



Fair Lending Monitorship of Upstart Network's Lending Model

Fourth and Final Report of the Independent Monitor

PUBLIC

Pursuant to agreement by the NAACP Legal Defense and Educational Fund, the Student Borrower Protection Center, and Upstart Network, Inc.

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Executive Summary

This is the Fourth and final Report of the independent fair lending Monitor regarding Upstart Network's ("Upstart") lending Model. This Report represents the conclusion of the Monitorship among Upstart, the NAACP Legal Defense Fund ("LDF"), and the Student Borrower Protection Center ("SBPC").¹ Over the last 3 years, we have issued three other public Reports.² Those Reports explained our application of fair lending methodologies to a prior version of Upstart's Model, including (1) finding no quantitative evidence that variables in Upstart's Model functioned as close proxies for race, national origin, sex, or age; but (2) identifying approval disparities for Black applicants.³ We also identified what the Monitor believes would likely have been a viable alternative model that would cause fewer disparities for Black applicants. In our prior reports, we recommended that Upstart apply those fair lending testing methodologies to its model updates, and that Upstart adopt any viable less discriminatory alternative models it identifies going forward.⁴

Upstart has adopted nearly all of the Monitor's recommendations and has made enhancements to its fair lending testing protocols during the course of the Monitorship, including implementing recommended criteria for searching for and adopting less discriminatory alternative models.

The Parties, however, remain at an impasse over a key recommendation: the appropriate and legally required methodology for assessing whether the performance of a potential less discriminatory alternative model would be comparable to the performance of the existing Model (the "Baseline" Model) in terms of reasonably meeting Upstart's proffered legitimate business needs. This question is critical under fair lending laws because the disparate impact doctrine requires adoption of less discriminatory alternatives that reasonably achieve those legitimate business needs. The Third Report recommended an approach that accounts for the fact that there is a range of uncertainty regarding how any model will perform, and a corresponding likelihood

¹ This Report uses the term Monitor to refer to the collective work of Relman Colfax PLLC, Sentrana Inc., and BLDS, LLC. Those respective teams were led by Stephen Hayes, Syeed Mansur, and Dr. Bernard Siskin.

² Relman Colfax, "Initial Report of the Independent Monitor," Fair Lending Monitorship of Upstart Network's Lending Model Pursuant to Agreement by the NAACP Legal Defense and Educational Fund, the Student Borrower Protection Center, and Upstart Network, Inc. (Apr. 14, 2021) ("Monitor's Initial Report"), https://www.relmanlaw.com/media/cases/1088_Upstart%20Initial%20Report%20-%20Final.pdf; Relman Colfax, "Second Report of the Independent Monitor (Public)," Fair Lending Monitorship of Upstart Network's Lending Model Pursuant to Agreement by the NAACP Legal Defense and Educational Fund, the Student Borrower Protection Center, and Upstart Network, Inc. (Nov. 10, 2021) ("Monitor's Second Report"), https://www.relmanlaw.com/media/cases/1180_PUBLIC%20Upstart%20Monitorship_2nd%20Report_FINAL.pdf; Relman Colfax, "Third Report of Independent Monitor," Fair Lending Monitorship of Upstart Network's Lending Model Pursuant to Agreement by the NAACP Legal Defense and Educational Fund, the Student Borrower Protection Center, and Upstart Network, Inc. (Sept. 16, 2022) ("Monitor's Third Report"), https://www.relmanlaw.com/media/cases/1333_PUBLIC%20Upstart%20Monitorship%203rd%20Report%20FINAL.pdf.

³ With respect to pricing, we identified some annual percentage rate ("APR") disparities for Black, Hispanic, and female applicants, but none of these disparities exceeded the "practical significance" metrics used in the Monitorship and so did not warrant further review under our framework.

⁴ We also provided recommendations to mitigate future potential age-proxy risks specifically related to non-traditional variables. See Monitor's Third Report, *supra* note 2, at 36.

that a court would find that an alternative model that is likely to perform within the performance range of the Baseline Model would achieve the business interests as well as the Baseline Model.

Upstart disagrees with this approach and presented technical counterarguments supporting its position that the methodology would unacceptably compromise the accuracy of its models. As discussed below, the Monitor is not persuaded by Upstart's technical arguments. But we do agree there is a possibility that a court could take a different analytical approach, for example by concluding that an alternative is not viable unless its measured performance is equal to the Baseline Model, regardless of uncertainty about that performance metric. After publication of the most recent Report, the Parties to this Monitorship engaged in extended discussions regarding our findings and recommendations. Given this disagreement, Upstart has declined to adopt this aspect of the Monitor's recommendations, and the Parties reached an impasse on this point.

This issue is critical. If a fair lending testing regime is designed around the assumption that a less discriminatory alternative model cannot be viable unless its performance is exactly equal to a baseline model on a chosen performance metric (regardless of uncertainty associated with that metric), less discriminatory models may rarely if ever be adopted. Under that position, even a complicated testing regime could largely favor process over substantive change.

This final Report provides an overview of our prior findings and observations, as well as enhancements Upstart has made to its fair lending testing protocols over the course of the Monitorship. The Report also explains the Parties' impasse and the importance that resolving that impasse has for ensuring fair lending testing of models is a meaningful exercise.

The Report then notes agreement by the Parties on the contributions the Monitorship has had to public dialogue about algorithmic discrimination. This Monitorship is unique insofar as Upstart took significant steps to make available data and other information. Upstart's transparency allowed for a concrete description of techniques, methodological questions, and an exploration of the analytical and legal principles underlying decisions about those methodologies. With this process in mind, the Report concludes by providing recommendations from the Parties and the Monitor to lenders, regulators, and policymakers:

- (1) All lenders should routinely assess their credit models for discrimination risks. Qualitative and quantitative model testing—including testing for disparate treatment and disparate impact risks—should be one component of a robust fair lending compliance management system that addresses risks throughout the loan lifecycle, including assessing marketing and acquisition processes that can affect applicant pools.
- (2) Regulators should provide guidance on how effective fair lending testing should be conducted, including clarifying expectations regarding identifying, assessing, and adopting less discriminatory alternative models.

(3) Regulators, legislators, and other entities should do more to advance transparency in credit markets. The Parties encourage others to follow Upstart's lead by providing transparency into real-world models and data. They also encourage regulators and lawmakers to advance transparency by helping structure data sharing and by making more lending data available via restricted access research initiatives or through publicly-available self-reported data programs, akin to what is available for mortgage and what will soon be available for small-business lending.

A. Background and History

1. Development and Goals of the Monitorship

Upstart is a lending platform that relies on Artificial Intelligence and Machine Learning (“AI/ML”) algorithms, and predictive models generated from those algorithms, that incorporate non-traditional applicant data—including data related to borrowers’ education—to underwrite and price consumer loans. Upstart initially introduced its lending platform in 2014, stating that its goal was to use non-traditional variables and advanced modeling techniques to more effectively underwrite and approve borrowers, particularly those with limited credit histories.⁵

In February 2020, SBPC released a report entitled “Educational Redlining,” examining fair lending issues related to student lending and the refinancing of educational loans.⁶ One section of that report focused on SBPC’s concerns that the use of educational data by fintech lenders such as Upstart might disadvantage students and graduates of Historically Black Colleges and Universities and Hispanic-Serving Institutions. SBPC concluded in that report that otherwise similarly-situated applicants who had attended these minority-serving institutions were charged more because of their choice of school.⁷ Upstart responded to the SBPC report disputing its findings and conclusions.⁸ Shortly after the SBPC study was released, Democratic members of the Senate Committee on Banking, Housing, and Urban Affairs sent letters to Upstart and other lenders and service providers utilizing education-related data for lending purposes.⁹ The letters expressed concern about the use of non-individualized education factors, which they noted the Consumer Financial Protection Bureau (“CFPB”), the Federal Deposit Insurance Corporation (“FDIC”), and the New York Attorney General’s Office had all found could, in at least some circumstances, result in violations of the Equal Credit Opportunity Act (“ECOA”).

Around this time, Upstart, SBPC, and LDF engaged in conversations regarding SBPC’s and LDF’s concerns, which ultimately led to this monitoring engagement.¹⁰ On December 1, 2020, LDF, Upstart, and SBPC entered into an agreement under which Relman Colfax would act as a neutral, independent, third-party Monitor charged with conducting ongoing fair lending testing of Upstart’s platform, including, but not limited to, Upstart’s use of educational variables. As discussed below, prior to the Monitorship, Upstart also made certain changes to how its

⁵ Upstart, “Application of Upstart Network, Inc. for CFPB No-Action Letter” at 1, 3 (2017), https://files.consumerfinance.gov/f/documents/cfpb_upstart-network-inc_no-action-letter-application_2020-11.pdf (hereinafter “2017 NAL Request”).

⁶ Student Borrower Protection Center, “Educational Redlining” at 15 (Feb. 2020), <https://protectborrowers.org/wp-content/uploads/2020/02/Education-Redlining-Report.pdf>.

⁷ *Id.* at 17.

⁸ Upstart, Response to SBPC report (on file with Monitor). The Monitor does not take any position on the SBPC’s study or the parties’ differing conclusions about its findings. The methodology used in the SBPC report is not the same fair lending methodology used by the Monitor when conducting fair lending testing with more complete access to Upstart’s model and underlying data.

⁹ Letter from Senators Sherrod Brown, Elizabeth Warren, Robert Menendez, Cory Booker, and Kamala D. Harris to Dave Girouard (Feb. 13, 2020), <https://www.brown.senate.gov/imo/media/doc/2020-02-13%20Senate%20letter%20to%20Upstart.pdf>.

¹⁰ *See, e.g.*, Letter from Ashok Chandran and Seth Frotman to Dave Girouard and Alison Nicoll re: Potential Discrimination in Upstart Lending Platform (July 30, 2020), <https://www.naacpldf.org/wp-content/uploads/2020-07-30-FINAL-Demand-Letter.pdf>.

underwriting model utilized educational data, including abolishing the use of average incoming SAT and ACT scores to group education institutions.

The Monitorship was designed to further three goals. First, the Monitor was responsible for conducting disparate treatment testing to analyze whether variables in Upstart’s Model are likely to function as close proxies for protected class status. Second, the Monitor was charged with assessing lending outcomes from Upstart’s Model to determine if the Model causes or results in an adverse impact on any protected class and, if so, whether there are less discriminatory alternative practices that maintain the Model’s predictiveness. Third, the Parties believed that public reports describing fair lending testing methodologies applied to an actual lending model would contribute to the ongoing dialogue about the growing use of AI/ML and alternative data, while deepening understanding of how to ensure that the use of models is consistent with antidiscrimination laws and equitable access to credit.

2. Background and Overview of Prior Findings and Recommendations

a. *Fair Lending Overview*

As discussed in more detail in our previous reports, antidiscrimination laws such as ECOA and the Fair Housing Act (“FHA”) prohibit entities in credit markets from discriminating on the basis of certain protected characteristics, such as race, color, religion, national origin, sex, age, disability, marital status, familial status, or receipt of income from a public assistance program.¹¹

Both ECOA and the FHA prohibit explicit differential treatment or intentional discrimination (known as “disparate treatment”). With limited explicit exceptions, it is a violation of the ECOA and FHA prohibitions against overt, intentional discrimination to use protected class status as a variable in a credit model. This prohibition also applies to a variable that functions in a model as a close proxy for a protected class.

ECOA and the FHA also prohibit more subtle forms of discrimination that may occur without any intent to discriminate (known as “disparate impact”). There are three steps involved in determining whether a policy or practice—here, the use of a model—has an unlawful disparate impact:

- (1) Does the model cause a disproportionate adverse impact on a protected class?
- (2) Does the model serve a legitimate business need?
- (3) If the model causes a disproportionate adverse impact on a protected class and serves a legitimate business need, does a less discriminatory alternative exist that continues to serve the legitimate business need?¹²

¹¹ 15 U.S.C. § 1691(a) (ECOA); 12 C.F.R. § 1002.2(z) (Reg. B); 42 U.S.C. §§ 3604, 3605 (FHA). For a more complete description of these requirements, see Monitor’s Second Report, *supra* note 2, at 6-8.

¹² See Monitor’s Second Report, *supra* note 2, at 6.

b. Overview of Proxy Findings and Observations

Our prior reports detail the tests we conducted to assess the risk that Upstart variables may be functioning as close proxies for protected class status. As noted, it is generally a violation of the ECOA and FHA prohibitions against overt, intentional discrimination (*i.e.*, disparate treatment) to use protected class status or a close proxy for protected class status as a variable in a credit scoring or pricing model.¹³ A close proxy is often understood to mean a variable whose predictive value in a model is attributable solely or largely to its correlation with a protected characteristic. This proxy analysis is independent of the disparate impact analysis described below: a model can raise disparate impact risks even if it does not contain any protected class or close proxy variables. Similarly, a model that uses protected class or proxy variables would raise disparate treatment risks even if that model did not cause disparate impacts adverse to a protected class.

In our reports, we concluded that based on the methodologies used, it did not appear that individual input variables in Upstart’s Model had a high likelihood of functioning as proxies for race, national origin, or sex. We also did not find sufficient evidence to conclude that input variables had a high likelihood of functioning as proxies for age. Although we did find evidence that individual input variables in Upstart’s Model had a high likelihood of being able to predict whether a borrower is age ≥ 62 , we did not find evidence that the predictive value of these attributes is solely or largely due to that correlation with age.¹⁴

As we noted in our Second and Third Reports, although more rigorous than many proxy review methodologies routinely used by some lenders, our technical methodology for identifying potential proxies has inherent limitations and cannot conclusively demonstrate that a model does or does not contain proxies for a protected class.¹⁵

c. Overview of Disparate Impact Findings and Observations

We also conducted quantitative tests to assess disparate impact risks. In our Second and Third Reports, we identified what we refer to as “statistically and practically significant” adverse

¹³ See, e.g., Monitor’s Initial Report, *supra* note 2, at 8; Monitor’s Second Report, *supra* note 2, at 22-23.

¹⁴ Separate from the types of quantitative tests described above, many financial institutions also conduct a *qualitative* variable review in which they remove from a model variables that they consider to be high risk because the variables may be perceived to be close proxies for protected classes, they may raise reputational risk, or for other reasons. Aside from determining that Upstart’s variable list does not include protected class statuses as attributes, we did not make any qualitative determinations about Upstart’s variables—meaning, we did not identify any variables as raising or not raising potential risks based on a qualitative assessment alone. Instead, as described below, we used quantitative methods to attempt to assess proxy risks across all variables.

¹⁵ Monitor’s Second Report, *supra* note 2 at 25; Monitor’s Third Report, *supra* note 2, at 36. Importantly, in certain models, namely nonlinear and nonparametric models that stem from AI/ML, input variables may combine inside of the model and interact with one another to produce temporary internal variables sometimes called “interaction variables.” These interaction variables that are automatically created within a model might correlate with or predict protected class labels in ways that could be considered proxies, even if the individual input variables do not. Our methodology does not show whether any interaction variables that are automatically created within a model are predictive of protected class labels. Because of these limitations, we cannot conclusively eliminate the possibility that proxies exist, although we did not find evidence that they do.

approval/denial disparities for Black applicants.¹⁶ These findings do not, standing alone, demonstrate a fair lending violation. In our experience with other credit models, it is not unusual to find statistically and practically significant disparities for at least one protected class at this stage of the analysis. But under our methodology, identification of these disparities triggers an obligation to investigate whether viable, less discriminatory alternatives exist.

Under Step 2 of the disparate impact analysis, if there are meaningful disparities adverse to a protected class, the entity should establish a legitimate business need for the model—in other words, show that the model is “necessary to achieve one or more substantial, legitimate, nondiscriminatory interests.”¹⁷ Upstart’s Model predicts default and pre-payment probabilities, which are combined to compute a cash-flow estimation. Upstart asserts a specific accuracy value in its prediction of these cash-flows across a population of applicants. As noted in our Second Report, meaningfully accurate prediction of default and pre-payment probabilities would likely be considered legitimate business interests at Step 2 of the disparate impact analysis, although we noted that the scope of what qualifies as a legitimate business interest in the credit context is not settled and some have argued that legitimate interests in this field should be construed narrowly.¹⁸ Assessing whether Upstart could satisfy its burden of showing its Model is necessary to achieve a legitimate interest was beyond the scope of our analysis, and we proceeded on the assumption that it could.

Finally, because we identified statistically and practically significant approval disparities for Black applicants, our analysis turned to the third step in the traditional disparate impact framework: whether less discriminatory alternatives exist.¹⁹ The technical methodology we used in this Monitorship for identifying the existence of less discriminatory alternative models is discussed in our Second Report.²⁰

Our Reports also explained conditions under which we would and would not recommend potential alternative models.²¹ In short, the process of identifying potentially viable less discriminatory alternatives is conducted within the following constraints (“**Alternative Model Constraints**”):

¹⁶ We relied on two common metrics for assessing disparities, the adverse impact ratio (“AIR”) and standardized mean difference (“SMD”). See Third Report, *supra* note 2, at 7. With respect to pricing disparities, Black, Hispanic, and female applicants experienced some APR disparities in our analyses. However, none of these disparities exceeded the practical significance metrics used in the Monitorship. See Monitor’s Second Report, *supra* note 2, at 17. We did not assess disparities with respect to American Indian/Alaskan Native, multiracial categories, or membership in other protected class groups because estimates for these groups are not sufficiently reliable. See Monitor’s Second Report, *supra* note 2, at 11.

¹⁷ See, e.g., *Mhany Mgmt., Inc. v. Cnty. of Nassau*, 819 F.3d 581, 617 (2d Cir. 2016) (quoting 24 C.F.R. § 100.500(c)). In litigation, it would be the defendant’s obligation to make an evidentiary showing to this effect.

¹⁸ See Monitor’s Second Report, *supra* note 2, at 18.

¹⁹ In litigation, it would be the plaintiff’s burden to make this showing. We focused our search on whether a less discriminatory alternative exists for Upstart’s core AI/ML Model used to predict default and prepayment probabilities for each borrower. Those outputs are eventually translated into APRs and approval/denial decisions.

²⁰ See Monitor’s Second Report, *supra* note 2, at 18-20. Other methodologies for identifying the existence of less discriminatory alternative models exist. We adopted this technique because it emulates characteristics of longstanding methods used on traditional models. See Monitor’s Second Report, *supra* note 2, at 19.

²¹ See Monitor’s Second Report, *supra* note 2, at 20-22; Monitor’s Third Report, *supra* note 2, at 10-11.

1. First, we would not recommend adopting a potential alternative model if its performance is meaningfully worse than the performance of the Baseline Model. We discuss this condition below.
2. Second, we would consider reasonable model risk management criteria in assessing whether to recommend an alternative model. For example, the alternative model should also satisfy reasonable validation metrics.
3. Third, we would not recommend an alternative model that introduces *new* statistically and practically significant disparities for other protected classes that were not present in the Baseline Model (for example, new statistically and practically significant disparities based on sex or age, assuming no such disparities existed for those classes in the Baseline Model).
4. Fourth, we would not recommend an alternative model that would exacerbate to a statistically significant extent *existing* statistically and practically significant disparities for other protected classes from the Baseline Model. In other words, if disparities in the Baseline Model are already practically significant (*e.g.*, < 90% AIR), the alternative model should not worsen those disparities in a statistically significant manner.
5. Fifth, we would not recommend an alternative model that would improve disparate impact for one protected class but that would introduce meaningful new adverse bias for a different protected class, such as predicting risk meaningfully less accurately for different protected class groups—a form of model bias that is sometimes referred to as “differential validity.”
6. It is possible that multiple alternative models could satisfy the above constraints. In such situations, we would apply more case-specific criteria.

The Third Report spent considerable space discussing the first Alternative Model Constraint—what standard should be used for determining whether the performance of a potential alternative model is acceptable? Under the disparate impact doctrine, a practice could be illegal if a business need can reasonably be achieved as well by an alternative with less impact.

The Third Report explained that practices differ across financial institutions conducting internal fair lending testing in terms of whether they will consider a less discriminatory alternative to be viable, in the sense that it reasonably serves their business needs.²² Some institutions adopt predetermined internal thresholds beyond which model performance metrics should not drop. These institutions have made the decision that alternatives that perform within that threshold are sufficiently effective to advance their legitimate business needs. Lenders might also align such thresholds with criteria they use to evaluate performance deterioration for general model training, development, and risk purposes. For example, if modelers consider a model to be acceptable as long as there is no more than a 5% deterioration in performance when comparing

²² Monitor’s Third Report, *supra* note 2, at 15.

model development and out-of-time validation data, then they might also apply a maximum 5% deterioration threshold when assessing the viability of potential alternative models. In other words, these institutions have determined that if performance deterioration is not significant enough to warrant rebuilding a model then it is unlikely to be significant as a real-world matter and so is not considered significant enough to warrant rejecting a less discriminatory alternative model.

Upstart argues that, although such practices may be viable for some financial institutions, as a technology service provider, Upstart faces different challenges than a traditional bank or lender because its business model is premised on providing the most accurate predictions possible. According to Upstart, it is reliant on lender and investor capital, which is highly sensitive to accuracy considerations about credit and prepayment risk.

Understanding that the viability of an approach is context-dependent, we ultimately recommended an approach based on the belief that there is a significant likelihood that a court would find that a less discriminatory alternative model could serve Upstart's legitimate business needs as well as the Baseline Model if there is a reasonable probability that the performance of that alternative would fall within the likely performance range of the Baseline Model. Accordingly, we identified a measure of that range for Upstart's Baseline Model—what we referred to as the **Uncertainty Interval**—and presumed an alternative model within that range would reasonably achieve Upstart's business interests as well as the Baseline.

Thus, we recommended a methodology based on the Uncertainty Interval, and relying on that methodology we identified a potential alternative model that would have reduced disparities experienced by Black applicants. However, Upstart updated its model prior to completion of the analyses discussed in the Third Report. Accordingly, rather than recommending adoption of a specific model alternative, we recommended that as Upstart continues to retrain and update its Model, it does so using the fair lending methodologies discussed in the Monitorship Reports²³:

- Those methodologies include identifying whether statistically and practically significant disparities exist for protected classes, ensuring the existence of a legitimate business need, and searching for less discriminatory alternative models.
- We applied a specific technical methodology for identifying alternative models.²⁴ Other technical methodologies for identifying less discriminatory alternative models exist. We recommended that Upstart apply the technical methodology for searching for alternatives we used or a different methodology Upstart develops, so long as we and Upstart agreed that the different methodology is comparable or more effective in its ability to identify less discriminatory alternatives.
- Regardless of the technical methodology used to search for alternatives, we recommended application of the Alternative Model Constraints described above, including that Upstart adopt alternative models that improve any identified statistically

²³ Given this posture, we did not assess whether the potential alternative we identified would have introduced meaningful new adverse differential validity, although we did confirm the potential alternative would have satisfied the other Alternative Model Constraints.

²⁴ Monitor's Third Report, *supra* note 2, at 9-10 nn.18-19 and accompanying text.

and practically significant disparities as long as the Alternative Model’s performance falls within the Uncertainty Interval of the Baseline Model.

- Finally, we recommended that, during the course of this Monitorship, Upstart report to the Monitor the results of its application of these methodologies and constraints as it applies them.

We acknowledged that there may be compliance and operational obstacles to immediate adoption and recommended that Upstart implement these steps within a reasonable amount of time following issuance of the Third Report.

B. Upstart’s Changes to Its Fair Lending Protocols and the Parties’ Impasse

1. Upstart’s Enhancements to Its Fair Lending Testing Protocols

As noted, the Parties reached an impasse over the appropriate standard for determining whether a less discriminatory alternative would be viable in terms of meeting Upstart’s legitimate business needs. That said, over the course of the Monitorship, Upstart made several enhancements to its Model and fair lending testing protocols, which are described below.

a. *Changes Made at the Outset of the Monitorship*

Prior to the Monitorship, before any testing began, Upstart made certain changes to how its underwriting model utilized educational data. Most notably, Upstart abolished the use of average incoming SAT and ACT scores to group education institutions in its underwriting model. While Upstart’s Model continues to incorporate information about the educational institution attended, it switched to grouping schools based on average post-graduation income.²⁵

Upstart also established a “normalization” process for “Minority Serving Institutions” (“MSIs”)—which Upstart defines as schools where 80 percent or more of the student body are members of the same racial demographic group.²⁶ Under that process, Upstart normalized MSIs as a group to have equal graduate incomes as non-MSIs by calculating and using the distance, as a percentage, between a school’s graduate incomes and its respective school group average (*i.e.*, MSIs, non-MSIs). This process results in MSIs and non-MSIs being on average equal. Put another way, above average MSIs (in terms of graduate income) are treated above average overall by as much as they are above the MSI average. Any decisioning, including tranching, is then performed on this normalized information.

b. *Changes Made to Proxy Testing Protocols*

During the course of the Monitorship, Upstart implemented a Proxy Identification Methodology modeled on the Monitor’s approach to assessing proxy risks described in the

²⁵ Upstart presentation to SBPC and LDF, August 12, 2020 (on file with Monitor).

²⁶ Upstart’s definition is not the same as federal definitions of “minority-serving institution.” See Monitor’s Initial Report, *supra* note 2, at 24 n.103.

Second Report.²⁷ This Methodology is designed to identify whether individual variables may have a high likelihood of functioning as close proxies for protected class status. After we shared our results related to age-proxy risks, Upstart also formalized an Age Proxy Policy reflecting what it represented was an existing practice. That Policy requires truncation of certain time-related variables that might otherwise raise a risk of functioning as close proxies for whether an applicant is elderly (*i.e.*, ≥ 62 years old).²⁸ And Upstart adopted the Monitor’s recommendation to strengthen that policy by further truncating certain non-traditional variables.²⁹

c. Changes Made to Disparate Impact Testing Protocols

Upstart also adopted many of the Monitor’s recommendations related to its disparate impact testing protocols:

1. Upstart enhanced how it conducts disparate impact testing prior to every model update.
2. Upstart implemented the Monitor’s recommended methodologies for identifying whether statistically and practically significant disparities exist for protected classes.
 - a. As part of this implementation, Upstart adopted the Monitor’s suggested “practical significance” threshold of less than 0.90 when measuring disparities using the adverse impact ratio (“AIR”). In other words, approval/denial disparities are considered “practically significant” and warrant a search for less discriminatory alternatives if AIR for any tested protected class group is less than 0.90.³⁰
3. Upstart made enhancements to its search procedures for less discriminatory alternative models whenever disparities are statistically and practically significant.
 - a. Upstart separately conducts a test to measure whether a model is over-predicting default risk for a protected group relative to its corresponding control group, which is separate from the disparate impact tests conducted and recommended by the Monitor. Upstart searches for less discriminatory alternatives if statistically and practically significant disparities are identified, even if acceptable model accuracy exists across groups.
4. Putting aside the significant impasse over the Monitor’s recommended approach for assessing whether an alternative model’s performance is meaningfully worse than the performance of the Baseline Model (discussed below), Upstart implemented the other Alternative Model Constraints discussed above.³¹

²⁷ See Monitor’s Second Report, *supra* note 2, at 24-29.

²⁸ See Monitor’s Third Report, *supra* note 2, at 31-32.

²⁹ See *id.*, *supra* note 2, at 31, 36.

³⁰ See *id.*, *supra* note 2, at 8. An AIR less than 90% can be roughly thought of as a more conservative version of the “four-fifths” or 80% rule of thumb developed by the Equal Employment Opportunity Commission—in other words, disparities will be considered significant more often using a 90% threshold. For a discussion of why a more conservative version is appropriate in this context, see Monitor’s Second Report, *supra* note 2, at 15.

³¹ See *supra* Section A.2.c.

Finally, Upstart represents that it has implemented updated technological methodologies to improve its searches for viable less discriminatory alternative models in certain scenarios. The technical approach we used in the Monitorship to search for less discriminatory alternatives was based on Hyperparameter Tuning and exploring variable combinations using mathematical optimization search techniques to identify combinations that yield reductions in disparate impact.³² Our Third Report, however, made clear that other technical methodologies exist for identifying less discriminatory alternative models, and we recommended that Upstart adopt either the methodology used in the Monitorship or a different methodology that is comparable or more effective.³³ Upstart represents that it has conducted internal research and deployed a methodology based on adversarial debiasing that Upstart suggests would be computationally efficient and effective at optimizing for reducing disparities.³⁴

Upstart presented a summary of its findings related to this new technology, but in light of the impasse and the end of the Monitorship, the Monitor did not validate the details of Upstart's suggested techniques. Regardless, we do note that Upstart plans to integrate this improved methodology to mitigate identified disparate impact only if AIR is less than 0.80 (rather than if AIR is less than our recommended 0.90 threshold); Upstart explains that this decision is based on its operational costs.³⁵ In scenarios where AIR is between 0.80 and 0.90 and the model is not over-predicting default risk for a protected class group relative to its control group, Upstart will continue to use a more traditional method to search for less discriminatory alternative models.

To the extent Upstart finds its updated techniques for searching for less discriminatory alternative models to be effective, we recommend that Upstart incorporate them in any case where practically significant disparate impact is identified (*i.e.*, in any case where AIR is < 0.90).

2. Impasse Over Standard for Assessing Whether a Less Discriminatory Model Would Reasonably Meet Upstart's Legitimate Business Needs

As noted, Upstart disagrees with and has declined to adopt the Monitor's recommended approach for assessing whether a less discriminatory alternative model would be considered comparable to a Baseline model in terms of reasonably meeting Upstart's legitimate business needs.

Upstart presented counterarguments to support its position that the approach is not technically or statistically sound and that adoption would unacceptably compromise the accuracy of its models. Those arguments are addressed in the Third Report, and neither the Monitor nor

³² See Monitor's Second Report, *supra* note 2, at 18-20.

³³ See Monitor's Third Report, *supra* note 2, at 30.

³⁴ Adversarial debiasing is a technique in which a separate model is used to analyze disparities in a baseline model and provide feedback to decrease those disparities while still maintaining model performance. See FinRegLab, "Explainability & Fairness in Machine Learning for Credit Underwriting" at 5, 7 (July 2023), https://finreglab.org/wp-content/uploads/2023/07/FRL_ML-FindingsOverview_Final.pdf.

³⁵ Upstart would also use this technology in another situation: Where practically significant disparate impact exists *and* the model is over-predicting default risk for a protected group relative to its corresponding control group, then Upstart would use this technology to identify models that mitigate the overprediction error. We agree that if these circumstances exist it would represent a serious fair lending risk that must be mitigated. We note, though, that mitigating a default overprediction error is separate from mitigating a disparate impact risk.

Upstart have persuaded the other regarding their respective positions. In short, Upstart argues that it considers inherent uncertainty in model performance metrics but differs from our methodology in the comparison it makes when determining the viability of an alternative model. Upstart measures the difference in accuracy between the baseline and alternative models directly, along with associated uncertainty in this difference; whereas the Monitor measures the uncertainty of performance of the Baseline Model and then assesses if the alternative model's estimated performance is within the Uncertainty Interval of the Baseline Model. That measurement is intended to address whether the magnitude of a difference is likely to matter in real-world performance. In other words, even if there is a statistically significant difference in Upstart's accuracy measure, that difference might be so small as to not be meaningful in a real-world sense. In our view, certain tests we conducted supported that position.³⁶ We also separately conducted analyses to estimate the expected change in business metrics and consumer impact from adopting an alternative model assuming that there was *no* uncertainty in how the models would behave and had mixed observations.³⁷

Despite these technical disagreements, we do agree that a court could take a different analytical approach. It could, for example, hold that an alternative model need not be adopted unless the accuracy measure of the proposed alternative is equal to the accuracy of Upstart's Baseline Model in a statistically significant manner. Our methodology, however, is designed to account for what we perceive to be a likelihood of a court concluding that a model need not meet that test to be viable under ECOA or the FHA because an alternative within the range we propose above has a reasonable probability of performing as well as the Baseline Model.

We also do not rule out the possibility that a regulatory agency or court might conclude that a different less discriminatory alternative, including one with greater performance metric deterioration, would be required in some circumstances. In our experience some financial institutions, as a matter of internal compliance, would consider alternative models to be viable despite what are likely larger potential drops in model performance metrics than what we recommended.³⁸ For example, an institution may not be able to argue plausibly that a drop in performance is unacceptable if evidence suggests the entity does not consider equivalent drops meaningful in other circumstances, such as model validation or performance monitoring. The acceptability of performance differences may vary across institution types and business models.

This is a difficult but extremely important issue in fair lending testing. When less discriminatory alternative models are identified, they often perform worse on whatever performance metric(s) are used to assess the baseline model because the baseline model is optimized specifically on that metric(s). Although a growing body of research exists questioning

³⁶ See the Out of Time analysis described in Section B.3.f of the Monitor's Third Report and the default-risk Out of Sample analysis described in Section B.3.h. of the Monitor's Third Report, *supra* note 2.

³⁷ See Monitor's Third Report, *supra* note 2, at 23-29. Potential less discriminatory models would be expected to have direct positive economic impacts for Upstart but also direct effects on lender and investor partners, with corresponding potential indirect negative effects on Upstart. We also found that a potential less discriminatory alternative would be essentially indistinguishable from the Baseline Model with respect to only considering ability to predict likelihood of default (as opposed to predicting both default and prepayment risks).

³⁸ See *supra* note 22 and accompanying text.

whether a “fairness-accuracy tradeoff” is inevitable,³⁹ in our experience it is common. Because at least some drop in performance is often expected, the Third Report addresses at length the following question: assuming a less discriminatory alternative model does exhibit a drop in that performance metric(s), at what point should one have confidence that the drop is likely to matter in real-world performance, particularly considering inherent uncertainty in the metric(s)? In other words, even if there is a drop in the performance metric, what is the likelihood that the less discriminatory alternative model would still reasonably achieve the legitimate business need as well as the baseline model?

If an entity takes the strict approach that an alternative model is not viable unless its performance is equal to a baseline model, it is likely that entity would rarely if ever adopt less discriminatory models, even if doing so would have little or no real-world impact on the entity’s business interests. If a testing protocol is designed such that less discriminatory alternatives are rarely if ever adopted, then even an elaborate model testing protocol risks simply becoming window-dressing. While stricter than the Monitor’s recommendation, Upstart represents that its approach can lead to substantial improvement with respect to any disparities, though the Monitor has not verified these claims.

Although there is not a single “right” answer to this issue, adopting a reasonable approach is pivotal because it can be the difference between an effective protocol and one that privileges process over substance. Ultimately, Upstart declined to adopt the Monitor’s recommended approach and the Monitor and Parties could not agree on an alternative approach.

3. Upstart’s Special Purpose Credit Program Proposal

The Parties did discuss other approaches for serving traditionally underserved credit applicant populations. For instance, Upstart proposed that the Parties and the Monitor work together to design and implement a tailored “special purpose credit program” (“SPCP”).

SPCPs are programs explicitly permitted by ECOA and Regulation B, and are meant to extend credit to meet special social needs and benefit economically disadvantaged groups.⁴⁰ SPCPs may require that participants “share one or more common characteristics (for example, race, national origin, or sex),”⁴¹ and are generally designed to extend credit to a class of persons who probably would not otherwise receive such credit or would receive it on less favorable

³⁹ See, e.g., Muhammad Bilal Zafar, et al., “Fairness Constraints: Mechanisms for Fair Classification,” 54 Proc. Of Mach. Learning Rsch. 962 (2017), <https://proceedings.mlr.press/v54/zafar17a/zafar17a.pdf>; Christian Hass, “The Price of Fairness—A Framework to Explore Trade-Offs in Algorithmic Fairness,” Int’l Conf. on Info. Sys. 2019 Proc. 1, 3 (2019).

⁴⁰ 12 C.F.R. § 1002.8; see generally Stephen Hayes, “Special Purpose Credit Programs: How a Powerful Tool for Addressing Lending Disparities Fits Within the Antidiscrimination Law Ecosystem,” National Fair Housing Alliance (Nov. 2020), https://nationalfairhousing.org/wp-content/uploads/2020/11/NFHA_Relman_SPCP_Article.pdf.

⁴¹ 12 C.F.R. § 1002.8(b)(2).

terms.⁴² Many SPCPs exist in the market and regulators have issued a series of guidance documents and statements facilitating the development of SPCPs.⁴³

In brief, Upstart’s proposed SPCP would offer certain groups a lower rate than they would otherwise receive based on a new pricing strategy targeted at traditionally disadvantaged applicants (by using instantaneous census tract geocoding). Upstart’s individual lending partners would decide whether to participate in the proposed SPCP.

The Parties discussed this proposal but, without expressing a view on its merits, the Monitor, LDF, and SBPC ultimately concluded that they were not in a position to collaborate on or endorse Upstart’s proposed SPCP.

C. Contributions to Ongoing Dialogue About Fair Lending Testing Models

As noted above, the Parties agreed to the Monitorship in part because they believed that public reports would contribute to the ongoing dialogue about the importance of fair lending testing models in a way that is consistent with antidiscrimination laws and furthers equitable access to credit.

The Parties and the Monitor believe that the public reports have contributed to that ongoing dialogue in meaningful ways. There is a growing body of literature and research on algorithmic fairness, but very few public materials describe commonly-used fair lending methodologies in detail. Similarly, few if any include application of those methodologies to real-world credit models and data. This context and Upstart’s transparency and participation allowed for a concrete description of techniques, difficult methodological questions, and an exploration of the analytical and legal principles underlying decisions about those methodologies.

Due in part to their unique nature, the public reports have been cited in materials ranging from leading publications exploring the intersection of antidiscrimination and credit

⁴² *Id.* § 1002.8(a)(3)(ii).

⁴³ CFPB Advisory Opinion, Special Purpose Credit Programs, 86 Fed. Reg. 3762, 3765 (Jan. 15, 2021), https://s3.amazonaws.com/files.consumerfinance.gov/f/documents/cfpb_advisory-opinion_special-purpose-credit-program_2020-12.pdf; Office of the General Counsel, Department of Housing and Urban Development, “Guidance on the Fair Housing Act’s Treatment of Certain Special Purpose Credit Programs That Are Designed and Implemented in Compliance with the Equal Credit Opportunity Act and Regulation B” (Dec. 6, 2021), https://www.hud.gov/sites/dfiles/GC/documents/Special_Purpose_Credit_Program_OGC_guidance_12-6-2021.pdf; Office of Fair Housing and Equal Opportunity, Department of Housing and Urban Development, “FHEO’s Statement by HUD’s Office of Fair Housing and Equal Opportunity on Special Purpose Credit Programs as a Remedy for Disparities in Access to Homeownership” (Dec. 7, 2021), https://www.hud.gov/sites/dfiles/FHEO/documents/FHEO_Statement_on_Fair_Housing_and_Special_Purpose_Programs_FINAL.pdf; Tim Lambert, CFPB, “Using Special Purpose Credit Programs to serve unmet credit needs” (July 19, 2022), <https://www.consumerfinance.gov/about-us/blog/using-special-purpose-credit-programs-to-serve-unmet-credit-needs/>; “Interagency Statement on Special Purpose Credit Programs Under the Equal Credit Opportunity Act and Regulation B” (Feb. 22, 2022) (joint statement by CFPB, FRB, FDIC, OCC, NCUA, HUD, FHFA, and DOJ), https://files.consumerfinance.gov/f/documents/cfpb_spcp_interagency-statement_2022-02.pdf.

underwriting,⁴⁴ to federally-commissioned analyses,⁴⁵ to comment letters and testimony by civil and consumer rights advocacy organizations.⁴⁶ The Monitor is also aware of private companies that have relied on the reports as they enhance their own fair lending and fair housing compliance programs. The Parties and Monitor agree that the Monitorship and resulting reports have helped advance this goal.

D. Public Policy Recommendations

As articulated in our Initial Report, Upstart, LDF, SBPC, and the Monitor share the view that with the growing availability and use of sophisticated modeling techniques and alternative data, it is increasingly important that lenders take steps to ensure equitable access to responsible credit and avoid the unnecessary perpetuation of discrimination, segregation, and inequality. To that end, the Parties and the Monitor offer the following recommendations:

First, all lenders should routinely assess their credit models for discrimination risks.

Certain companies, including many financial services companies, have been testing models for discrimination for years and have systems in place guiding those assessments. Unfortunately, there is an uneven landscape with respect to how or whether institutions assess their models for discrimination, and the effectiveness of existing programs. The methodologies that institutions use to test their models for fair lending vary, but as a general matter the most effective systems are designed to align with regulatory expectations and traditional principles gleaned from antidiscrimination jurisprudence, as discussed in these public reports.

At a minimum, these model assessments should include both qualitative and quantitative reviews. As explained in our Second Report, many financial institutions conduct a qualitative variable review in which they remove variables that they consider to be high risk because the variables may be perceived to be close proxies for protected classes, they may raise reputational risk, or for other reasons. These reviews are important but insufficient; they must be paired with rigorous quantitative reviews to assess discrimination risks, including the risk of unlawful disparate impact. This testing should be done regularly, as models in production are monitored.

⁴⁴ See, e.g., FinRegLab, Explainability & Fairness in Machine Learning for Credit Underwriting (Dec. 2023), https://finreglab.org/wp-content/uploads/2023/12/FinRegLab_2023-12-07_Research-Report_Explainability-and-Fairness-in-Machine-Learning-for-Credit-Underwriting_Policy-Analysis.pdf.

⁴⁵ “Identifying Bias and Barriers, Promoting Equity: An Analysis of the USPAP Standards and Appraiser Qualifications Criteria,” Commissioned by the Appraisal Subcommittee of the FFIEC (Jan. 2022), https://nationalfairhousing.org/wp-content/uploads/2022/02/2022-01-28-NFHA-et-al_Analysis-of-Appraisal-Standards-and-Appraiser-Criteria_FINAL.pdf.

⁴⁶ National Consumer Law Center, “Request for Information and Comment on the Financial Institutions’ Use of Artificial Intelligence, Including Machine Learning” (July 1, 2021), https://www.nclc.org/wp-content/uploads/2022/08/comments_RFI_AI.pdf; Joint Civil Rights, Consumer, and Technology Organization Ltr. Re: Draft NIST Special Publication 1270 – A Proposal for Identifying and Managing Bias within Artificial Intelligence (Sept. 10, 2021), https://www.nist.gov/system/files/documents/2021/09/10/NFHA%20et%20al%20Comment%20on%20NIST%20Prposal%20re%20Bias%20in%20AI_FINAL_2021%2009%2010.pdf; Testimony of Emily Paul, et al., Upturn, on DC’s Stop Discrimination by Algorithms Act of 2021 (Oct. 6, 2022), <https://www.upturn.org/work/testimony-on-dcs-stop-discrimination-by-algorithms-act-of-2021/>.

As models become more complicated, quantitative testing techniques must also be sophisticated enough to remain effective.

Moreover, model testing should be one component of a robust fair lending compliance management program that addresses risks throughout the loan lifecycle, including marketing, acquisition, credit policy design, use of discretionary overrides or exceptions, servicing, default management, and the like. Marketing and application analyses are particularly important as lenders rely on acquisition strategies that assess not only interest in credit but also the likelihood of qualification, which can affect applicant pools and accordingly impact approval/denial disparity analyses.⁴⁷ In other words, if upstream marketing or acquisition strategies have screened out historically disadvantaged applicants, a lender should not take comfort solely because a fair lending assessment of its underwriting practices does not reveal disparities.

Second, regulatory agencies should take steps to ensure consistent fair lending model testing and provide guidance on appropriate methodologies.

Regulatory agencies need to play a stronger role in ensuring consistent robust fair lending testing is conducted, including of AI/ML models. First, agencies with supervisory authority like the CFPB, the Office of the Comptroller of the Currency, the FDIC, the Board of Governors of the Federal Reserve System, and the National Credit Union Administration should routinely review financial institutions' model testing protocols and results in supervisory exams. These supervisory reviews should include non-depository institutions subject to the CFPB's authority, as well as the protocols used by third-party model developers and service providers.

Second, agencies should publicly describe the pros and cons of methodological approaches they have observed or that the agencies themselves use to test models for discrimination, including clarifying expectations regarding identifying, assessing, and adopting less discriminatory alternative models. Recently, the agencies have publicly, albeit informally, highlighted the importance of fair lending testing models, including implementing less discriminatory alternatives. For example, Patrice Ficklin, Associate Director of the CFPB's Office of Fair Lending and Equal Opportunity, stated that “[r]igorous searches for less discriminatory alternatives are a critical component of fair lending compliance management. . . . Testing and updating models regularly to reflect less discriminatory alternatives is critical to ensure that models are fair lending compliant.”⁴⁸

But more formal and detailed guidance is necessary. Even among financial institutions that conduct fair lending model testing, questions exist as to acceptable methodologies. This leaves some institutions dedicating resources towards compliance without a clear picture of regulatory expectations. The CFPB and similar agencies should announce in Supervisory

⁴⁷ See Jason Cover, “Digital Targeted Marketing, Business Regulation & Regulated Industries” (Feb. 9, 2022), <https://businesslawtoday.org/2022/02/digital-targeted-marketing-fair-lending-clickbait/>; Br. of Amici Curiae National Fair Housing Alliance, et al., *Consumer Financial Protection Bureau v. Townstone Financial, Inc.*, No. 23-1654, Doc. 20, at 25 (May 21, 2023).

⁴⁸ National Community Reinvestment Coalition, “CFPB Puts Lenders & FinTechs on Notice: Their Models Must Search for Less Discriminatory Alternatives or Face Fair Lending Non-Compliance Risk” (Apr. 5, 2023), <https://ncrc.org/cfpb-puts-lenders-fintechs-on-notice-their-models-must-search-for-less-discriminatory-alternatives-or-face-fair-lending-non-compliance-risk/>.

Highlights or other vehicles their observations on the approaches they have reviewed that are effective and the ones that are not or that otherwise carry risks. The agencies should also announce what methodologies they use or expect to see in supervision and enforcement so that entities can align their internal systems accordingly.⁴⁹ These expectations should include considerations relevant to assessing whether potential alternatives are in fact likely to reasonably achieve a legitimate business need. Agencies like the Federal Trade Commission and the Department of Housing and Urban Development that have broad authority over entities that have not historically been supervised should take similar steps based on their investigative and enforcement experiences to foster more widespread adoption of these techniques by entities beyond those that are directly supervised by the federal banking agencies.

Third, regulators, legislators, and other entities should take steps to enhance transparency in credit markets.

This Monitorship is unique insofar as Upstart took significant steps to make available data, modeling techniques, and other information, understanding that at least some resulting observations and findings would be made public. We suspect many other private companies would not have been willing to share similar information regarding their data and processes. As noted, the resulting public reports have contributed to ongoing public discussions about algorithmic discrimination, as well as enhancements to Upstart's fair lending protocols. The Parties and Monitor encourage other entities to undertake similar efforts to help create a more comprehensive picture of lending patterns and fair lending possibilities.

Agencies and legislators can facilitate these efforts. First, Upstart and the Monitor needed to design and implement cumbersome safeguards and testing methodologies to protect confidential information.⁵⁰ These safeguards meant that testing was significantly more labor and time intensive than similar testing is when conducted internally by a company or confidentially by a regulatory agency. Governmental entities can assist. Supervisory agencies have a direct line of sight into significant portions of the market and can provide more transparency around their observations and techniques, as discussed above. Moreover, government entities can help structure data transparency initiatives such as restricted access programs that would provide select industry and community researchers and academics with access to confidential or sensitive data in highly secure environments.⁵¹

Regulators and legislators should also explore broader ways to enhance transparency in credit markets. One significant step would be to create a data reporting and publication regime for all credit products, modeled after the existing Home Mortgage Disclosure Act and soon-to-

⁴⁹ The CFPB's public report describing its reliance on the Bayesian Improved Surname Geocoding (BISG) proxy methodology in its supervisory and enforcement work is a good example of this type of publication. *See* Consumer Financial Protection Bureau, "Using publicly available information to proxy for unidentified race and ethnicity: A methodology and assessment" (Summer 2014), https://files.consumerfinance.gov/f/201409_cfpb_report_proxy-methodology.pdf.

⁵⁰ *See* Monitor's Second Report, *supra* note 2, at 12.

⁵¹ The CFPB has considered but not adopted such a program as a method to provide greater access to Home Mortgage Disclosure Act data. *See* Final Policy Guidance, Disclosure of Loan-Level HMDA Data (Dec. 21, 2018), https://files.consumerfinance.gov/f/documents/HMDA_Disclosure_FPG_-_Final_12.21.2018_for_website_with_date.pdf.

be-effective Dodd-Frank Section 1071 regimes, which provide publicly available loan level data reflecting consumer self-identified demographic information for the mortgage and small business credit markets respectively. Similar regimes covering personal loans, auto loans, credit cards, and student loans would go a long way toward spurring more uniform, robust fair lending compliance efforts in those markets. The Parties acknowledge that this would be a long-term project, but a worthwhile one given the importance of improving fairness in these significant markets.

Conclusion

Pursuant to the Parties' agreement, the Monitorship concludes with the issuance of this Report.