairness that may seem just as compelling as, but be mutually exclusive with, parity. The arity of disparity is larger than DI has acknowledged.

We propose formalizing LDA analysis as an explicit constraint on choices over screening models and data inputs. The constraint restricts model-induced disparities in both parity and a competing notion of fairness—accuracy—relative to a “budget” that depends straightforwardly on overall model performance. We also show how this trade-off leads to balancing other notions of fairness, as weighted combinations of parity and accuracy span many other fairness notions in a helpful way.

For concreteness, our legal argument and our applied examples focus on DI under the Equal Credit Opportunity Act (“ECOA”). We address tension between DI’s traditional focus on parity and ECOA’s statutory emphasis on “credit-worthy” consumers and discuss implications for new frontiers in credit underwriting, including the use of machine learning and alternative data sources.

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I. Introduction

There is emerging consensus that antidiscrimination law needs updating.¹ Whether because of new data or new analytic tools, ECOA’s familiar disparate impact (“DI”) framework is ill-equipped to achieve fair outcomes in modern underwriting, hiring, and other screening. Whereas historically DI has relied on scrutinizing a small set of inputs used by relatively simple screening technology—and assessing, for example, whether these inputs are sufficiently causal of the later outcomes, such as loan repayment, that are being screened for—modern screening is sufficiently complex as to render such causal scrutiny impossible.² Modern screening is, as Gillis puts it, “a world of correlation and not causation.”³

DI also has longstanding issues not related to modern technology. DI compliance rests on indeterminate criteria that render it difficult, if not impossible, to guarantee a successful compliance strategy ex-ante except through inefficiently risk-averse governance of decision processes. Moreover, DI compliance has long focused on a singular notion of fairness—parity, or the equality of screening decisions such as loan approval across protected class groups—whereas scholarship highlights that parity is only one of several equally compelling and mutually exclusive notions of fairness.⁴ In short,

¹ See, e.g., Talia B. Gillis, *The Input Fallacy*, 106 MINN. L. REV. 1175-1263 (2022); Pauline T. Kim, *Data-Driven Discrimination at Work*, 58 WM. & MARY L. REV. 857-935 (2017); Pauline T. Kim, *Race-Aware Algorithms: Fairness, Nondiscrimination and Affirmative Action*, 110 CAL. L. REV. 1539-96 (2022); Solon Barocas & Andrew D. Selbst, *Big Data’s Disparate Impact*, 104 CAL. L. REV. 671-732 (2016); Crystal S. Yang & Will Dobbie, *Equal Protection Under Algorithms: A New Statistical and Legal Framework*, 119 MICH. L. REV. 291-396 (2020); Aziz Z. Huq, *Racial Equity in Algorithmic Criminal Justice*, 68 DUKE L. J. 1043-1134 (2019).

² See generally Gillis, *supra* note 1; Laura Blattner et al., *Unpacking the Black Box: Regulating Algorithmic Decisions* (2021), <https://arxiv.org/pdf/2110.03443.pdf>.

³ Gillis, *supra* note 1, at 1185.

⁴ These notions include calibration, “balance for the positive class,” “balance for the negative class,” etc. See Kleinberg et al., *Inherent Trade-Offs in the Fair Determination of Risk Scores*, 8th Innovations in Theoretical Computer Science Conference (ITCS 2017), for a discussion of how these three are incompatible with each other and, typically, with parity as well.

the arity of disparity is more numerous than DI analyses traditionally acknowledge, rendering DI compliance costly and fraught.

In this Article, we propose solving these issues by updating extant DI frameworks' traditional least discriminatory alternative ("LDA") analysis. Traditional LDA analysis is "one-way" in the following sense: it minimizes parity violations among all sensible business choices. But modern screening technologies present an unprecedented number of sensible business choices, which in turn creates an unprecedented spread of trade-offs among different notions of fairness. Disparities do not exist in a vacuum. For example, violations of parity can be inversely related to inequality across groups in the *accuracy* of a screening technology.⁵ Should DI regulation always prioritize parity over accuracy? Intuitively, no. We rigorously formalize a generalized version of this intuition and provide a workable protocol for resolving "competing" disparities.

For concreteness, our focus is on disparate impact in lending and the fair-lending analyses that are governed largely by the Equal Credit Opportunity Act ("ECOA"). One motivation for this focus is that the trade-off we emphasize—between parity and accuracy—is already manifest in a tension between the text of ECOA and modern fair-lending practice. On the one hand, ECOA's purpose, per the statutory text, is to ensure that credit is "equally available to all *credit-worthy* customers" (emphasis added). "Credit-worthy" signals a focus on borrowers who are a good match for a loan, such that fair underwriting technology need accurately identify such borrowers; in other words, ensuring credit-worthy consumers' equal access to credit is importantly distinct from making credit equally available to *all* consumers unconditionally. However, fair lending practice also frequently emphasizes parity over accuracy. A recent CFPB Request for Information ("RFI") about the agency's "approach to

⁵ An extreme example is using a weighted coinflip for one protected class group that achieves parity in loan approval rates with another protected class group, while the latter group is afforded a screening technology that more accurately—less randomly—allocates loans to borrowers who are a good match for a loan. But affording less random underwriting decisions to the former group may then lead to violations of parity.

disparate impact analysis under ECOA,” for example, emphasized a goal of “ensur[ing]... innovation can increase access to credit for all consumers.”⁶ This emphasis on parity is coherent in a world where DI is seen as cognizable under ECOA, as parity is traditionally the focus of any DI analysis.⁷ And seeing DI as cognizable under ECOA is, while not uncontroversial, a reasonably well-founded and widely-held view.⁸ Disparate impact is cognizable under the Title VII and ADEA in order to unearth otherwise undetectable disparate treatment, and similarly for ECOA, courts have observed, “discrimination in credit transactions is more likely to be of the unintentional, rather than the intentional, variety.”⁹ Thus, to achieve its purpose, ECOA needs DI. But DI’s lodestar of parity is often at odds with accuracy, yielding difficult trade-offs. We explain how to make them.

Specifically, we propose adapting the DI framework’s search for an LDA in order to require efficient, explicit trade-offs between one disparity (differential inaccuracy) and another (nonparity). We formalize LDA analysis as an explicit constraint on lenders’ choices over underwriting models and data inputs. The constraint restricts model-induced disparities in both parity and accuracy relative to a “budget” that depends straightforwardly on overall model performance. We also show how balancing these two notions of fairness has the added benefit that it leads to balancing other notions of fairness as well, as weighted combinations of parity and accuracy “span” many other fairness notions in a helpful way.

⁶ See, e.g., a recent Request for Information (“RFI”) from the CFPB, Docket No. CFPB-2020-0026 (emphasis added).

⁷ See *Watson v. Fort Worth Bank & Trust*, 487 U.S. 977, 987 (1988) (noting that DI cases “usually focus[] on statistical disparities....”).

⁸ See Winnie F. Taylor, *The ECOA and Disparate Impact Theory: A Historical Perspective*, 26 J. L. & POL’Y. 575, 581 (2018) (imploiring the legislature “to amend the ECOA’s text to overtly state what the drafters implicitly understood—that the statute authorizes disparate impact.”). But see Peter N. Cubita & Michelle Hartmann, *The ECOA Discrimination Proscription and Disparate Impact—Interpreting the Meaning of the Words That Actually Are There*, 61 BUS. LAW. 829, 833 (2006) (arguing that “the ECOA credit discrimination proscription does not speak in terms of the ‘effects’ of a practice on an applicant nor does it speak in terms of practices that deprive, tend to deprive or otherwise adversely affect applicants because of their race, color, national origin or gender.”).

⁹ *Cherry v. Amoco Oil Co.*, 490 F. Supp. 1026, 1030 (N.D. Ga. 1980).

Our approach using an LDA constraint contrasts with existing practice in two important ways. First, current notions of LDA analysis focus exclusively on parity as the measure of discrimination, while a growing body of research shows that disparities in accuracy are also important drivers of inequality.¹⁰ Second, current practice lacks formal guidance on how to trade off between disparities and performance, even as courts have sympathized with such tradeoffs in general.¹¹

The upshot is we provide guidelines for how lenders can implement alt data, machine learning, and other modern underwriting. If lenders efficiently trade-off between disparities under our conception of an LDA constraint, then they have implemented an LDA from the outset, precluding discrimination liability.

We also illustrate how to implement the LDA constraint quantitatively. A necessary step is to estimate counterfactual default outcomes among rejected loan applicants. We illustrate three strategies toward this goal: a surrogate-outcomes strategy from other loan products;¹² outcomes observed with competing lenders, an approach which incentivizes competitors to lend to each other's rejected applicants; and an approval lottery implemented as part of fair-lending compliance exams. We illustrate these ideas with a concrete example using simulated data on consumer lending inputs and outcomes.

¹⁰ See Ayşegül Şahin et al., *Mismatch Unemployment*, 104 AM. ECON. REV. 3529-64 (2014); Chang-Tai Hsieh et al., *The Allocation of Talent and U.S. Economic Growth*, 87 ECONOMETRICA 1439-74 (2019); Erik Hurst et al., *The Distributional Impact of the Minimum Wage in the Long Run* (2022), https://www.nber.org/system/files/working_papers/w30294/w30294.pdf; Laura Blattner & Scott Nelson, *How Costly is Noise? Data and Disparities in Consumer Credit* (2022), <https://arxiv.org/abs/2105.07554>; Disa M. Hynsjö & Luca Perdoni, *The Effects of Federal "Redlining" Maps: a Novel Estimation Strategy* (2022), <http://congress-files.s3.amazonaws.com/2022-07/The%2520Effects%2520of%2520Federal%2520Redlining%2520Maps.pdf>.

¹¹ See John K. Lucey, *The Redlining Battle Continues: Discriminatory Effect v. Business Necessity under the Fair Housing Act*, 8 ENVTL. AFF. 357, 390 (1979) (“[T]he viability of less discriminatory alternatives will be a function of both the increase in costs borne by the defendant and the amount by which the disproportionate impact is reduced.”).

¹² See also Blattner & Nelson, *supra* note ____.

We proceed as follows. Section II formalizes our proposal. Section III situates the proposal in the context of case law and regulations. Section IV places the proposal in dialogue with recent legal scholarship, and Section V addresses objections. Section VI concludes.

II. Proposal

Traditional DI frameworks focus on a particular notion of fairness. This fairness is typically referred to as *parity*, or equality across groups in the average of some outcome of interest (e.g., an approval rate). For example, an underwriting algorithm would satisfy parity across white and non-white loan applicants if it were to approve some share α of non-white applicants and the same share α of white applicants. While violations of parity are legally permitted in certain circumstances (discussed in Section III.B below), parity is the singular notion of fairness that DI analyses aim to protect.

Emerging research however highlights other, competing notions of fairness. Many of these may seem just as compelling as, but be mutually exclusive with, parity.¹³ We propose a reframing of fair-lending regulation that balances different notions of fairness explicitly. At the same time, our proposal clarifies when and why a regulator would possibly tolerate violations of any of these notions of fairness.

A key insight in our approach is to consider individuals' membership across two types of "classes." The first is the familiar notion of a protected characteristic (e.g., gender, race, ethnicity), which divide the population into classes such as male and non-male, white and non-white, etc.; in this

¹³ These notions include calibration, "balance for the positive class," "balance for the negative class," etc. See Kleinberg et al., *supra* note ___, for a discussion of how these three are incompatible with each other and, typically, with parity as well.

article we take both the set of protected classes and individuals' membership in them as given.¹⁴ The second is the notion of outcome class, which divides the population into a *positive class* and a *negative class*. Following Kleinberg et al. (2016), we use these to refer to individuals with and without some characteristic a lender is trying to identify when making a lending decision, which typically will be individuals who ultimately default on a loan, if given one, and individuals who do not. We argue that many notions of fairness can be helpfully clarified by considering individuals' membership in these two types of classes.

We proceed with the convention that the *positive class* contains individuals who ultimately do not default on a loan if given one. Therefore, in an underwriting decision that seeks to lend to individuals who will repay, lending to a member of the positive class can be termed a *true positive* ("TP"). In contrast, making a loan to a member of the negative class—that is, lending to someone who ultimately defaults on the loan—is a *false positive* ("FP"). Likewise, denying a loan to someone who would have defaulted is a *true negative* ("TN"), and denying a loan to someone who would have repaid it is a *false negative* ("FN"). In situations where credit risk is described by membership in the true or positive class, and where the underwriting decision can be viewed as a binary decision, these four categories exhaustively describe the outcomes and potential outcomes of a lending decision.

These four categories naturally can be overlaid on protected class membership. We focus on one protected class and assume for notational simplicity that class membership is binary: we write that each individual either is in class g or class g' , for example white and non-white loan applicants. This leads to notation such as TP_g and $TP_{g'}$, for example white true positives and non-white true positives.

The above framework and notation allow us to express competing notions of fairness in simple terms. For a binary outcome such as loan approval, there are *only* three ways to characterize

¹⁴ This of course is a simplification, both in view of intersectionality and of constructivist perspectives on racial and ethnic identity. See generally Evan K. Rose, *A Constructivist Perspective on Empirical Discrimination Research* (2022), <https://ekrose.github.io/files/constructivism.pdf>.

whether the outcome occurs equally across protected classes: one can examine whether approval rates (1) are equal unconditionally, (2) are equal conditional on membership in the positive class, or (3) are equal conditional on membership in the negative class. These three are collectively exhaustive in the sense that there simply are no other conditional or unconditional probabilities that can be constructed in this framework, other than combinations of these three. Competing notions of fairness, then, are concerned either directly with, or with different weightings of, these three “elemental” approval rates.¹⁵

These three approval rates also have familiar and intuitive appeal. Equality in the first of these—that is, unconditionally equal approval rates—is the familiar notion of *parity*. Equality in the second of these—that is, equal approval rates in the positive class—has been termed “equality of opportunity.”¹⁶ This notion can also be understood intuitively as equality in credit access for creditworthy consumers, if being creditworthy is equated with being a consumer who ultimately repays the loan.¹⁷ Equality in the third of these – that is, equal approval rates in the negative class – is best understood through the equivalent statement that *rejection* rates are equal within the negative class. Under this equivalent statement, equality conditional on negative class membership can be understood as equal chances of avoiding giving a loan to an individual who will be unable to repay it. This notion

¹⁵ We therefore “span,” in the mathematical sense, other notions of fairness that are also concerned with how decision outcomes are allocated across class membership. One such notion of fairness is “predictive rate parity,” which, in contrast with our (2) and (3), emphasizes the share of individuals approved for a loan (or otherwise predicted to be members of the positive class) are indeed members of the positive class. This notion of fairness is covered by the three notions herein simply by applying Bayes’ rule.

¹⁶ Moritz Hardt et al., *Equality of Opportunity in Supervised Learning* (2016), <https://arxiv.org/abs/1610.02413>. The term “equalized odds” has also been used to refer to equality of opportunity.

¹⁷ While many determinants of being a member of the positive subgroup may be outside of an individual’s control, it is helpful to understand the “equality of opportunity” label as stemming from a premise that individual effort determines membership in the positive subgroup. Under this premise, equality of opportunity comes from guaranteeing equal outcomes for individuals who end up in the positive subgroup, rather than for all individuals unconditionally.

of fairness also has clear intuitive appeal, especially in view of how mortgage foreclosures have historically exacerbated racial wealth disparities in the US.¹⁸

We refer to any inequality in approvals conditional on outcome class as *differential accuracy*. To help establish why differential accuracy may be undesirable, consider a brief allegory of a lender that has purchased an expensive underwriting tool: the CreditScore-omatic. This tool takes data input from a loan applicant and recommends that the lender “Accept” or “Reject.” We suppose the CreditScore-omatic has the remarkable feature that it guarantees parity across protected classes. However, we show that this feature leads to clearly objectionable problems with differential accuracy.

To show this, we suppose the designers of the CreditScore-omatic faced a challenge with applicants’ input data: many applicants in protected class g' had no available input data (e.g., no credit history). To guarantee parity—that is, the equality of unconditional approval rates across classes g and g' —the designers decided the CreditScore-omatic would use a weighted coinflip to decide on “Approve” or “Reject” for these limited-data applicants. While this achieves parity, this has the clearly objectionable outcome that credit access is being decided by coinflip for many members of protected class g' , whereas credit access is more closely determined by ability to repay for class g . This situation is a stark example of differential accuracy, as it induces higher approval rates among g than among g' conditional on being in the positive class.

While lenders of course do not use coinflips in practice, the presence of statistical noise in credit scoring means that most modern underwriting relies on inputs that can be, in whole or in part, tantamount to coinflips. Recent research points to modern credit scores being more like a coinflip for members of racial and ethnic minorities than for majority group members, principally because of

¹⁸ Amir Kermani & Francis Wong, *Racial Disparities in Housing Returns* (2021), <https://www.nber.org/papers/w29306>.

disparities in the length or richness of individuals' credit histories.¹⁹ Reliance on underwriting inputs that are statistically noisier for some protected class subgroups has both immediate costs, in the sense of inducing disparities in how much credit flows to individuals that plausibly have the most productive use for a loan, and dynamic costs, in the sense of further contributing to noise in the data used to train the credit scoring models of the future.²⁰ These concerns echo those raised in other contexts where the *misallocation* of opportunities like loans, education, or jobs is seen as holding first-order importance.²¹

Importantly, however, in most settings it is impossible for a lender to simultaneously achieve parity and avoid differential accuracy. The dilemma faced by the designers of the allegorical CreditScore-omatic is a general one: whenever two protected classes g and g' differ in their rates of positive and negative class membership, parity can only be achieved by introducing differential accuracy.²² Given the growing body of research discussed above on the costs of differential accuracy, and the clear instances of unfairness discussed above that arise from differential accuracy, we argue that fair-lending regulation needs to thoughtfully balance violations of parity and model accuracy rather than focus on unalloyed parity alone.

To write our proposal formally, consider a lender that chooses a model f from a set of possible models F , and data inputs x from a set X of possible groups of inputs, in order to maximize a private benefit Π . The lender's LDA-constrained choice can then be written as,

¹⁹ See Blattner & Nelson, *supra* note ____.

²⁰ See Blattner & Nelson, *supra* note ____.

²¹ See Şahin et al., *supra* note ____; Hsieh et al., *supra* note ____; Hurst et al., *supra* note ____; Blattner & Nelson, *supra* note ____; Hynsjö & Perdoni, *supra* note ____.

²² This impossibility result is complementary to but distinct from that in Kleinberg et al., *supra* note ____, which focuses on calibration rather than parity. The most closely related impossibility result is that from Alexandra Chouldechova, which implies the impossibility result stated here. See Alexandra Chouldechova, *Fair Prediction with Disparate Impact: A Study of Bias in Recidivism Prediction Instruments*, 5 BIG DATA 153-163 (2017).

$$\max_{f \in F, x \in X} \Pi(f(x))$$

$$\text{s.t. } x \in \tilde{X} \text{ and } \alpha \text{ Nonparity}(f(x)) + \beta \text{ Inaccuracy}(f(x)) \leq A + \gamma \text{ Performance}(f(x))$$

In this LDA constraint, nonparity refers to inequalities in average outcomes across protected classes; differential inaccuracy refers to inequalities in the rate of false positives and false negatives across protected classes; performance refers to the model’s ability to allocate credit efficiently overall. Intuitively, a regulator may tolerate some quantum of disparity (on the left-hand-side of the constraint) in order to achieve greater model performance (on the right-hand-side), while the terms α , β , and γ quantify this tolerance. The endowment term A can be chosen in view of what outcomes are currently feasible for a particular protected class, line of business, and lender, or equivalently to “grandfather-in” the status quo for lenders seen as in compliance with current fair-lending regulation.²³

Specifically, we formulate nonparity for a given underwriting model f as,

$$\text{Nonparity}(f(x)) = \left| \frac{TP_g + FP_g}{N_g} - \frac{TP_{g'} + FP_{g'}}{N_{g'}} \right|$$

The denominators N_g and $N_{g'}$ denote the total number of applicants in each protected class, while the numerators are counts of true positives and false positives in each class. Intuitively, this measure is simply the absolute difference in approval rates across groups. Parity is violated if and only if this difference is nonzero, while greater differences in approval rates imply a larger difference and hence a greater value for the $\text{Nonparity}(f(x))$ term in our constraint.

²³ C.f. Muhammad Zafar et al., *Fairness Beyond Disparate Treatment & Disparate Impact: Learning Classification without Disparate Mistreatment* (2017), <https://arxiv.org/abs/1610.08452> (introducing a notion of “disparate mistreatment” that grounds another optimization problem subject to a differential accuracy constraint). In contrast to Zafar et al., our approach formalizes a “budget” that allows efficient trade-offs between parity, accuracy, and performance goals, all of which can differ from the lender’s own objective. The endowment term A in this budget allows for the fact that, in some markets or contexts where the LDA constraint is deployed, predicting outcome class membership may be either sufficiently difficult, or sufficiently different for different protected classes (e.g., due to heteroskedastic risk that varies with class membership), such that the constraint can only be slack when A takes a positive nonzero value. The “grandfathering-in” approach described in the text guarantees that A takes an appropriate value to enable the appropriate slackness in the constraint.

Likewise, we formulate inaccuracy for a given underwriting model f as,

$$\text{Differential Inaccuracy}(f(x)) = \left[\left| \frac{TP_g}{TP_g + FN_g} - \frac{TP_{g'}}{TP_{g'} + FN_{g'}} \right| + \left| \frac{TN_g}{TN_g + FP_g} - \frac{TN_{g'}}{TN_{g'} + FP_{g'}} \right| \right]$$

The numerators and denominators consist of the counts of true positives, false negatives, true negatives, and false positives in each protected class. Intuitively, the first absolute difference that appears in this definition is the gap between protected classes in the true positive rate (TPR), or the share of positive class members who are accurately screened as positives and granted a loan. The second absolute difference in this definition is the gap between protected classes in the true negative rate (TNR), or the share of negative class members who are accurately screened as negatives and denied a loan. It would be straightforward to put different weights on these two measures of accuracy—a regulator may, for example, view it as more of a problem if credit-worthy borrowers are denied a loan than if borrowers who default are granted loans, or in a different context the regulator may take the opposite view. For the sake of simplicity, we focus on the case where the TPR and TNR are weighted equally in our *Differential Inaccuracy*($f(x)$) definition.²⁴

Finally, we formulate performance for a given underwriting model f as,

$$\text{Performance}(f(x)) = \left[\left| \frac{TP_g + TP_{g'}}{TP_g + FN_g + TP_{g'} + FN_{g'}} \right| + \left| \frac{TN_g + TN_{g'}}{TN_g + FP_g + TN_{g'} + FP_{g'}} \right| \right]$$

This expression is similar to that for differential inaccuracy, but rather than emphasizing a difference between protected classes in TPRs and TNRs, it sums the TPR across both protected classes with the TNR across both protected classes. As with our expression for differential inaccuracy, these two terms could be weighted to reflect different social preferences for true positives versus true negatives, based on whether it is more costly to erroneously deny a loan or erroneously grant a loan. In our baseline

²⁴ This notion of accuracy is related to, but different from, the concepts of balance for the positive class and balance for the negative class, as in Kleinberg et al, *supra* note ____.

case, we focus on equal weights for overall TPRs and TNRs in our $Performance(f(x))$ definition. These TPR and TNR outcomes are those that a high-performing underwriting model would maximize. Hence, the “ \leq ” inequality in our constraint captures the idea that a regulator might tolerate, depending on the value of the weighting terms α , β , and γ , some quantum of disparity on the left-hand side of the constraint when faced with a high-performing model that achieves allocative efficiency through high TPRs and TNRs—that is, a high value of $Performance(f(x))$ on the right-hand-side of the constraint.²⁵ A regulator with no tolerance for disparity, regardless of model performance, would simply set the γ weight on performance equal to zero.

By way of analogy, the regulator’s chosen balance between false positives and false negatives can be seen as a balance between *Type I* and *Type II* errors at the level of each loan application: each applicant presents a risk of either falsely rejecting an applicant who should be approved, or falsely approving an applicant who should be rejected. Each type of error has costs. And while the appropriate balance between these two error types has been prominent in other regulatory frameworks, for example FDA trials of drug efficacy,²⁶ we argue this balance has been puzzlingly absent from DI analyses.

One last aspect of our proposed constraint deserves clarification. As can be seen above, in addition to the LDA constraint itself we also impose the constraint $x \in \tilde{X}$. This auxiliary constraint can be thought of as capturing any input variables that are deemed socially objectionable to use in underwriting. For example, a regulator may wish to exclude protected class membership itself from

²⁵ This trade-off between model performance and competing fairness concerns can be viewed as a higher dimensional version of the “Pareto fair frontier” discussed in MICHAEL KEARNS & AARON ROTH, THE ETHICAL ALGORITHM: THE SCIENCE OF SOCIALLY AWARE ALGORITHM DESIGN (2019). See also Annie Liang et al., *Algorithmic Design: Fairness Versus Accuracy*, PROCEEDINGS 23RD ACM CONF. ECON. & COMPUTATION, 58-9 (2022); Laura Blattner et al., *supra* note ____.

²⁶ See Michael Intriligator, Drug Evaluations: Type I vs. Type II Errors (1996) (unpublished manuscript), <https://escholarship.org/uc/item/5fg9n284>.

the set of permissible inputs, in which case the set \tilde{X} could be specified to exclude these. In this way, our proposed constraint also achieves some of the goals of disparate *treatment* regulation.²⁷

In fact, the constraint may prevent other forms of disparate treatment that arise through use of proxy variables, in addition to blocking explicit disparate treatment through the design of the set \tilde{X} . To see this, consider a proxy variable that a lender uses with the goal of discriminating against a protected class, such that this proxy does not enhance model performance. Any use of this proxy would increase the Nonparity term on the left-hand-side of the constraint without increasing the Performance term on the right-hand-side, leading to a violation of the LDA. Because the focus of our work is on disparate impact, we leave a fuller treatment of these disparate treatment concerns to future work.

We now discuss how to put the LDA constraint into practice. We propose that existing fair-lending regulators test for compliance with LDA constraints as part of their periodic fair-lending exams and other supervision activities, such as issuing NALs under ECOA. Doing so requires computing the count of true positives, true negatives, false positives, and false negatives for each protected class group. While calculating true positives and false positives is straightforward, tantamount just to calculating default rates on originated loans, calculating the count of true negatives

²⁷ See *Price Waterhouse v. Hopkins*, 490 U.S. 228, 243 (1989) (quoting congressional records that said Title VII “expressly protects the employer’s right to insist that any prospective applicant, Negro or white, must meet the applicable job qualifications. Indeed, the very purpose of Title VII is to promote hiring on the basis of job qualifications, rather than on the basis of race or color.”). Cf. *Int’l Bhd. of Teamsters v. United States*, 431 U.S. 324, 335 (1977) (“Disparate treatment ... is the most easily understood type of discrimination. The employer simply treats some people less favorably than others because of their race, color, religion, sex, or national origin. Undoubtedly disparate treatment was the most obvious evil Congress had in mind when it enacted Title VII. ... Claims of disparate treatment may be distinguished from claims that stress ‘disparate impact.’ The latter involve employment practices that are facially neutral in their treatment of different groups but that in fact fall more harshly on one group than another and cannot be justified by business necessity.”).

More generally, our proposed constraint can accommodate any input restrictions, such as the “Input Accountability Test” proposed in Robert P. Bartlett et al., *Algorithmic Discrimination and Input Accountability under the Civil Rights Acts*, 36 BERKELEY TECH. L.J. 675-736 (2021).

and false positives requires discerning how rejected loan applicants would have performed if granted a loan. We propose four approaches for assessing these counterfactual if-not-rejected loan outcomes.

The most easily implementable approach is to use default on other loan products to assess default risk on denied loans. For example, an applicant rejected for a credit card might have an existing student loan on which subsequent default is straightforwardly observed in existing US consumer credit report data. This approach does not require that *every* borrower who would have defaulted on, for example, their rejected credit card loan will also default on their student loan. Rather, this only requires that, on average, group-level default rates on one type of loan are informative about average default rates on other loans in a known way. This approach can be particularly successful in contexts like mortgage lending, where the vast majority of rejected applicants have other, non-mortgage loans on which subsequent default can be observed.²⁸ However, this approach may also be vulnerable to confounds from selection effects, as rejected borrowers from certain lenders may select endogenously into different alternative credit products than rejected borrowers from other lenders, such that differences in prevailing default rates across alternative products would imply different true-negative rates and false-negative rates in ways that make the LDA constraint spuriously tighter for some lenders than for others within a given market.²⁹ Each of our other proposals below uses different strategies to address such endogeneity concerns.

A second approach is to assess whether one lender's rejected loans are true negatives or false negatives using loans from competing lenders who provided the same loan product. Like the first

²⁸ See Blattner and Nelson, *supra* note __, for one such implementation.

²⁹ For example, suppose one mortgage lender's rejected applicants' other credit products are predominantly auto loans, and another mortgage lender's rejected applicants' other credit products are predominantly credit cards. For any given borrower, default rates on credit cards are typically higher than default rates on auto loans, so even if these two lenders' applicant pool and underwriting decisions were otherwise identical, the former lender would erroneously be inferred to have more true negatives and fewer false negatives than the latter lender. See Sewin Chan et al., *Determinants of Mortgage Default and Consumer Credit Use: The Effects of Foreclosure Laws and Foreclosure Delays*, 732 FED. RESERVE BANK N.Y. STAFF REP. (2015).

approach, this is also readily implementable using existing U.S. consumer credit report data. However, this approach would have the additional advantage of incentivizing competitors to lend to each other's rejected applicants, in order to reveal to the regulator cases where a competitor's rejected loans were false negatives. This approach would not require an unbiased estimate of true-negative and false-negative rates, and in that way, this approach is robust to the selection concern we noted in our first approach: in our second approach each lender would face similar efforts by its competitors in a given market to lend to its rejected applicants, and the effects of these competitive pressures would imply that estimates of true-negative and false-negative rates would have similar statistical properties across different lenders in a market. Even in the absence of an unbiased estimates of true-negative and false-negative rates, the constant term " \mathcal{A} " in the LDA constraint would absorb such effect, making the LDA constraint comparable across lenders within market.

A third approach is more costly to implement but uses gold-standard methodology for classifying a lender's rejected applicants: fair lending exams can require small-scale randomized trials in which rejected applicants are randomly granted loans. By construction, these trials are robust to selection concerns and provide unbiased estimates of true-negative and false-negative rates. Regulators could require that defaults on these loans not be furnished to credit bureaus and that defaulted loan balances not be pursued in collections, such that any consumers affected by a loan default in these randomized trials to not endure other hardship as a result of that default. And to be clear, these loans would only be provided to consumers who had *applied* for them, assuaging concerns about unwilling participation in the evaluation. The advantage of this approach would be an unbiased estimate of rejected applicants' positive or negative class membership that requires no extrapolation from other loans' performance. Moreover, while defaults on the randomly granted loans would generate some costs for lenders, this kind of randomized testing is already used at many lenders to assess underwriting criteria, and any costs net of testing the lender already implements could either be subsidized directly

or could be deferred through other revenue streams. Considering the ample resources that lenders devote to fair-lending compliance, this approach may in fact lead to cost *savings* at many lenders even after accounting for loan defaults in the randomized acceptances.

A fourth approach would build on Gillis and Spiess's insightful suggestion of "stress testing" an underwriting model.³⁰ Rather than using real-world data to evaluate factors like the nonparity and differential accuracy induced by a given model, a regulator could deploy a lender's underwriting practices on a pre-determined dataset or a range of hypothetical applicant scenarios, similar to how banks' safety-and-soundness regulators evaluate use stress tests to evaluate how bank assets and capital ratios respond to various hypotheticals. Relative to our three other approaches, this "stress test" approach would entail a different set of costs and benefits for both the regulator and the lender; these costs and benefits include the need for the underwriting to be sufficiently algorithmic that it could be deployed on *hypothetical* loan applicants, the simplicity of not using data from many different banks' actual applicant pools, and the need for the regulator to develop a battery of stress tests that are sufficiently representative of the range of real-world applicants a lender might face.

Regardless of which of these approaches is used to quantify the TN_g and FN_g terms in our LDA constraint, we next illustrate how the LDA constraint would be used to evaluate whether a particular underwriting model is fair-lending compliant. To do so, we develop an empirical example on simulated data. The example illustrates quantitatively and graphically how certain models or underwriting criteria are accepted by a hypothetical LDA constraint despite introducing some quantum of additional parity violations, by virtue of generating improvements in differential accuracy or in model performance.

This illustrative example focuses on a lender's loan approval decisions. The lender faces a list of data to potentially use to make these decisions, and a choice over different underwriting models that

³⁰ Talia B. Gillis & Jann L. Spiess, *Big Data and Discrimination*, 86 U. CHI. L. REV. 459-88 (2019).

use those data. The list of data options includes a mix of traditional credit report variables, for example credit card utilization and history of past default, as well as a number of new variables not traditionally used in US underwriting, for example cash-flow data from consumer bank accounts, utility bill payments, or history of payday loan use. We show how the LDA constraint facilitates the use of underwriting models that reduce overall inequality among loan applicants, by trading off efficiently between nonparity and differential accuracy. Moreover, we show how the LDA constraint allows the lender to know from the outset whether its underwriting is fair-lending compliant when selecting among underwriting models, rather than determining compliance in an ex-post litigation process.

To make loan approval decisions, the lender develops (or equivalently, “trains” or “estimates”) a predictive model using data on past loan applicants. Once developed, the model can use similar input data from future loan applicants to predict their default probability, and the lender approves loans for all applicants with predicted default probabilities below some threshold. The LDA constraint allows the lender to search across all possible models it might develop in a setting like this one and determine which models are fair-lending compliant, *before* deploying the model for use on future applicants.

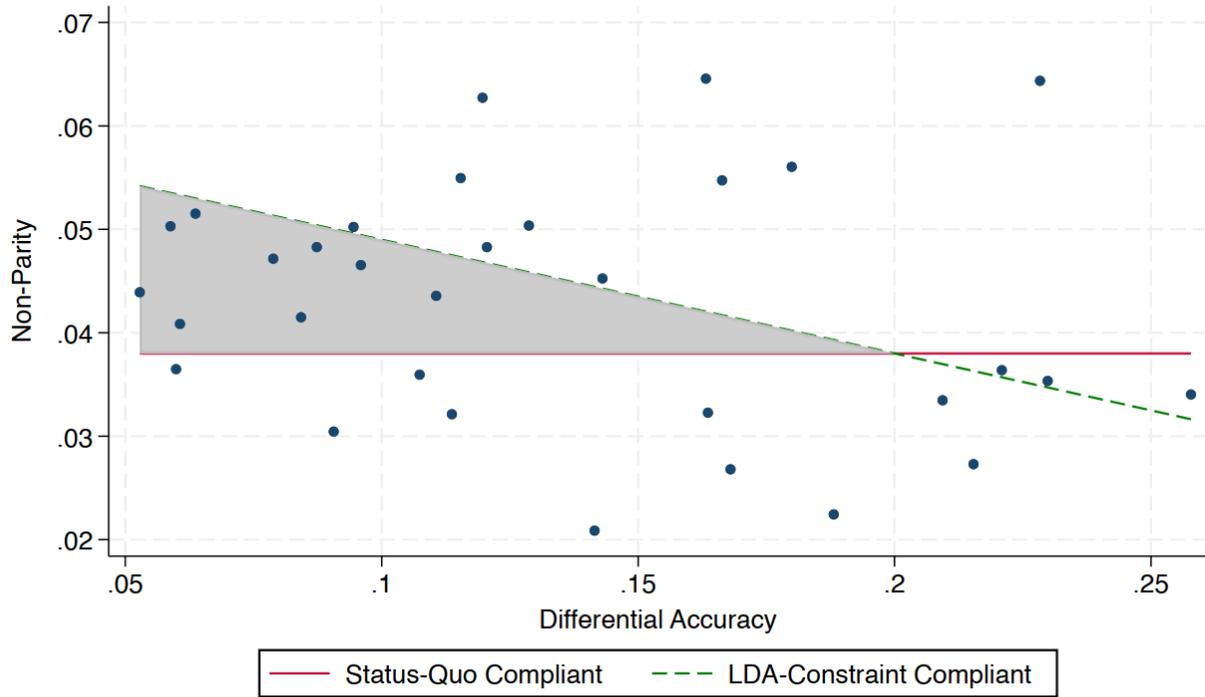
For expositional simplicity we focus on the case where the lender searches across ordinary-least-squares models that are linear in a subset of the available input data; however, the example easily generalizes to a search over more complex models. We create simulated data that match the characteristics of traditional credit report data and of potential new variables (e.g., cash-flow data) in the sense that each data point is differentially predictive of default for different groups, differentially correlated with group membership, and differently distributed for different groups.³¹ We then estimate

³¹ For example, given the correlation of payday loan use with racial and ethnic group membership, a simulated data feature that corresponds to past payday loan use and performance might be positively correlated with minority status and might have higher variance for members of a minority group. *See generally* Paige Marta Skiba & Jeremy Tobacman, *Do Payday Loans Cause Bankruptcy?*, 62 J. L. ECON. 485-519 (2019); Mario L. Small et al., *Banks, Alternative Institutions and the Spatial-Temporal Ecology of Racial Inequality in U.S. Cities*, 5 NATURE HUM. BEHAV. 1622-8 (2021).

an ordinary-least-squares predictive model for each possible combination or subset of these input data, and we calculate the shares of TP_g , FP_g , TN_g , and FN_g for each model and for each of two protected class groups g , supposing that the shares of TN_g and FN_g are measured using one of the four methods outlined above. From there, simple arithmetic yields the terms *Performance*, *Differential Accuracy*, and *Nonparity* that appear in the LDA constraint. By knowing these terms, the lender can assess whether each model is fair-lending compliant for a given LDA constraint (e.g., values of α , β , etc. as determined by a regulator).

Figure 1 illustrates in a scatterplot the values of the LDA constraint terms *Differential Accuracy* and *Nonparity*. As can be seen in our definitions of these terms above, higher values of these terms correspond to greater inequality across protected class groups. We suppose that under a status-quo fair lending regime, models are seen as compliant whenever nonparity falls below a given level—the red solid line shown in the figure. In contrast, for a fixed degree of model performance, the LDA constraint determines a sloped line (the green dashed line in the figure) where models with higher levels of nonparity remain fair-lending compliant if they have particularly low levels of differential accuracy. The key takeaway from the sloped LDA constraint in the figure is that, by using the LDA constraint, a regulator can facilitate the use of alternative models that alleviate other sources of unfairness in lending besides parity; the shaded area of the figure illustrates the space of models that are newly compliant. These models might include the use of new variables like cash-flow data or payday lending histories that, through their correlation with group membership, exacerbate nonparity but also make underwriting decisions less differentially accurate—less similar to a coinflip for members of a protected group.

Figure 1: The LDA Constraint in Action



In what sense is coinflip lending discriminatory? Even under maximally differential accuracy, the ratios of Ps to Ns across protected classes might end up identical completely by chance. So, coinflip lending is not discriminatory in the sense of ensuring that fewer loans reach disadvantaged borrowers. Rather, differential accuracy represents a lack of principled justification behind a given credit score. Loans could get denied not because of red flags on the credit file, but because the proverbial coinflip landed on tails.³²

³² Importantly, for this metaphor, we assume that the coinflips were collected correctly (e.g., a proverbial “heads” was not counted as a proverbial “tails”) and solely focus on the issues with using coinflips in the first place to predict the unrelated property of creditworthiness. In stipulating that any underlying data be correctly collected, we also bracket the issue of whether credit scores can, by their nature, be “true” or “false” and in this sense more or less “accurate.” This question is especially important when courts interpret the Fair Credit Reporting Act (“FCRA”), a federal statute mandating “reasonable steps” to ensure “maximum possible accuracy” in credit reporting.

Courts have held that FCRA does not regulate the accuracy of credit scores, specifically, because algorithmically generated credit scores are mere opinions about the probability of default and thus cannot be true or false in the first place. *See, e.g., Jefferson Cnty. Sch. Dist. No. R-1 v. Moody’s Investor’s Servs., Inc.*, 175 F.3d 848, 854–56 (10th Cir. 1999) (affirming dismissal on grounds that credit ratings “did not contain a provably false factual connotation” and such evaluation “could well

One takeaway from Blattner & Nelson³³ is that historically disadvantaged borrowers are disproportionately subjected to such coinflip lending. This disparity in access to accurate credit scoring across protected class membership is ripe for DI analysis. The discrimination need not be understood in comparative terms, however. It is also arguably discriminatory to have a purportedly meritocratic institution use coinflip decision rules, even if implemented uniformly so as to preclude disparity across protected classes. Regardless of one’s philosophical theory of discrimination, so long as coinflips are suboptimal decision rules for consumer lending, reform is needed.

A promising way forward could be to scale up the CFPB’s Project Catalyst, which allows lenders to apply for a regulatory No-Action Letter (“NAL”) under ECOA. With a NAL, the CFPB refrains from bringing an action under ECOA for a limited period of time, so that the lender can implement a pre-approved experimental program. However, in the seven years since Project Catalyst began, the CFPB has only issued 1 NAL under ECOA, given to Upstart in 2017.³⁴ Upstart has faced significant criticism for its potential to exacerbate nonparity, most notably through its use of SAT scores to screen potential borrowers.³⁵ In particular, only 4% of HBCUs had an average SAT score in

depend on [assessing] a myriad of factors”); *see also Plumbers’ Union Local No. 12 Pension Fund*, 632 F.3d at 775–77 (“The ratings are opinions purportedly expressing the agencies’ professional judgment about the value and prospects of the certificates.”).

³³ Blattner & Nelson, *supra* note ____.

³⁴ CFPB, *CFPB Announces First No-Action Letter: Upstart Network*, (Sept. 14, 2017), <https://www.consumerfinance.gov/about-us/newsroom/cfpb-announces-first-no-action-letter-upstart-network/>.

³⁵ Katherine Welbeck & Ben Kaufman, *Fintech Lenders’ Responses to Senate Probe Heighten Fears of Educational Redlining*, STUDENT BORROWER PROTECTION CENTER, (July 31, 2022), <https://protectborrowers.org/fintech-lenders-response-to-senate-probe-heightens-fears-of-educational-redlining>.

the top 50% of Upstart’s SAT groupings.³⁶ Upstart’s NAL terminated, by its own request, in 2022,³⁷ leaving the legality of using SAT data to remain uncertain.

Another example of “alt data” in consumer credit is utility bill payment history.³⁸ Adding this information is promising for improving the signal-to-noise ratio in credit files, but there are well-documented racial disparities in utility bill delinquency and default, arguably due to exogenous forces such as energy unreliability and shoddy infrastructure.³⁹ So, even though utility bill payment history can be highly informative in the aggregate, thus drastically improving differential accuracy, the data may introduce measurable nonparity that tracks the protected characteristic of race. If the CFPB were to quantify bounds of parity-accuracy trade-offs to qualify for a limited time NAL, firms will likely be encouraged to pursue innovation through participating in Project Catalyst, instead of having to estimate the risk of a regulatory action and favoring the status quo to mitigate it.

Under current procedure, lenders can apply for a NAL at any time and can expect to receive a decision within 60 days.⁴⁰ The CFPB reserves sole discretion in making this decision.⁴¹ Regulation provides some examples of factors in the CFPB’s NAL analysis, such as “the quality and persuasiveness of the NAL request, with particular emphasis on the proposed products’ or services’ potential consumer benefits and risks,” “how the applicant intends to mitigate any potential risks,”

³⁶ Katherine Welbeck & Ben Kaufman, *Fintech Lenders’ Responses to Senate Probe Heighten Fears of Educational Redlining*, STUDENT BORROWER PROTECTION CENTER, (July 31, 2022), <https://protectborrowers.org/fintech-lenders-response-to-senate-probe-heightens-fears-of-educational-redlining>.

³⁷ CFPB, *CFPB Issues Order to Terminate Upstart No Action Letter*, (June 8, 2022), <https://www.consumerfinance.gov/about-us/newsroom/cfpb-issues-order-to-terminate-upstart-no-action-letter/>.

³⁸ Brianna McGurran, *How Utility Bills Can Boost Your Credit Score*, EXPERIAN (Aug. 16, 2023), <https://www.experian.com/blogs/ask-experian/does-paying-utility-bills-help-your-credit-score/>.

³⁹ *See generally Taylor v. City of Detroit*, No. 2:20-cv-11860-SDD-APP, 2020 WL 3883610 (E.D. Mich. July 9, 2020).

⁴⁰ CFPB, POLICY ON NO-ACTION LETTERS, 84 FR 48229-01 (2019).

⁴¹ CFPB, POLICY ON NO-ACTION LETTERS, 84 FR 48229-01 (2019).

“the applicant’s explanation of why the NAL is needed and the underlying statutory and regulatory provisions” and “potential litigation risk.”⁴²

However, it is not transparent just how the CFPB analyzes these factors. What makes for a request high in “quality”? What constitutes “persuasiveness” in assessing consumer benefits and risks? To view NALs as opportunities to test specific, quantified trade-offs between parity and accuracy would provide a clear set of criteria for both lenders and regulators. The CFPB could plug in different values for α , β , and γ to calculate a threshold firms must meet to qualify for a NAL. Clarifying regulatory expectations in this way would encourage firms to develop new innovations and apply for NALs with a better idea of their business will be impacted.

Such a threshold need not be sufficient. The CFPB could still reserve total discretion to ultimately deny a request, even one within the bounds of the LDA constraint. Every NAL could still be for a limited, specified duration and subject to continuous review.⁴³ These safeguards help to mitigate parity risk, as exemplified in a 2020 Senate letter arguing that “the CFPB should not issue ‘No Action’ letters related to ECOA to any lender or company ... where Black and brown borrowers unwillingly serve as the test subjects.”⁴⁴ Granting NALs to one firm at a time allows for an incremental, piecemeal rollout of temporary new credit scoring techniques. This would, in turn, minimize “unwilling service” as test subjects by mostly preserving the status quo. Ideally, an experiment benefits everyone by more efficiently matching lenders with qualified applicants.

Further, a lender might avoid or offset losses of parity by implementing a Special Purpose Credit Program (“SPCP”) that acts as an affirmative-action equivalent in the consumer credit space.

⁴² CFPB, POLICY ON NO-ACTION LETTERS, 84 FR 48229-01 (2019).

⁴³ CFPB, POLICY ON NO-ACTION LETTERS, 84 FR 48229-01 (2019).

⁴⁴ Sen. Sherrod Brown, Sen. Elizabeth Warren, & Sen. Kamala Harris, Letter to CFPB (July 30, 2020), https://www.banking.senate.gov/imo/media/doc/2020-07-30_Letter%20to%20CFPB%20re%20use%20of%20educational%20data.pdf.

Reg B instructs that ECOA permits lenders to implement SPCPs that explicitly favor members of historically disadvantaged protected classes.⁴⁵ The CFPB reiterated in 2020 that lenders can establish SPCPs without formal regulatory approval so long as the program “is not administered with the purpose of evading the requirements of [ECOA].”⁴⁶ But how differentially accurate can a credit score be without undermining the antidiscrimination requirement under ECOA?

This issue is even more volatile in light of the Supreme Court’s recent holding in *Students for Fair Admissions, Inc.*, striking down affirmative action in the context of university admissions as unconstitutional on grounds of equal protection, given that the programs explicitly favor protected class membership, such as race.⁴⁷ But, in several key respects, SPCPs differ from the perhaps more familiar context of affirmative action in university admissions. First, universities had an expected time limit,⁴⁸ and the Court determined that the programs were too close to the expiration date to justify its unsatisfactory performance. In contrast, Congress outlined safeguards for SPCPs over half a century ago, specifically designed to satisfy a strict scrutiny analysis under Equal Protection, such as one implicating race. These safeguards are the mandates that an SPCP administrator must “identif[y] the class of persons that the program is designed to benefit and sets forth the procedures and standards for extending credit pursuant to the program” and ensure that the goal of any SPCP is to provide credit to people “who, under the organization’s customary standards of creditworthiness, probably would not receive such credit or would receive it on less favorable terms than are ordinarily available to other applicants[.]”⁴⁹

⁴⁵ 12 C.F.R. §1002.8.

⁴⁶ 12 C.F.R. §1002.8.

⁴⁷ *Students for Fair Admissions, Inc. v. President & Fellows of Harvard Coll.*, 600 U.S. 181 (2023).

⁴⁸ *Grutter v. Bollinger*, 539 U.S. 306 (2003).

⁴⁹ 12 C.F.R. §1002.8.

However, the standard-like⁵⁰ nature of these mandates might be deterring firms from establishing SPCPs. There are two categories of underbanked consumers: those with too much negative data on a credit report and those with too little positive data. Remedying each issue may require exacerbating the other, at least at first. Without straightforward guidance on how to balance this trade-off, firms will hesitate to address either issue. But quantifying the trade-off *ex ante* using our LDA constraint will allow both firms and regulators to benefit from a more predictable and streamlined assessment of fairness in lending. The dynamicity of our variables also permits easy updating in light of future developments in both the law and the industry.

In sum, trying different balances in a streamlined, quantifiable, and flexible way is a promising path forward to addressing systemic inequalities in access to credit. In what follows, we provide a legal justification for a regulatory compliance regime to oversee this process.

III. Legal Analysis

A. The Problem

Nonparity and differential accuracy cause distinct harms to the consumer. The harms from nonparity are familiar: a group disadvantaged by nonparity faces a greater likelihood of being denied a loan (when there is nonparity on the approval margin) or of paying higher interest rates (when there is nonparity on the interest rate margin). The harms from differential accuracy are more subtle. When a screening technology such as a credit score exhibits differential accuracy across groups, the group with lower accuracy will both have more individuals for whom the credit score is “too high” relative

⁵⁰ Legal commands are often characterized as either bright-line rules (e.g., “do not exceed 70 miles per hour on the highway”) or relatively more ambiguous standards (e.g., “do not drive recklessly on the highway”). *See generally* Louis Kaplow, *Rules Versus Standards: An Economic Analysis*, 42 DUKE L. J. 557-629 (1992). Our proposal can be interpreted as a procedure for ‘rulifying’ LDA analysis under ECOA, where such analysis operates more like a standard in current practice, without enumerated thresholds for making the relevant trade-offs. However, the LDA constraint does not necessarily yield one particular rule—for example, every point in the shaded area of Figure 1 constitutes a different rule for achieving an LDA that satisfies our constraint.

to the individual's inherent creditworthiness,⁵¹ and also have more individuals for whom the credit score is “too low.” In other words, the score exhibits greater variance, in a statistical sense, or equivalently contains greater signal noise, around what the fully accurate credit score for each consumer would be. This means some applicants whose score is too high will be approved for a loan when they would not otherwise be approved if the score were perfectly accurate, or will pay an interest rate lower than what they otherwise would pay; other applicants whose score is too low will be rejected when they would not otherwise be rejected if the score were perfectly accurate, or will pay an interest rate higher than what they otherwise would pay.

Hence for a group disadvantaged by differential accuracy, the nature of the consumer harm depends on whether the realization of signal noise for a particular consumer leads to a score that is “too low” or “too high.” In the former case, consumers whose score is too low face harm similar to that of consumers disadvantaged by nonparity: higher likelihood of rejection or of facing an interest rate higher than what a fully accurate credit score would imply. In the latter case, consumers whose score is too high face the possibility of being granted a loan they ultimately are not able to repay, or being assigned an interest rate that may induce over-borrowing relative to what the consumer's inherent creditworthiness can support. Because of the myriad adverse consequences of loan default for consumers—which can extend even to incarceration in jurisdictions with particularly aggressive debt collection practices⁵²—being granted a loan that one is not able to repay can commonly lead to harm, regardless of whether the inaccurately high credit score led to apparently favorable loan terms.

⁵¹ We use the term “creditworthy” only in the technical sense of denoting membership in the TP group, even though the term carries fraught moral connotations that we categorically disown. *See generally* JOSH LAUER, CREDITWORTHY: A HISTORY OF CONSUMER SURVEILLANCE AND FINANCIAL IDENTITY IN AMERICA (2017).

⁵² *See generally* ACLU, A POUND OF FLESH: THE CRIMINALIZATION OF PRIVATE DEBT (2018), <https://www.aclu.org/report/pound-flesh-criminalization-private-debt>.

However, courts generally do not consider a group-level disparity to constitute a “concrete injury” redressable in a private ECOA action.⁵³ To sue a creditor for discrimination under ECOA, the consumer ““must have (1) suffered an injury in fact, (2) that is fairly traceable to the challenged conduct of the defendant, and (3) that is likely to be redressed by a favorable judicial decision.””⁵⁴ The standing analysis often short-circuits at whether there exists a real problem in the first place, i.e., an “injury in fact” that must be “concrete and particularized” rather than “abstract.”⁵⁵ A group-level disparity in Ps and Ns is a mere “abstract” injury because it does not indicate that any specific individual plaintiff “suffered an injury that was the result of . . . discrimination at the time that she entered the loan.”⁵⁶

Accordingly, it is unlikely that a court would confer standing for a private ECOA action merely on the basis of group-level disparities in differential inaccuracy. For consumers affected by scores being too high in particular, the consequences of subsequent loan default can unfold over a lifetime: the process of collecting on an unpaid debt can take years or, in cases where the consumer may inadvertently reaffirm the debt during the debt collection process,⁵⁷ can even take decades. Moreover, because it may be unobservable what a consumer’s fully accurate score would have been in the absence of differential accuracy, harms from differential accuracy may inherently only be quantifiable at the

⁵³ A creditor is broadly defined to be “a person who, in the ordinary course of business, regularly participates in a credit decision, including setting the terms of the credit.” 12 CFR § 1002.2(l).

⁵⁴ *Spokeo, Inc. v. Robins*, 136 S.Ct. 1540, 1547 (2016).

⁵⁵ *Id.* at 1548 (quoting *Lujan v. Defenders of Wildlife*, 504 U.S. 555, 560, 112 S.Ct. 2130, 119 L.Ed.2d 351 (1992)).

⁵⁶ *Gilmore v. Ally Fin. Inc.*, No. 15-CV-6240 (RER), 2017 WL 1476596, at *6 (E.D.N.Y. Apr. 24, 2017). *Cf. Masudi v. Ford Motor Credit Co.*, No. 07-CV-1082 (CBA)(LB), 2008 WL 2944643, at *4 (E.D.N.Y. July 31, 2008) (dismissing an ECOA complaint because it “d[id] not allege a single event, policy or action taken by either of the defendants regarding *plaintiff’s* car loan, nor d[id] plaintiffs allege how the finance charges imposed on *their* loan were discriminatory.” (emphasis in original)).

⁵⁷ *See, e.g., Berthoud Nat. Bank v. Dunn*, 762 P.2d 759 (Colo. Ct. App. 1988) (“[An] express promise to pay a debt acts to take the case out of the statute of limitations.”).

group level rather than the individual level.⁵⁸ Being disadvantaged by differential accuracy in credit scores may therefore lead to unobservable risk of later harm. And in 2021, the Supreme Court held that “in a suit for damages, the mere risk of future harm, standing alone, cannot qualify as a concrete harm.”⁵⁹ So, even though group-level inequities raise the risk of future harm, such as an individual being denied a loan and unable to access the concrete things the loan would have provided, the probabilistic inequities alone will not confer standing to a private consumer under ECOA.

The timescale is also relevant for delineating who counts as an “applicant” under ECOA and therefore enjoys statutory protections. The CFPB has repeatedly argued that this term “is not expressly limited to those currently in the process of seeking credit” but instead “include[s] both those who are currently seeking credit and those who sought and have now received credit.”⁶⁰ This distinction matters because discriminatory practices can happen even after the application is closed and loan money is disbursed, such as later revoking the credit on a prohibited basis. Recognizing the risk of future harm as an injury-in-fact is also contiguous with practice in ECOA’s touchstone of employment law—the Supreme Court has held 9-0 that “employees” protected against discrimination in Title VII includes those who are no longer employees when the discrimination occurs.⁶¹

At the very least, getting a fuller picture of credit discrimination will require broadening the time scale to recognize the longer-term harms imposed by differential inaccuracy. In particular, the trouble with FPs is that they are not free — they are *inefficient approvals*. Because an FP is a defaulted

⁵⁸ In other words, economic analysis is able to quantify differential accuracy across groups by showing that a credit score has greater statistical noise for one group than for another (Blattner & Nelson, *supra* note __), but it may be unobservable which particular individuals in the group faced a score that was “too high” versus “too low.”

⁵⁹ *TransUnion LLC v. Ramirez*, 141 S.Ct. 2190, 2209-10.

⁶⁰ See, e.g., Brief for the CFPB as Amicus Curiae, p. 4, *Fralish v. Bank of Am., N.A.*, No. 3:20-CV-418 RLM-MGG, 2021 WL 4453735 (N.D. Ind. Sept. 29, 2021), *appeal dismissed*, No. 21-2846, 2022 WL 1089194 (7th Cir. Jan. 28, 2022).

⁶¹ *Robinson v. Shell Oil Co.*, 519 U.S. 337 (1997). Justice Thomas, writing for the majority, noted that there is “no temporal qualifier in the statute such as would make plain that § 704(a) protects only persons still employed at the time of the retaliation.” *Id.*

loan, minimizing FPs means sparing consumers from the process of loan delinquency and eventual default, which imposes costs stemming from various sources such as late fees, predatory interest rates, and possible court expenses.⁶²

Our proposal for a regulatory compliance regime aims to avoid the harms of nonparity and differential inaccuracy at the outset, rather than navigate the thorny distinctions between “abstract” and “concrete” injuries. Under the DI interpretation of ECOA’s antidiscrimination provision, firms must comply by both providing accuracy and parity. But it is not obvious how much is enough, and firms may decline to use an underwriting strategy that would achieve valuable improvements in parity, accuracy, or efficiency out of concern about getting the balance wrong. But if regulators such as the CFPB use our LDA constraint to describe exactly how to make this trade-off, then firms will not need to guess or hazard avoidable inefficiencies.

ECOA also authorizes the recovery of class action damages for discrimination.⁶³ But ECOA class action filings in general, and those for discrimination especially, seem uncommon because the maximum class recovery is low, and because class certification can be difficult to obtain for discrimination claims more generally. ECOA caps the punitive damages that a plaintiff class may receive in an ECOA class action at \$500,000 or 1% of the net worth of the creditor, whichever is less.⁶⁴ Plaintiffs can also recover actual damages. But because plaintiffs must specifically prove their actual damages,⁶⁵ courts are unlikely to certify classes seeking recovery of actual damages due to the

⁶² See Blattner & Nelson, *supra* note ___, for a general approach to quantifying the costs of noise.

⁶³ 15 U.S.C. § 1691e(b).

⁶⁴ 15 U.S.C. § 1691e(b).

⁶⁵ See *Anderson*, 666 F.2d at 1277-78.

individualized nature of that inquiry.⁶⁶ Further, plaintiffs face strong difficulties with attaining class certification, particularly with respect to establishing the “commonality” in harm and questions of law and fact.⁶⁷ Courts require plaintiffs to show evidence licensing an inference that members of the class suffered from a common policy of discrimination,⁶⁸ but it seems creditors commonly argue successfully that plaintiffs cannot satisfy the commonality prong, and the failure generally turns on the individual nature of the issues, such as the discretion of individual employees that make decisions on credit applications.⁶⁹ Additionally, in opposing class certification in discrimination class actions, counsel for creditors commonly argue that individual issues concerning each class member’s experiences with the creditor predominate over common questions of law and fact, rendering class resolution inappropriate.⁷⁰

Rather than navigating these thorny issues, regulation is likely the way to achieve more robust fair-lending policy. Unlike courts, federal agencies are subject matter experts and are well-equipped to identify an LDA. So, the best way to implement this constraint is through a preemptive compliance regime. In other words, regulators should certify, *a priori*, that a firm would satisfy Step 3, instead of having the courts make it all the way to Step 3 with scant guidance on what to do from there.

An analogue for the regulators’ role we seek can be found in regulatory interpretation of Title VI, the federal statute proscribing the use of funds that produces discriminatory disparate impacts. In Title VI administrative investigations of discrimination in programs receiving federal funding, the

⁶⁶ See, e.g., *Coleman v. Gen. Motors Acceptance Corp.*, 296 F.3d 443, 447 (6th Cir. 2002) (certifying only an injunctive class); *Cason v. Nissan Motor Acceptance Corp.*, 212 F.R.D. 518, 521 (M.D. Tenn. 2002) (same).

⁶⁷ See 212 F.R.D. 518, 521 (M.D. Tenn. 2002).

⁶⁸ See *Love v. Johanns*, 439 F.3d 723, 728 (D.C. Cir. 2006)).

⁶⁹ See, e.g., *In re Countrywide Fin. Corp. Mortg. Lending Practices Litig.*, 708 F.3d 704, 707 (6th Cir. 2013); *Rodriguez v. Nat’l City Bank*, 726 F.3d 372, 381-386 (3d Cir. 2013); *In re Wells Fargo Residential Mortg. Lending Discrimination Litig.*, 2011 WL 3903117, at *1-4 (N.D. Cal. Sept. 6, 2011).

⁷⁰ See *Love*, 439 F.3d at 726.

evidentiary burden rests with the investigating agency rather than with the complainant. EPA guidance explains this important distinction:⁷¹

The investigation of Title VI administrative complaints by [EPA] does not involve an adversarial process, as in litigation, between the complainant and the recipient. Rather, it should be viewed as EPA investigating allegations that EPA financial assistance is being used improperly. Consequently, the complainants do not have the burden of proving that their allegations are true and *are not obligated to offer less discriminatory alternatives*. Instead, EPA has the responsibility to determine whether a violation exists and, where appropriate, to uncover less discriminatory alternatives. Nonetheless, EPA encourages complainants to provide whatever relevant information they may have.

In sum, our proposal can be seen as a response to the several calls for regulatory clarification on how to comply with ECOA. In what follows, we provide several sources that indicate legal support for our proposed answer to that question.

B. Disparate Impact

⁷¹ EPA INVESTIGATIONS GUIDANCE, 65 FED. REG. AT 39,696 (emphasis added).

Further, the DOJ's Title VI Manual provides a practice tip for a preemptive compliance regime: "PRACTICE TIP. Agencies sometimes impose additional requirements on recipients to consider alternatives before taking action. These requirements can affect the legal framework by requiring recipients to develop the evidentiary record related to alternatives as a matter of course, before and regardless of whether an administrative complaint is even filed. Such requirements recognize that the recipient is in the best position to complete this task, having the best understanding of its goals, and far more ready access to the information necessary to identify alternatives and conduct a meaningful analysis. Courts have recognized that agencies have authority to impose additional obligations." U.S. D.O.J. TITLE VI MANUAL VII.C.3.B (citations omitted).

Many agencies have established additional requirements related to less discriminatory alternatives, under both Title VI and other authorities. For example, the Federal Transit Administration requires certain recipients to consider alternatives before implementing key decisions. A recipient's failure to do so, and to gather sufficient data to establish it has selected the least discriminatory alternative, is a procedural violation of agency regulatory requirements, and may put the recipient at risk of a substantive violation as well. *See* FTA TITLE VI CIRCULAR, CHAP IV-16.

The FTA explains the requirement to examine alternatives as follows:

"Examining Alternatives. If the transit provider determines that a proposed service change will have a disparate impact, the transit provider shall analyze the alternatives ... to determine whether alternatives exist that would serve the same legitimate objectives but with less of a disparate effect on the basis of race, color, or national origin. The existence of such an alternative method of accomplishing the transit provider's substantial and legitimate interests demonstrates that the disparate effects can be avoided by adoption of the alternative methods without harming such interests.... At that point, the transit provider must revisit the service changes and make adjustments that will eliminate unnecessary disparate effects on populations defined by race, color, or national origin. Where disparate impacts are identified, the transit provider shall provide a meaningful opportunity for public comment on any proposed mitigation measures, including the less discriminatory alternatives that may be available." *Id.*

Regulation B (“Reg B”), the regulation implementing ECOA, instructs that employment law jurisprudence forms the basis of DI analysis under ECOA.⁷² Thus, for ECOA purposes, courts use the same three-step test familiar from employment law. First, “the plaintiff must demonstrate that the use of a certain factor has a disproportionately negative impact on a protected group.”⁷³ Second, if the plaintiff successfully convinces the court that a given criterion violates parity (usually by showing that a protected class, e.g., a racial or ethnic minority, is selected less than 80% as often as other applicants⁷⁴), then “the creditor must show that the criterion makes the credit evaluation system “more predictive than it would be otherwise”⁷⁵ or that it is justified by a “legitimate business need.”⁷⁶ Third, the plaintiff receives “the opportunity to show that the creditor’s legitimate business needs could be met by a less discriminatory alternative.”⁷⁷

Historically, due to lack of data, Step 1 was less plaintiff-friendly than it is today. At first, Reg B categorically proscribed “inquir[ing] about the race, color, religion, national origin, or sex of an applicant or any other person in connection with a credit transaction.”⁷⁸ So, since creditors did not have data on the variables they were prohibited from asking about, plaintiffs could not furnish the relevant statistics to show prima facie discrimination against members of legally protected classes.⁷⁹

⁷² § 202.6(a) n.2 (“The legislative history of the act indicates that the Congress intended an ‘effects test’ concept, as outlined in the employment field by the Supreme Court in the cases of *Griggs v. Duke Power Co.* and *Albemarle Paper Co. v. Moody*, to be applicable to a creditor’s determination of creditworthiness.”) (citations omitted).

⁷³ 490 F. Supp. 1026 (N.D. Ga. 1980).

⁷⁴ See 29 C.F.R. § 1607.4 (D) (1992).

⁷⁵ 490 F. Supp. 1026 (N.D. Ga. 1980).

⁷⁶ OFFICIAL STAFF INTERPRETATION, § 202.6(A)(2), 50 FED. REG. 48,050 (1985).

⁷⁷ OFFICIAL STAFF INTERPRETATION, § 202.6(A)(2), 50 FED. REG. 48,050 (1985).

⁷⁸ 12 C.F.R. § 202.5. See also Matheson, *The Equal Credit Opportunity Act: A Functional Failure*, 21 HARV. J. LEGIS. 371, 382-91 (1984).

⁷⁹ See, e.g., 490 F. Supp. 1026 (plaintiff did not have adequate data to show that zip code criterion had a disparate impact on African Americans who applied for credit but were rejected).

However, Congress amended the Home Mortgage Disclosure Act (“HMDA”) in 1989 to mandate that lenders collect and disclose data about each applicant’s race, sex, and income, precisely to monitor rates of nonparity in mortgage lending.⁸⁰ Ten years later, Reg B was amended to allow the voluntary collection of data on race, color, religion, or national origin of applicants seeking non-mortgage credit.⁸¹ Such data, along with extensive HMDA disclosures, help plaintiffs stay in court by satisfying Step 1.

For Step 2, once the plaintiff makes a prima facie case that a practice yields an intolerable level of nonparity, the defendant has the burden of persuasion⁸² to prove that the practice is consistent with business necessity. Regulatory guidance on ECOA states that creditors can defend a policy that produces disparity by showing “a demonstrable relationship between” the challenged policy and “creditworthiness.”⁸³ Some have argued that the variable must be related to creditworthiness and not merely included for the purpose of maximizing profit.⁸⁴ However, the justification could include some appeals to profitability if they are “manifest” and not “hypothetical” or “speculative.”⁸⁵ Agencies “recognize the relevance to credit decisions of factors related to the adequacy of the borrower’s income to carry the loan, the likely continuation of that income, the adequacy of the collateral to secure the loan, the borrower’s past performance in paying obligations, the availability of funds to

⁸⁰ See Home Mortgage Disclosure, 54 Fed. Reg. 51,356, 51,359-60 (1989) (codified at Equal Credit Opportunity Act (Reg B), 12 C.F.R. § 203.4(a)(10) (2011)) (noting the HMDA’s amended mandate of collecting and disclosing “data on the race, sex, and income of applicants and borrowers, in addition to the geographic itemization of loans that is currently required.”).

⁸¹ 64 Fed. Reg. 44582, 44586 (Aug. 16, 1999).

⁸² Susan S. Grover, *The Business Necessity Defense in Disparate Impact Discrimination Cases*, 30 GA. L. REV. 387, 403 n.53 (1996) (“[When] placing a burden of production on the defendant, the defendant is compelled to introduce evidence sufficient to permit an inference of the fact it is attempting to prove. This is a lesser burden than the burden of persuasion, which means that if the defendant fails to prove the existence of the fact at issue, the plaintiff immediately prevails.”).

close, and the existence of adequate reserves.”⁸⁶ Such considerations are crucial for a profitable lending operation, but are also ripe vectors for discrimination, so “business necessity” ends up without bite. Indeed, as Schmidt and Stevens note, the business necessity test is “nearly always met.”⁸⁷

Assuming such necessity is established, next is Step 3: whether the business practice is the “least discriminatory alternative” (“LDA”). Shortly after *Griggs*, the Supreme Court held in *Albemarle Paper Co. v. Moody*, that “[i]f an employer does then meet the burden of proving that its tests are ‘job related,’ it remains open to the complaining party to show that other tests or selection devices, without a similarly undesirable racial effect, would also serve the employer’s legitimate interest in ‘efficient and trustworthy workmanship.’”⁸⁸ The 1991 Act codified this burden-shifting regime as the “alternative employment practice” requirement.⁸⁹ Congress did not define the phrase, and its substantive meaning remains uncertain. The closest thing to a definition in *Albemarle* is a reference to “other tests or selection devices, without a similarly undesirable racial effect.”⁹⁰

⁸⁸ 422 U.S. 405, 425 (1975) (quoting *McDonnell Douglas Corp. v. Green*, 411 U.S. 792, 801 (1973)).

⁸⁹ 42 U.S.C. § 2000e-2(k)(1)(A) (2012). The LDA test has not always been treated as a separate step. See, e.g., *Wards Cove Packing Co. v. Atonio*, 490 U.S. 642, 659 (1989) (treating the alternative employment practice test as part of the “business justification” phase); *Dotbard v. Rawlinson*, 433 U.S. 321, 332 (1977) (treating the alternative employment practice test as a narrow tailoring requirement for the business necessity defense).

But every circuit to decide the issue has held that the 1991 Act returned the doctrine to the *Albemarle* burden-shifting scheme, so we follow suit. *Jones v. City of Boston*, 752 F.3d 38, 54 (1st Cir. 2014); *Hove v. City of Akron*, 723 F.3d 651, 658 (6th Cir. 2013); *Tabor v. Hilti, Inc.*, 703 F.3d 1206, 1220 (10th Cir. 2013); *Puffer v. Allstate Ins. Co.*, 675 F.3d 709, 717 (7th Cir. 2012); *Gallagher v. Magner*, 619 F.3d 823, 833 (8th Cir. 2010); *Gulino v. N.Y. State Educ. Dep’t*, 460 F.3d 361, 382 (2d Cir. 2006); *Int’l Bhd. of Elec. Workers Local Unions Nos. 605 & 985 v. Miss. Power & Light Co.*, 442 F.3d 313, 318 (5th Cir. 2006); *Anderson v. Westinghouse Savannah River Co.*, 406 F.3d 248, 277 (4th Cir. 2005); *Ass’n of Mexican-Am. Educators v. California*, 231 F.3d 572, 584 (9th Cir. 2000); *EEOC v. Joe’s Stone Crab, Inc.*, 220 F.3d 1263, 1275 (11th Cir. 2000); *Lanning v. Se. Pa. Transp. Auth.*, 181 F.3d 478, 485 (3d Cir. 1999). The D.C. Circuit has not explicitly observed that a burden-shifting framework exists.

However, our proposal does not take a strong view on which DI step(s), precisely, implicate LDA analysis. We merely focus on the LDA analysis itself.

⁹⁰ *Albemarle*, 422 U.S. at 425; accord, e.g., *Jones*, 752 F.3d at 53 (citing *Albemarle* to interpret the 1991 Act’s text); *Allen v. City of Chicago*, 351 F.3d 306, 312 (7th Cir. 2003) (same using a “see also” signal).

ECOA cases “rarely have discussed, much less reached, the ‘third prong’ of less discriminatory alternatives analysis.”⁹¹ This dearth of case law is especially unfortunate given recent scholarship arguing that, for nearly any underwriting model, an LDA likely exists.⁹² At a minimum, the Commentary to Reg B provides that this prong requires the plaintiff to prove that an LDA would be “equally effective” in meeting the defendant’s legitimate business objectives.⁹³ Reg B requires credit scoring systems to be “[d]eveloped for the purpose of evaluating the creditworthiness of applicants with respect to the legitimate business interests of the creditor utilizing the system (including, but not limited to, minimizing bad debt losses and operating expenses in accordance with the creditor’s business judgment).”⁹⁴ This language suggests that an LDA must perform at or close to the level of the challenged practice.⁹⁵

In *Wards Cove*, the Court explicitly endorsed the relevance of costs in conducting LDA analysis.⁹⁶ Both the *Watson* plurality and the *Wards Cove* Court explicitly stated that cost is relevant in

⁹¹ Peter E. Mahoney, *The End(s) of Disparate Impact*, 47 EMORY L.J. 409, 490 (1998).

⁹² See Emily Black et al., *Less Discriminatory Algorithms* (2023) (unpublished manuscript), https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4590481.

⁹³ See 12 C.F.R. § 202.6(a), Supplement I to Part 202, Comment 6(a)-2 (1994) (a disparate output yields liability “unless the creditor practice meets a legitimate business need that cannot reasonably be achieved as well by means that are less disparate in their impact”).

⁹⁴ 12 C.F.R. § 202.2(p)(1)(ii) (1997).

⁹⁵ See Mahoney, *supra* note ___, at 490.

⁹⁶ See *Wards Cove*, 490 U.S. 661 (1989) (stating that “[f]actors such as the cost or other burdens of proposed alternative selection devices are relevant in determining whether they would be equally effective as the challenged practice in serving the employer’s legitimate business goals” (quoting *Watson*, 487 U.S. at 998)).

The Court also stated that “[i]f [employees], having established a prima facie case, come forward with alternatives to [the employer’s] hiring practices that reduce the racially disparate impact of practices currently being used, and [employers] refuse to adopt these alternatives, such a refusal would belie a claim [by the employer] that [employer’s] incumbent practices are being employed for non-discriminatory reasons.” *Wards Cove*, 490 U.S. at 660-1. This language, which seems to make liability depend on whether the defendant “refuses to adopt [the] alternative employment practice,” was adopted by Congress. See Civil Rights Act of 1991 § 105, 42 U.S.C.A. § 2000e-2(k)(1).

determining an LDA.⁹⁷ Moreover, Congress’ willingness to codify the disparate impact cause of action and the role of LDAs sent a powerful signal that Congress is prepared to weigh at least some short-term costs.⁹⁸ Our proposal extends this notion of costs being part of an LDA analysis by enabling a regulator to evaluate how an LDA has costs not just in monetary terms, but also in terms of different notions of fairness—for example, reductions in parity may come at the cost of differential accuracy or model performance.

Our proposal also may be a path to resolving uncertainty about *how* LDA costs should be considered. Courts in other pre-*Wards Cove* cases⁹⁹ have split on whether and when costs should be relevant and have not clarified *how* costs are important. Moreover, the 1991 Act does not indicate whether the costs of proposed LDAs are relevant,¹⁰⁰ and the Act does not outline criteria for a legally sufficient LDA.¹⁰¹ Our proposal provides a coherent path to weighing the costs of different business practices when deciding if a lender has implemented an LDA.

C. Articulated Goal of ECOA

⁹⁷ See *Watson*, 487 U.S. at 998 (1988) (plurality opinion) (“[C]ost or other burdens of proposed alternative selection devices are relevant in determining whether [the proposed alternative] would be equally as effective”); *Wards Cove*, 490 U.S. at 661 (quoting *id.* at 998).

⁹⁸ See *UAW v. Johnson Controls, Inc.*, 111 S. Ct. 1196, 1209 (1991) (“[I]n passing the PDA, Congress considered at length the considerable cost of providing equal treatment of pregnancy ... despite the social costs associated therewith” (internal citation omitted)).

⁹⁹ Compare *Clady v. County of Los Angeles*, 770 F.2d 1421, 1432 (9th Cir. 1985) (holding that cost is a legitimate basis for using discriminatory selection procedures) with *City of Los Angeles Dep’t of Water & Power v. Manhart*, 435 U.S. 702, 717 (1978) (“[N]either Congress nor the courts have recognized [a cost-justification] defense under Title VII.”) and *Johnson v. Pike Corp. of America*, 332 F. Supp. 490, 495 (C.D. Cal. 1971) (“The sole permissible reason for discriminating against actual or prospective employees involves the individual’s capability to perform the job effectively. This approach leaves no room for arguments regarding inconvenience, annoyance, or even expense to the employer.”)

¹⁰⁰ But as the Harvard Law Review notes: “Congress’s silence on costs, but rejection of *Wards Cove*, could mean that Congress also knew it was rejecting *Wards Cove*’s attempt to make costs a factor.” *The Civil Rights Act of 1991 and Less Discriminatory Alternatives in Disparate Impact Litigation*, 106 HARV. L. REV. 1621, 1638 (1993).

¹⁰¹ See 29 C.F.R. § 1607.4 (D) (1992). The Uniform Guidelines adopted the “four-fifths” rule as the default test of disparate impact (i.e., a disparate impact exists if minority groups are not selected at least four-fifths, or 80%, as often as majority groups). No such test governs whether an alternative qualifies as a cognizable LDA.

ECOA's articulated goal is to provide equal access to credit among all creditworthy individuals. Accordingly, the statute's text prohibits creditors from discriminating against applicants "in any aspect of a credit transaction on the basis of race, color, religion, national origin, sex, marital status, age, or because the applicant receives income from any public assistance program."¹⁰² Such aspects include "discrimination in the terms, conditions, or privileges of credit, or in the denial of credit altogether."¹⁰³

Reg B emphasizes the breadth of ECOA's scope, noting that the "prohibitions apply to every aspect of an applicant's dealings with a creditor regarding an application for credit or an existing extension of credit (including, but not limited to: information requirements; investigation procedures; standards of creditworthiness; terms of credit; furnishing of credit information; revocation, alteration, or termination of credit; and collection procedures)."¹⁰⁴ Statutory clarification instructs as follows:¹⁰⁵

Congress finds that there is a need to insure that the various financial institutions and other firms engaged in the extensions of credit exercise their responsibility to make credit available with fairness, impartiality, and without discrimination on the basis of sex or marital status. Economic stabilization would be enhanced and competition among the various financial institutions and other firms engaged in the extension of credit would be strengthened by an absence of discrimination on the basis of sex or marital status, as well as by the informed use of credit which Congress has heretofore sought to promote. It is the purpose of this Act ... to require that financial institutions and other firms engaged in the extension of credit make that credit equally available to all credit-worthy customers without regard to sex or marital status.

Indeed, ECOA's legislative history demonstrates that it was enacted to combat discriminatory barriers in lending by providing everyone with an equal opportunity to credit according to their creditworthiness. Although Congress rejected proposals to protect against discrimination because of race, color, national origin, age, and religion, Congress opted to protect women from such

¹⁰² 15 U.S.C.A. § 1691.

¹⁰³ 15 U.S.C.A. § 1691.

¹⁰⁴ ¶ 65-135 FAIR LENDING EXAMINATION PROCEDURES, BK. COMPL. GD. P 65-135.

¹⁰⁵ Pub. L. 93-495, title V, §502, Oct. 28, 1974, 88 Stat. 1521.

discrimination, and passed the Equal Credit Opportunity Act as part of the Depository Institutions Amendments Act of 1974.¹²¹ According to Congresswoman Sullivan, “the discrimination provision is not as strong as we would have gotten if this had been handled as a separate bill ... [i]t’s a start, but it’s not as far as it should have gone.”¹²² Congress went further two years later, and amended ECOA to extend protection against discrimination because of “race, color, age, religion, national origin, status as a public benefit recipient, or victim of creditor retaliation for suing under the Consumer Credit Protection Act.”¹⁰⁶

Surely, creditors cannot enhance economic stabilization, promote the informed use of credit, or make credit equally available to all credit-worthy customers if a protected class of credit-worthy customers are disproportionately impacted by what amounts to randomness in the credit determinations. Effectuating ECOA’s articulated goal requires fine-tuning the errors of credit determination. And such fine-tuning will require trade-offs.

In sum, the goal of ECOA is to ensure equal opportunity to credit among the creditworthy, and we provide an LDA constraint that implements this goal amid the unique challenges of modern-day underwriting.

D. ECOA Case Law

¹⁰⁶ Winnie Taylor also documents how this history supports using the disparate impact framework under ECOA.

In pertinent part: “Importantly, a House of Representatives report that pertains to the proposed ECOA amendments mentioned a proposal ‘that would provide that no consumer could successfully seek punitive damages unless the creditor ‘willfully’ violates the law.’ As part of her objection to this proposal, Congresswoman Abzug stated, ‘Where credit criteria, though discriminatory, are on their face legitimate, it would become nearly impossible to demonstrate an intent to discriminate. This would mean that plaintiffs who rely on the effects test would be limited to the recovery of actual damages.’ Furthermore, Congresswoman Abzug noted that the proposal, ‘in disallowing any civil penalties, except in the rare case of proven willful discrimination, would be a full retreat from effective private enforcement.’ Congresswoman Sullivan agreed, and noted that ‘the present law’ does not contain the word ‘willfully.’ Apparently, the arguments of Congresswoman Abzug and Sullivan prevailed because the enacted amendments did not include a requirement that ECOA plaintiffs must show that lenders intentionally violated the statute to recover punitive damages. The implication is that lawmakers tacitly understood that disparate impact claims were included in the ECOA when they initially enacted the statute and that they intended for victims to recover punitive damages for intentional as well as unintended violations.” Taylor, *supra* note ___, at 600-1 (citations omitted).

We have seen that effectuating the articulated goal of ECOA requires fine-tuning the different potential avenues of discrimination. But the ECOA case law depicts a general hesitance for courts to be the ones doing it.¹⁰⁷ So, courts would likely defer to sensible weighings by regulators. And in other statutory contexts (Title VI), courts have held that an LDA can consist of separate mitigation measures,¹⁰⁸ which is precisely the sort of trade-off our model provides. Such an LDA “need not be merely substitutes of the same type as the challenged practice, but may include practices or policies of a different manner or that include other actions by the defendant that ameliorate the disparate impact.”¹⁰⁹ For example, in one Third Circuit case, plaintiffs brought a DI claim of discrimination when a recipient of federal funds planned to build a medical center in a suburban site disproportionately far from minority communities. The court rejected the challenge, noting that other sites would not meet the recipient’s needs, such as geographic consolidation and financial feasibility. And, crucially, the hospital implemented the mitigating measure of providing a shuttle to the new facility. So, even though the disparity of distance still exists, the alternate means of transport provides a new kind of access to reasonably offset it. Similarly, in the context of environmental permitting complaints, the use of “practical mitigation measures associated with the permitting action could be considered as less discriminatory alternatives, including, in some cases, modifying permit conditions to lessen or eliminate the demonstrated adverse disparate impact.”¹¹⁰

E. ECOA Regulations

¹⁰⁷ See, e.g., *Bryan v. Koch*, 627 F.2d 612, 619 (2d Cir. 1980) (“We are skeptical of the capacity and appropriateness of courts to conduct such broad inquiries concerning alternative ways to carry out municipal functions. Once a court is drawn into such a complex inquiry, it will inevitably be assessing the wisdom of competing political and economic alternatives.”).

¹⁰⁸ EPA INVESTIGATIONS GUIDANCE, 65 FED. REG. AT 39,683 (“[P]ractical mitigation measures associated with the permitting action could be considered as less discriminatory alternatives, including, in some cases, modifying permit conditions to lessen or eliminate the demonstrated adverse disparate impact.”).

¹⁰⁹ *Meek v. Martinez*, 724 F. Supp. 998-1000, 1060-61 (S.D. Fla. 1987).

¹¹⁰ EPA INVESTIGATIONS GUIDANCE, 65 FED. REG. AT 39,683.

In 1976, two years after ECOA's passage, Congress amended it to shield lenders from discrimination liability for including age as a variable in "any empirically derived credit system that is "demonstrably and statistically sound in accordance with regulations of the [Federal Reserve] Board, except that in the operation of such system the age of an elderly applicant may not be assigned a negative factor or value."¹¹¹ The Board determined that an empirically derived system must be based on data from the empirical distribution of the applicant population.¹¹² This data is "demonstrably and statistically sound" according to two tests. The first requires that the model be "statistically significant," where $p < 0.05$ would likely satisfy a court.¹¹³ The second requires re-running the model on new data every so often, in order to "revalidate" its statistical significance. Any competitive creditor would likely already be doing both, if not much more.¹¹⁴ So, this regulation seemingly functions primarily to prohibit building "judgmental" systems involving age that derive merely from human guesswork and discretion.¹¹⁵

In so doing, Reg B interprets ECOA in a way that seeks to increase the available signal in determining creditworthiness. One pertinent example is in Section 202.6(b)(5), which instructs that creditors "may consider the amount and probable continuance of any income," and specifically when "an applicant relies on alimony, child support, or separate maintenance payments in applying for credit, the creditor shall consider such payments as income to the extent that they are likely to be

¹¹¹ Public Law 93-495, sec. 503, 88 Stat. at 1522.

¹¹² David C. Hsia, *Credit Scoring and the Equal Credit Opportunity Act*, 30 HASTINGS L.J. 371, 405 (1978).

¹¹³ Hsia, *supra* note ___, at 405.

¹¹⁴ See Hsia, *supra* note ___, at 405 (noting that that these three standards "impose only minimal statistical standards for predictive accuracy" and "any system with a modicum of predictive power should easily pass government specifications").

¹¹⁵ Hsia, *supra* note ___, at 406. See also Victoria Angelova et al., *Algorithmic Recommendations and Human Discretion* (2023), https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4589709.

consistently made.”¹¹⁶ Reliable income sources such as alimony or child support genuinely inform the recipient’s ability to repay; i.e., these sources are signals. To usher in credit equality, ECOA needs to increase the signal available to creditors to determine creditworthiness for historically disadvantaged groups of people, as Section 202.6(b)(5) achieved for women.

Conversely, Reg B also interprets ECOA in a way that decreases the level of noise in determining creditworthiness. One pertinent example is in Section 202.6(b)(6), which mandates that creditors distinguish “accounts that the applicant and the applicant’s spouse are permitted to use or for which both are contractually liable.”¹¹⁷ Further, creditors must consider “any information the applicant may present that tends to indicate the credit history ... does not accurately reflect the applicant’s creditworthiness.”¹¹⁸ So, women who are married, divorced, or separated have their own credit files as a result, and can also “disconnect themselves from a spouse’s negative credit report that does not accurately reflect their credit behavior.”¹¹⁹ And for married women, creditors must designate that “[a]ny new account to reflect the participation of both spouses if the applicant’s spouse is permitted to use or for which both are contractually liable.”¹²⁰ Section 202.6(6) removed noisy data that “[did] not accurately reflect” female applicant’s creditworthiness, and in so doing “removed a major obstacle that previously hindered credit availability for women.”¹²¹

But the more signal we introduce, the more potential we see for violations of parity. For example, payday loan use can be predictive of future loan default, but payday loan use is also strongly

¹¹⁶ 12 C.F.R. §1002.8.

¹¹⁷ 12 C.F.R. § 202.6 (b)(6)(i).

¹¹⁸ 12 C.F.R. § 202.6 (b)(6)(ii).

¹¹⁹ Taylor, *supra* note __, at 613.

¹²⁰ 12 C.F.R. § 202.10 (a)(1).

¹²¹ Taylor, *supra* note __, at 614.

correlated with protected class membership and in particular with racial or ethnic minority status.¹²² So incorporating data on payday loan use into mainstream credit scoring—a process underway for at least two of the three main U.S. credit bureaus—may improve credit score predictive performance while worsening credit score disparities between white and non-white loan applicants. Do improvements in performance or in differential inaccuracy justify violations of parity? Our LDA constraint makes regulatory guidance on such questions possible.

At bottom, Reg B is fundamentally concerned with using ECOA to increase signal (e.g., including women’s child support and alimony income) and decrease noise (e.g., untethering women from the data on their ex-husband’s file). Eventually, though, realizing this goal may require decreasing parity. But similar trade-offs have already been recognized in regulatory interpretations of Title VI and Title VII, and we want the same for ECOA.¹²³

Under ECOA’s touchstone of employment law, the federal government’s Uniform Guidelines on Employee Selection Procedures (“UGESP”), the concept of validity refers to a satisfactory correlation between the predictor (e.g., SAT score) and outcome (e.g., completing a bachelor’s degree).¹²⁴ Differential validity, then, is an unsatisfactory difference in this correlation coefficient

¹²² See generally Skiba & Tobacman, *supra* note __; Small et al., *supra* note __.

¹²³ A relevant practice tip instructs as follows: “PRACTICE TIP. These cases and guidelines show that “less discriminatory alternatives” may take the form of mitigation measures to be applied to the original challenged practice. Accordingly, investigating agencies should ensure that they consider not only alternative policies and practices when evaluating “less discriminatory alternatives,” but also the measures the recipient could implement in order to lessen the harm that the challenged practice causes. Informal resolution efforts often involve identification of mitigation efforts which, if applied, would result in compliance with Title VI through implementation of a less discriminatory alternative.” U.S. D.O.J. TITLE VI MANUAL VII.C.3.B.

¹²⁴ THE COLLEGE BOARD, DIFFERENTIAL VALIDITY, DIFFERENTIAL PREDICTION, AND COLLEGE ADMISSION TESTING: A COMPREHENSIVE REVIEW AND ANALYSIS, Research Report No. 2001-6 at 4 (2001), <https://files.eric.ed.gov/fulltext/ED562661.pdf>.

between groups (e.g., white and nonwhite).¹²⁵ Meanwhile UGESP’s concept of differential prediction refers to an unsatisfactory difference in the “relationship between [a predictor] and criteria differs across groups.”¹²⁶ Both concepts can be shown to relate statistically to what our proposal presents as a fundamental fairness goal that may be in tension with parity: differential accuracy. UGESP recognizes the need to sometimes make this trade-off, because, as Trindel et al. note, “employers should *first* evaluate alternatives in terms of their *fairness* and *then* consider the prospect of *validation*; in other words, it is not the case that an employer should explore alternative procedures as a means of simply bolstering their compliance with prong two alone.”¹²⁷

Similarly, SIOP takes validity to be “a unitary concept with different sources of evidence contributing to an understanding of the inferences that can be drawn from a selection procedure.”¹²⁸ Interestingly, SIOP flat-out “rejects the concept of parity of outcomes as the main definition of test fairness,”¹²⁹ so unsurprisingly “the Principles say very little on the issue of alternative procedures with less adverse impact.”¹³⁰ The assessment of alternatives is referenced only once, briefly, in the document’s guidance on writing a technical validation report: “The report should document any search for selection procedures (including alternate combinations of the procedures) that show substantially

¹²⁵ THE COLLEGE BOARD, DIFFERENTIAL VALIDITY, DIFFERENTIAL PREDICTION, AND COLLEGE ADMISSION TESTING: A COMPREHENSIVE REVIEW AND ANALYSIS, Research Report No. 2001-6 at 4 (2001), <https://files.eric.ed.gov/fulltext/ED562661.pdf>.

¹²⁶ See WAYNE F. CASCIO & HERMON AGUINIS, APPLIED PSYCHOLOGY IN HUMAN RESOURCE MANAGEMENT (7th ed., 2014) 193.

¹²⁷ Kelly Trindel et al., *Fairness in Algorithmic Employment Selection: How to Comply with Title VII*, 35 ABA J. LABOR & EMP. L. 241, 267 (2021).

¹²⁸ See SOCIETY FOR INDUS. ORGAN. PSYCH., PRINCIPLES FOR THE VALIDATION AND USE OF PERSONNEL SELECTION PROCEDURES 38 (5th ed. 2018), <https://www.apa.org/ed/accreditation/about/policies/personnel-selection-procedures.pdf> [“SIOP”].

¹²⁹ Trindel et al., *supra* note __, at 268.

¹³⁰ Trindel et al., *supra* note __, at 268.

equal or greater validity for the given selection situation with an accompanying reduction in subgroup differences.”¹³¹ SIOP supports engaging with a trade-off between parity and accuracy because it instructs to find alternatives with “substantially equal or greater validity for the given selection situation with an accompanying reduction in subgroup differences” while explicitly rejecting parity as the lodestar of fairness in selection procedures.

An instructive case of such selection procedures can be found in cognitive ability testing, which is “often cited by I/O psychologists as the most predictive type of hiring assessment,” but “such tests also yield significant adverse impact against racial minority group members.”¹³² Several such psychologists have suggested that “any efforts to reduce the adverse impact of a cognitive ability test can only occur at the expense of the test’s predictive power,” dubbing this problem the “diversity-validity dilemma.”¹³³ In a section titled “Combining Selection Procedures into a Selection System,” SIOP acknowledges the need to make this trade-off, stating that “some organizations may put more emphasis on maximizing validity relative to minimizing subgroup differences” and “other organizations may put more emphasis on minimizing subgroup differences relative to maximizing validity.”¹³⁴ Our constraint is flexible enough to accommodate this insight—but we argue leaders should be given guidance on how to balance these goals, rather than choosing their own “emphasis” on one goal or another.

IV. Legal Scholarship

A. Overview

¹³¹ See SIOP at 34.

¹³² Trindel et al., *supra* note __, at 269.

¹³³ Trindel et al., *supra* note __, at 269.

¹³⁴ See SIOP, *supra* note __, at 31-32.

In analyzing DI, legal scholars have expressed magnitude concerns (how much less discriminatory must the LDA be than the challenged practice?),¹³⁵ subsequent litigation concerns (one case’s LDA is another case’s disparity),¹³⁶ and black box concerns (if we do not know how an algorithm works, we cannot determine whether competing models are genuine alternatives).¹³⁷ Our proposal addresses all of them.

B. Magnitude

First, how much less discriminatory must the LDA be? A recent article by Kevin Tobia argues that “practical significance testing ... should not be relevant to assessing an alternative policy.”¹³⁸ In other words, “[a] suitable alternative policy should be accepted regardless of whether it decreases discriminatory impact by a small or large amount.”¹³⁹ The idea is that “[d]isparate impact aims to remove all unnecessary discriminatory barriers, not just the largest ones.”¹⁴⁰ Given the statutory language, this approach makes sense; the LDA “need not have dramatically, substantially, or even significantly less disparate impact—just ‘less.’”¹⁴¹

But this view remains open to the concern of disparity trade-offs. What if a plaintiff produces an alternative that, for example, that slightly improves parity but is much less calibrated? On Tobia’s theory, the slight improvement suffices to count the alternative as an LDA. But this seems implausible,

¹³⁵ Kevin Tobia, *Disparate Statistics*, 126 YALE L.J. 2382, 2411 (2017) (“A suitable alternative policy should be accepted regardless of whether it decreases discriminatory impact by a small or large amount.”).

¹³⁶ See *The Civil Rights Act of 1991 and Less Discriminatory Alternatives in Disparate Impact Litigation Impact*, 106 HARV. L. REV. 1621, 1627 (1993) (“LDAs may themselves have disparate impacts on different identifiable groups.”).

¹³⁷ Michael Selmi, *Algorithms, Discrimination and the Law*, 82 OHIO ST. L.J. 611-51 (2021).

¹³⁸ Tobia, *supra* note __, at 2411.

¹³⁹ Tobia, *supra* note __, at 2411.

¹⁴⁰ Tobia, *supra* note __, at 2411.

¹⁴¹ Tobia, *supra* note __, at 2412.

opening up creditors to litigation any time plaintiffs come up with any alternative that increases parity. By contrast, our constraint allows creditors to balance these considerations at the outset, precluding liability unless the creditor leaves substantial parity gains on the table.

C. Successive Suits

Second, when does an LDA preclude successive disparate impact suits? For instance: “if a court ordered a defendant to adopt an LDA based on a ten percent differential, will the defendant be insulated from a second suit by women who propose an alternative that further reduces discrimination?”¹⁴² Section 108 of the 1991 Act seems to foreclose successive suits by members of the same protected class.¹⁴³ On one hand, foreclosing future suits would permit defendants to evade liability even if they refuse to implement any LDAs developed in the future. On the other hand, allowing successive suits seems to impose an undue burden on defendants.

The problem of successive suits is particularly troublesome because “LDAs may themselves have disparate impacts on different identifiable groups.”¹⁴⁴ Is it a plaintiff’s responsibility to ensure that an LDA meets with the approval of all groups, or just its own? Under the 1991 Act, if a group is not given notice of the suit and an opportunity to present objections to a proposed LDA, or is not adequately represented by someone else who objected to the LDA on the same legal grounds and with a similar factual situation, adopting the LDA does not shield the defendant from future liability.¹⁴⁵ Even if the adversely affected group was notified or represented, the defendant may be subject to future liability if the subsequent discovery that the court-ordered LDA disparately impacts other

¹⁴² *The Civil Rights Act of 1991 and Less Discriminatory Alternatives in Disparate Impact Litigation Impact*, 106 HARV. L. REV. 1621, 1627 (1993).

¹⁴³ See Civil Rights Act of 1991 § 108, 42 U.S.C.A. § 2000e-2(n).

¹⁴⁴ *Civil Rights Act of 1991 and Less Discriminatory Alternatives in Disparate Impact Litigation Impact*, 106 HARV. L. REV. 1621, 1627 (1993).

¹⁴⁵ See Civil Rights Act of 1991 § 108, 42 U.S.C.A. § 2000e-2(n).

groups is deemed to be an intervening change in law or fact.¹⁴⁶ Although imposing liability in such cases is troubling, holding otherwise would be inconsistent with the goals of Title VII.¹⁴⁷

D. Black Box

Third, Selmi argues that the “third prong of the disparate impact theory has generally been underdeveloped in the case law, but it is likely to play a significant role with respect to algorithmic decision-making because altering the algorithm may reduce discrimination without significantly affecting the quality of the decisions.”¹⁴⁸ For example, “[t]his has been true in a number of testing cases where plaintiffs propose an alteration of the scoring regime,” such as weighing inputs differently.¹⁴⁹

As Selmi points out, Step 3 “is only viable if the algorithm can be revealed and analyzed.”¹⁵⁰ Otherwise, “[i]f a defendant were allowed to prevail under a general claim that the algorithm is inherently accurate though we do not know why, it would be impossible for a plaintiff to offer any alternative.”¹⁵¹ And “not only would such a defense stretch the concept of the burden of proof, but it would eliminate the third step in the analysis, a step that has been enshrined in disparate impact law for nearly fifty years and now safely ensconced in the statutes.”¹⁵²

Selmi also calls attention to a legal paradox ensuing from Step 3: “assuming that a court will not accept a defense based solely on a statistically significant correlation between the algorithm and

¹⁴⁶ See 42 U.S.C.A. § 2000e-2(n).

¹⁴⁷ See Civil Rights Act of 1991 §§ 2-3, 105 Stat. 1071 (1991) (describing purpose).

¹⁴⁸ Selmi, *supra* note ___, at 644.

¹⁴⁹ Selmi, *supra* note ___, at 644.

¹⁵⁰ Selmi, *supra* note ___, at 644.

¹⁵¹ Selmi, *supra* note ___, at 644.

¹⁵² Selmi, *supra* note ___, at 644.

some meaningful measure of performance, this likely means that a defendant could not survive a challenge to a black-box algorithm.”¹⁵³ That is because “[i]t is possible that a defendant would be able to offer alternative algorithms to show the superiority of its own, though unless one knows the underlying construct it would be hard to compare the algorithms and equally difficult to know whether the alternative was used solely to demonstrate the merits of the company’s algorithm rather than as a true considered alternative.”¹⁵⁴ So, absent some metric of alternatives, we must decide to either always rule in favor of either plaintiffs or defendants, as a matter of mere policy.¹⁵⁵

But we provide exactly such a comparison measure. Recall Gillis’s insight on the input fallacy—even if we were able to scrutinize the black box, we can still miss the mark because the outcomes can still be problematic. In proposing an outcome-oriented constraint, we also adopt this stance. Having a principled standard for outcomes obviates the need to scrutinize the black box to begin with. And scrutinizing what we put into the black box may prove counterproductive. As discussed above, to increase access to credit, Reg B already permits scoring models to include age as a variable, assuming the model is “empirically validated” (otherwise the model is dubbed merely “judgmental”).¹⁵⁶ We might generalize this by permitting other historically prohibited variables so long as we trade-off between disparities in a principled way that is ‘empirically validated.’¹⁵⁷ And as we argued earlier, our proposal constrains such validity.

¹⁵³ Selmi, *supra* note __, at 644.

¹⁵⁴ Selmi, *supra* note __, at 644.

¹⁵⁵ See Selmi, *supra* note __, at 644.

¹⁵⁶ 12 C.F.R. § 1002.2(p).

¹⁵⁷ See generally Meursault et al., *One Threshold Doesn’t Fit All: Tailoring Machine Learning Predictions of Consumer Default for Lower-Income Areas* (2022), <https://www.philadelphiafed.org/consumer-finance/consumer-credit/one-threshold-doesnt-fit-all>.

V. Objections

A. Inputs and Outputs

Not all scholars have given up on regulating inputs as a means to prevent DI. Bartlett et al. provide an instructive analysis of business necessity, which they dub the Input Accountability Test (“IAT”). The IAT interprets Step 2 requires asking two questions: “First, is the use of proxies for an unobservable “target” characteristic done in pursuit of a fundamental business necessity?”¹⁵⁸ And second, even with a legitimate target characteristic and predictive proxy input variables, are these input variables noisy at estimating the legitimate business necessity in a way that will systematically penalize members of a protected group who are otherwise qualified?”¹⁵⁹ For example, consider the well-known case of *Ricci v. DeStefano*.¹⁶⁰ There, the City of New Haven discarded the results of an “objective examination” that sought to identify the most qualified firefighters for promotion.¹⁶¹ The city justified its decision to discard the results on the basis that they revealed a statistical racial disparity, raising the risk of disparate impact liability under Title VII.¹⁶² A group of white and Hispanic firefighters sued, alleging that the city’s discarding of the test results constituted race-based disparate treatment.¹⁶³ In upholding their claim, the Court emphasized the extensive efforts that the city took to ensure the test was job-related and that there was “no genuine dispute that the examinations were job-related and consistent with business necessity.”¹⁶⁴ Nor did the city offer “a strong basis in evidence of an equally

¹⁵⁸ See Bartlett et al., *supra* note __, at 679.

¹⁵⁹ See Bartlett et al., *supra* note __, at 679.

¹⁶⁰ 557 U.S. 557 (2009).

¹⁶¹ *Id.*

¹⁶² *Id.*

¹⁶³ *Id.*

¹⁶⁴ *Id.*

valid, less-discriminatory testing alternative.”¹⁶⁵ Prohibiting the city from discarding the test results was therefore required to prevent the city from discriminating against “qualified candidates on the basis of their race.”¹⁶⁶

Some of the theoretical virtues of our proposal discussed in Section IV stem from our position that the dispositive factor for compliance is the model’s output¹⁶⁷ (although the constraint can also accommodate restrictions on input¹⁶⁸). But Bartlett et al. argue that output-focused measures of compliance, which they dub “output accountability tests” (“OATs”), were rejected by the Court in *Ricci*.¹⁶⁹ In upholding the plaintiffs’ claim that discarding the test results constituted race-based disparate-treatment, the Court stressed that there was “no genuine dispute that the examinations were job-related and consistent with business necessity”¹⁷⁰ and New Haven failed to proffer “a strong basis in evidence of an equally valid, less-discriminatory testing alternative.”¹⁷¹ So, argue Bartlett et al., “*Ricci* underscores the fundamental importance of ensuring that decision-making processes do not systematically discriminate against qualified individuals because of their race.”¹⁷² And IAT sympathizers may object to our constraint by claiming it’s this kind of OAT proscribed by *Ricci*.

But does *Ricci* really categorically reject OATs, or simply demand a higher standard for them? Consider the following excerpt from the majority opinion in that case:

¹⁶⁵ *Id.*

¹⁶⁶ *Id.*

¹⁶⁷ See Section IV.D, *supra* note ____.

¹⁶⁸ See Section II, *supra* note ____.

¹⁶⁹ See Bartlett et al., *supra* note ____, at 690.

¹⁷⁰ Bartlett et al., *supra* note ____, at 690.

¹⁷¹ 557 U.S. at 589.

¹⁷² 557 U.S. at 584.

“Title VII does not prohibit an employer from considering, before administering a test or practice, how to design that test or practice in order to provide a fair opportunity for all individuals, regardless of their race. And when, during the test-design stage, an employer invites comments to ensure the test is fair, that process can provide a common ground for open discussions toward that end. We hold only that, under Title VII, before an employer can engage in intentional discrimination for the asserted purpose of avoiding or remedying an unintentional disparate impact, *the employer must have a strong basis in evidence to believe it will be subject to disparate-impact liability if it fails to take the race-conscious, discriminatory action.*”¹⁷³

It’s not that a mere OAT can *never* be an appropriate measure of business necessity. Rather, New Haven did not have the requisite “strong basis in evidence” to adequately show the outcome of its test would have subjected it to DI liability. In other words, the Court seems to take issue with the quality of the outcome analysis, rather than the fact that an outcome analysis occurred.

B. Bottom Line

1. Defined

A more pressing objection for our proposal comes from another wrinkle of DI known as “bottom line analysis.” Such analysis looks for nonparity only in the final outcome, or ‘bottom line,’ rather than any particular aspect of the selection process.¹⁷⁴ The Supreme Court rejected precisely this defense in *Connecticut v. Teal*.¹⁷⁵ In that case, the employer had a 2-stage promotion process, where stage 1 was a written test that had a disparate impact and stage 2 was an interview with affirmative action. The employer argued that the “bottom line” outcome of the process wasn’t discriminatory, given the affirmative action in stage 2. But the Court held that the employer was still liable for the disparate impact in stage 1.

2. So, one might object to our proposal as amounting to a kind of bottom line analysis—even if the outcome is efficient, one might view the parity term in our

¹⁷³ 557 U.S. at 585 (emphasis added).

¹⁷⁴ See Katherine C. Callahan (defining bottom line analysis as that which “focuses on the actual number of women or minorities hired rather than on any single aspect of the selection process.”)

¹⁷⁵ *Connecticut v. Teal*, 457 U.S. 440 (1982).

constraint is unacceptably high, even in a case where the LDA is numerically satisfied. On the one hand, calibration of the constraint parameters (e.g., β , γ) by the regulator can be done to avoid such cases. On the other hand, consider the *Ricci* context and suppose that the firefighters disqualified by the test were genuinely unable to fight fires. In this case, a focus on parity alone would seem self-evidently inappropriate, regardless of how large the parity violation in question is. Our LDA constraint allows the regulator to robustly measure this kind of balancing-out of a severe parity violation with equally severe issues of either model performance or differential accuracy. More generally, however, we think that bottom line analysis as conducted pre-*Teal* is not categorically barred post-*Teal*, as we discuss in the following section. Response

We now respond to the bottom line objection in two parts: first, by noting the insights from courts pre-*Teal*, and second, by discussing the confusion post-*Teal*. We conclude that our proposal offers a promising way forward.

a) Bottom Lines Pre-*Teal*

We first respond by drawing on the insights of the lower courts pre-*Teal*, noting two rationales for why they permitted bottom-line defenses that are still relevant today. First, interpreting parity as ultimately a measure of relative representation in screening outcomes means that the bottom line ends up dispositive anyway. This interpretation yields a sensible limiting principle for determining disparate impacts that are genuinely adverse.

Disparate impact, as a concept, requires “actual discrimination.”¹⁷⁶ The idea is that disparate impact does not abolish every policy with any outcome that correlates with protected class membership—only policies with specific kinds of adverse outcomes. An example of the former kind of impact can be found in *EEOC v. Greyhound Lines, Inc.*, where the Third Circuit rejected a DI claim for a company’s no-beard policy disproportionately affecting Black men.¹⁷⁷ The court ruled that the policy did not constitute “actual discrimination” because Black men comprised over 20% of the workforce subject to the no-beards policy but only 14% of the relevant labor market, so the policy did not cause underrepresentation in employment. The court stated that “[t]his conclusion should be as obvious as it is tautological: there can be no disparate impact unless there is a disparate impact.”¹⁷⁸ To adversely impact parity is to adversely impact relative representation.

Further, because parity is a measure of ultimate relative representation, it seems unduly burdensome to have courts scrutinize every step of a screening procedure when the final outcome is what ends up as the decisive metric.¹⁷⁹ On this reasoning, the Sixth Circuit embraced bottom-line analysis out of hesitation to scrutinize sub-parts of sub-parts of sub-tests, and so on.¹⁸⁰ And a district court in Connecticut argued that this process “[sends] a court on a course that has no clear boundaries and no clear end.”¹⁸¹

b) Confusion Post-*Teal*

¹⁷⁶ Callahan, *supra* note ___, at 828.

¹⁷⁷ 635 F.2d 188 (3d Cir. 1980).

¹⁷⁸ 635 F.2d at 191-92.

¹⁷⁹ *See* Callahan, *supra* note ___, at 828 (noting that “[a] justification for restricting the scope of judicial inquiry to final results is the prospect of forcing courts to evaluate every feature of a challenged employment procedure for disparate impact.”).

¹⁸⁰ *Smith v. Troyan*, 520 F.2d 492 (6th Cir. 1975), *cert. denied*, 426 U.S. 934, *reb’g denied*, 429 U.S. 1124 (1976).

¹⁸¹ *Brown v. New Haven Civil Service Board*, 474 F. Supp. 1256, 1262 (D.Conn. 1979).

We now respond by noting the confusion about bottom lines post-*Teal*. As Katherine C. Callahan points out, *Teal* created confusion “because the particular facts of *Teal* lent themselves to a rejection of the bottom line defense, future decisions may distinguish *Teal* on its facts.”¹⁸²In *Costa v. Markey*, the first “bottom line” case after *Teal*, the First Circuit initially viewed *Teal* as reaching beyond its fact pattern.¹⁸³ There the First Circuit determined that a minimum height requirement for hiring police officers had a disparate impact on women even though women were 100% of the applicants for the particular job. The court felt compelled to reach this verdict to avoid contravening *Teal*.¹⁸⁴ However, upon re-hearing the case *en banc*, the First Circuit concluded that because it was already the case that all the applicants themselves were women, the “[p]laintiff simply failed to make it over the initial hurdle of demonstrating that the challenged barrier had a discriminatory effect on women.”¹⁸⁵ So while *Teal* may suggest that bottom line analysis is *per se* illegal, *Markey* demonstrates that this interpretation yields strange results outside of fact patterns that closely resemble the two-stage process from *Teal*. Indeed, as Katherine C. Callahan notes:

The particular facts of *Connecticut v. Teal* warranted the Court’s rejection of the bottom line defense in the case. However, the bottom line defense should be available to employers who use a multi-component cumulative selection process that does not produce disparate results. Title VII encompasses two broad goals: the elimination of discrimination on an individual basis and the improvement of the economic status of minorities and women, as classes, in society. ... The bottom line approach, as defense and perhaps penalty, may be the most effective means of opening significant numbers of employment opportunities to minorities and women.”¹⁸⁶

¹⁸² Callahan, *supra* note ___, at 845.

¹⁸³ 706 F.2d 1 (1st Cir. 1982).

¹⁸⁴ But see the dissent: “Judge Coffin dissented, concluding that the majority provided a remedy where there had been no wrong and carried abstract disparate impact analysis far beyond the mandate of *Teal*. Judge Coffin’s view eventually prevailed.” Callahan, *supra*, at 845.

¹⁸⁵ 706 F.2d 1 at 12.

¹⁸⁶ Callahan, *supra* note ___, at 846.

So, the peculiar facts of Teal suggest that other cases involving bottom line analysis could be successfully distinguished, and insights from the lower courts provide good reasons to do so. In a similar vein as Gillis’s proposed “input fallacy,” we propose a kind of “bottom line” fallacy. Gillis’s insight is that evaluating the fairness of algorithmic outputs is the only tenable way forward for antidiscrimination law in the age of big data. Similarly, evaluating the bottom line is the only tenable way forward for balancing the competing objectives of parity and accuracy under a DI interpretation of ECOA.

VI. Conclusion

In this Article, we confronted traditional DI analysis with an impossibility result: whenever two protected classes differ in their rates of positive and negative class membership, parity can only be achieved by introducing differential accuracy. We argued that in the tradeoff between parity and accuracy as fairness goals, neither should have exclusive preference over the other – especially in a world of algorithmic screening. Accuracy, like the access to credit that it can enable, is crucial to economic opportunity, and a singular focus on parity has become too costly to sustain. Then, as a path forward we provided a generalized model of this trade-off so that regulators such as the CFPB can “plug and play” with the variables to quantify, *ex ante*, which trade-off thresholds will not prompt enforcement of ECOA. We argued that there is abundant legal support for permitting such trade-offs under ECOA, based on the statutory text and the regulations, case law, and scholarship interpreting it. Our model is designed to be an LDA constraint so as to “bake in” all three Steps of DI analysis. In practice, this design yields quantifiable criteria for SPCPs and NALs to address parity and differential accuracy shortfalls. As the Supreme Court observed in *Inclusive Communities*, DI is a tool for

“eradicat[ing] discriminatory practices within a sector of our Nation’s economy.”¹⁸⁷ The way to fight discrimination in the consumer finance sector must entail, at bottom, a transparent, legally grounded, and concretely quantifiable balance between innovative technologies that reduce signal noise in screening, and the longstanding goal of protecting parity in credit access.

¹⁸⁷ Taylor, *supra* note __, at 630.