December 1, 2020
Via Electronic Submission to: www.regulations.gov

Kathleen L. Kraninger, Director
Pavy Bacon, Senior Counsel
Bureau of Consumer Financial Protection
1700 G St., N.W.
Washington, DC 20552

Re: Request for Information: Equal Credit Opportunity Act and Regulation B [Docket No. CFPB-2020-0026] (Question 9: AI/Machine Learning)

Dear Director Kraninger:

The UC Berkeley Center for Consumer Law & Economic Justice and the East Bay Community Law Center submit these comments on the Request for Information with gratitude to the Consumer Financial Protection Bureau for taking on such an urgent task. The Equal Credit Opportunity Act is a critically important tool to protect consumers from discrimination, and technological advances have created new opportunities — and new problems. Our organizations work with and on behalf of low-income consumers who have faced discrimination and other issues related to lending. We are increasingly concerned about the use of Artificial Intelligence and Machine Learning (AI/ML) systems (Question 9) to determine the creditworthiness of our community members, especially since these systems lack crucial transparency and have the ability to create disparate impacts disadvantaging the communities that we serve.

The Center for Consumer Law and Economic Justice is a research center at UC Berkeley Law School. The Center works to enhance the study and practice of consumer law by delivering research and analysis to fuel meaningful policy change at the state and federal levels.

The Center strives to create a society where economic security and opportunity are available to all.

The East Bay Community Law Center, which is affiliated with UC Berkeley Law School, is one of the largest legal service providers for low-income individuals in the San Francisco Bay Area. The Consumer Justice Clinic at EBCLC runs clinics in Oakland and Berkeley, and assists clients with matters involving loans from both traditional and fintech lenders, debt collection matters, and credit reporting.

I. Any Changes to Regulation B Must Be in Furtherance of the Fundamental Purpose of ECOA.

The purpose of the Equal Credit Opportunity Act is to ensure that all Americans are free from discrimination in all of their financial dealings. Any changes to Regulation B must be made with that purpose in mind.

ECOA reaches broadly, prohibiting discrimination on the basis of race, color, religion, national origin, sex, marital status, age, receipt of public assistance, or good faith exercise of any rights under the Consumer Credit Protection Act.[1] The Act also requires creditors to provide applicants, upon request, with the reasons underlying decisions to deny credit — i.e., adverse action notices.[2]

Crucially, ECOA prohibits practices that have a disparate impact on members of protected classes. That is, the law bars practices that are neutral on their face, but treat protected classes more harshly than other consumers. For example, a lending policy that denies applications for individuals

[1] 15 U.S.C. §§ 1691-1691f.
[2] *Id.*

whose home value is less than $60,000 may create an illegal disparate impact because BIPOC loan applicants are more likely to live in neighborhoods with lower home values.[3]

With the ever-increasing prevalence of Artificial Intelligence and Machine Learning (AI/ML) systems in the realm of consumer finance, the Bureau must ensure these systems do not discriminate against protected classes of consumers under ECOA. While fintech lending has the potential to expand affordable credit options to those with low or no credit under traditional systems, it also has the potential to discriminate against protected borrowers. Even when protected categories such as race and sex are excluded from the algorithm's calculations, other categories can unintentionally become proxies for protected classes. As such, the Bureau must take steps to help fintech lenders reduce and remedy discrimination in their lending practices to align with ECOA.

II. The Benefits and Challenges of Using AI/ML to Determine Creditworthiness.

The CFPB can harness the benefits of AI/ML while mitigating potential discriminatory impacts through effective regulatory oversight. When used properly, Big Data can help to greatly expand credit opportunities to the over 64 million Americans who are unbanked or underbanked.[4] Low-income consumers often face a vicious cycle of having limited credit history, which in turn makes it difficult — if not impossible — to access affordable credit options.[5] These borrowers are then often left only with high-cost options, such as payday loans, or no financial products at all. Fintech lenders who use more data beyond the traditional factors have more information to assess someone's creditworthiness; as a result, they have lower rejection rates than traditional lenders.[6]

---

[3] Bartlett, Morse, Stanton, & Wallace, *Consumer-Lending Discrimination in the FinTech Era*, 5 (Nov. 2019), http://faculty.haas.berkeley.edu/morse/research/papers/discrim.pdf.

[4] National Consumer Law Center (NCLC), *Big Data: A Big Disappointment for Scoring Consumer Credit Risk*, 3 (2014).

[5] *Id*. at 8.

[6] Bartlett, *supra* note 3 at 23-24.

However, without proper regulatory oversight, these algorithms pose a serious risk of discrimination against the very groups these systems are trying to help. From inaccurate data inputs, to flawed processing systems, to nontransparent outputs, AI/ML systems face risks of error at every stage. The Bureau must provide much-needed guardrails as these algorithms become increasingly prevalent.

A. Fintech Lenders Can Expand Credit Opportunities for Traditionally Underserved Borrowers.

By using a larger number of variables and data points to assess an individual's creditworthiness, lenders using Big Data models can expand credit access to underserved borrowers. For example, Big Data models can generate a credit score using alternative, non-traditional data points about a person like their internet searches, purchase history, and social media. Increased access to affordable credit could be highly beneficial for groups historically overlooked by traditional financial institutions, especially marginalized groups and other protected classes of borrowers under ECOA. A study comparing the discriminatory impacts of fintech lenders to traditional lenders in the mortgage market found that the former has only a 1% chance of denial, which is a "significantly lower" incidence of discriminatory credit scoring than the latter's 5-6% chance of denial.[7] Additionally, a study published by the Federal Deposit Insurance Corporation found that the use of a "digital footprint" model for borrowers in emerging economies without credit scores predicted default with the same accuracy as traditional credit bureau scores.[8] The study also concluded that lenders that complement traditional scores with a user's "digital footprint" can make "superior lending decisions" to those that only use one or the other, suggesting that non-traditional data about borrowers can boost access to credit because the rejection

[7] *Ibid*.
[8] FDIC, *On the Rise of the FinTechs—Credit Scoring using Digital Footprints*, 27 (2018), https://www.fdic.gov/bank/analytical/cfr/2018/wp2018/cfr-wp2018-04.pdf.

rates are lower.[9] Credit reports with an increased number of variables and data points may make lenders more comfortable lending to borrowers with "thin credit files."[10]

B. Fintech Lenders Use Non-Traditional Data Points That Can Create Discriminatory Outcomes.

Despite their potential benefits, AL/ML algorithms have a significant downside: they can also discriminate against borrowers. Use of an increased number of variables to determine creditworthiness does not automatically lead to more accurate evaluations. More information — whether from social media, internet searches, or purchase histories — is not necessarily better. Not every one of these new variables is guaranteed to be meaningful; sometimes the data is just noise, rather than providing a meaningful signal.[11]

From the inception of ML algorithms' use in lender decision-making, cases of discrimination have been well documented. In 2019, Apple's credit card algorithm was revealed to have provided smaller lines of credit to women than to men.[12] The algorithm explicitly excluded gender as a variable in calculating an individual's available credit; nevertheless, the factors that the algorithm did consider collectively recreated a biased effect.[13] A study conducted by the UC Berkeley Haas School of Business and Berkeley Law School found that fintech mortgage lenders charged accepted, otherwise-equivalent "Latinx and African-American borrowers 7.9 and 3.6 basis points more in interest for home-purchase and refinance mortgages, respectively, because of discrimination."[14]

Using nontraditional, never-before-used data points to evaluate creditworthiness creates new possibilities for discrimination. Data regarding a person's annual income, net worth, regional cost of

---

[9] *Id.*, 27-28.
[10] NCLC, *supra* note 4 at 12.
[11] Nate Silver, *The Signal and the Noise*, 13 (2012).
[12] Will Knight, *The Apple Card Didn't 'See' Gender—and That's the Problem*, Wired (Nov. 19, 2019, 9:15 AM) https://www.wired.com/story/the-apple-card-didnt-see-genderand-thats-the-problem/.
[13] *Ibid.*
[14] Bartlett, *supra* note 3 at 5.

living, or education can serve as a proxy for protected classes such as race or receipt of public assistance. When algorithms train themselves to factor in these proxy categories, they disproportionately reject minority applicants – in violation of ECOA.

Fintech lenders are increasingly using nontraditional and potentially discriminatory data. Lenddo analyzes creditworthiness through "social data," i.e. reputation and social standing.[15] It considers a user's number of social media followers, background of peers, education and employers, and repayment history of friends. Neo Finance, Inc. reviews a user's LinkedIn profile to determine job stability, duration of employment, as well as the number, quality, geography, and seniority of one's connections.[16] Affirm, Inc. uses Facebook or Gmail login information to access publicly available data such as social networks, locations, and personal connections to create a credit score.[17]

Given the nature of ML, lenders often do not know how their algorithms are generating their outcomes, which makes it all the more important that fintech lenders have high standards of transparency in their systems. ML algorithms take large inputs of data and "learn" to identify patterns and predict future outcomes, like an individual's likelihood of paying back a loan. However, the actual steps that it takes to identify and weigh variables are unclear. The ability to observe the ML algorithms' outputs but not their internal workings has led to widespread characterization of algorithms as a "black box."[18] Accurate or not, the metaphor underscores the urgent need for transparency and disclosure in ML-driven credit determinations.[19]

---

[15] Lenddo, http://www.lenddo.com (last visited Nov. 18, 2020).
[16] Evelyn M. Rusli, *Bad Credit? Start Tweeting*, Wall Street Journal (April 1, 2013), https://www.wsj.com/articles/SB10001424127887324883604578396852612756398.
[17] *Id*.
[18] Dallas Card, *The "Black Box" Metaphor in Machine Learning*, Towards Data Science, (July 5, 2017), https://towardsdatascience.com/the-black-box-metaphor-in-machine-learning-4e57a3a1d2b0
[19] Rusli, *supra* note 16.

C. Algorithm-Based Credit Evaluations Lead to Insufficient Adverse Action Notices.

Lenders already fall short of providing clear, understandable adverse action notices to credit applicants when they are denied credit — a problem that worsens when lending decisions are made by "black-box" ML algorithms. Existing regulation allows lenders who use AI/ML algorithms "flexibility" in their adverse action notices by not requiring them to state how or why a factor influenced a credit rejection, or how the factor relates to creditworthiness.[20] The experiences of EBCLC's clients emphasize the critical need for rules that increase transparency about application denials, in particular by fintech lenders. As both ECOA and the Fair Credit Reporting Act[21] emphasize, applicants have a right to know specifically why they were denied credit.

<u>Client Stories</u>

<u>Mr. S.'s Story</u>

> Mr. S., a college-educated African American man, applied for a personal loan from Bank of America and Avant, a Chicago-based fintech lender. Avant is a leader in the application of ML with nontraditional data to determine creditworthiness of borrowers. Mr. S. received an adverse action notice from Bank of America that cited an erroneous tradeline in his Experian report – an error that Mr. S. was disputing and litigating. However, the notice he received from Avant gave no specific reason for his denial.

<u>Ms. P.'s Story</u>

> Ms. P., an African American homeowner, was denied credit by San Francisco based lender LendingClub. The communications she received from LendingClub did not make clear what the reason for the denial was. Ms. P. is left to speculate – and in the meantime cannot access the credit she needs.

Mr. S. and Ms. P. are among EBCLC's many clients who have received vague adverse action notices after being denied credit. Many are Black or Latinx. With no knowledge of what personal data led to their being denied, Mr. S. and Ms. P. were unable to seek a remedy, resulting in significant financial losses and losses of opportunity. Even when EBCLC's clients do receive adverse action

---

[20] 12 CFR 1002.9, comment 9(b)(2)-3, 4.
[21] See 15 U.S.C. §1681m.

notices, they often do not seek legal help, believing that they have no control over the denial and no awareness of avenues for possible legal redress.

Research on Big Data collection companies corroborates EBCLC's clients' experiences. In a report to the FTC, researchers attempted to retrieve consumer information files about themselves from the top Big Data collection companies.[22] They found the results were consistently nontransparent, incomplete, and inaccurate.[23] The amount of information given to them vastly underreported the total data that the brokers had on them.[24] This lack of transparency is more than just frustrating to consumers — it deprives them of effective redress and access to credit. Inconclusive adverse action notices illuminate the concerning "black-box" effect of AI/ML algorithms.

III. The Bureau Should Hold Fintech Lenders Accountable for Providing Transparent and Understandable Adverse Action Notices.

The Bureau should take significant measures to increase the transparency and accountability of financial algorithms, in particular with respect to adverse action notices. Under ECOA, creditors must supply an adverse action notice (either written or verbal) to applicants that states the specific reasons why adverse action was taken.[25] At present, credit denials based on AI/ML algorithms provide minimal useful information to consumers and thus do not meet the ECOA standard for adverse action notices. Fintech companies are generating adverse action notices that fail to explicitly provide reasons why applicants were denied access to credit. The Bureau should require fintech lenders to generate more robust, transparent, and understandable adverse action notices, which will help to reveal what's going on inside the "black box" and decrease risk of unlawful discrimination.

---

[22] NCLC, *supra* note 4 at 15.
[23] *Id.* at 18.
[24] *Id*. at 17.
[25] 15 U.S.C. § 1691(d).

The Bureau needs to act to ensure that consumers know exactly why they have been denied credit. The ECOA and FCRA demand no less. Currently, when an adverse action has been taken because of an AI/ML algorithm, it is frequently unclear to consumers where the information is coming from or how that determination has been made. The common theme among the numerous comments already submitted on this question is an emphasis on stronger regulation.[26] That increased level of regulation should encompass at least three principles: (1) increasing the transparency of adverse action notices; (2) using anti-bias modeling; and (3) allowing manual review and third-party audits.

A. Increase the Transparency of Adverse Action Notices.

While meaningful transparency should exist at all levels of the decision-making process, it is particularly vital for adverse action notices. Fortunately, there is a readily available model that the Bureau may adapt. The General Data Protection Regulation (GDPR) of the European Union provides explicitly for algorithmic transparency as a tool of preventing discrimination.[27]

Like the GDPR, Regulation B should require that firms specify which factors led to a denial of credit. Non-protected identity traits can still act as proxies for protected classes, causing disparate impact on potential borrowers. In general, the CFPB should require lenders to provide "meaningful information about the logic involved, as well as the significance and envisaged consequences" of automated decision making.[28] Specifically with respect to adverse action notices, firms should be compelled to identify which nontraditional data points were used in the decision-making process. The notice should be

---

[26] See Electronic Privacy Information Center, Comment Letter on Request for Information on the Equal Credit Opportunity Act and Regulation B (Aug. 3, 2020), https://beta.regulations.gov/comment/CFPB-2020-0026-0052; Divya Babbula, Comment Letter on Request for Information on the Equal Credit Opportunity Act and Regulation B (Aug. 3, 2020), https://beta.regulations.gov/comment/CFPB-2020-0026-0058; Robert Sweet, Comment Letter on Request for Information on the Equal Credit Opportunity Act and Regulation B (Aug. 3, 2020), https://beta.regulations.gov/comment/CFPB-2020-0026-0065.
[27] GDPR art. 13(2)(f); art. 14(2)(g).
[28] *Id.*

provided in a concise, transparent, and intelligible manner, so that it is accessible to less sophisticated applicants.

Such information is critical to empowering applicants, especially economically vulnerable applicants, to act upon receiving adverse action notices. Many of EBCLC's clients face situations of mistaken identity or fraud. If such data points are explicit in their notices, they can take the steps necessary to remedy possible detrimental impacts on their credit scores and access to affordable financial services.

B. Use Anti-Bias Modeling.

Anti-bias modeling within fintech algorithms can counteract the impact of nontraditional data serving as a proxy for discrimination in credit reporting, and could help ensure that adverse action notices contain relevant information. Anti-bias models are inputted into the existing algorithms and actively identify and counter results that may be biased. Anti-bias models can also identify meaningful data points, including those that are proxies for discrimination, to increase algorithmic transparency.

One example of a successful anti-bias model, Quantitative Input Influence (QII),[29] can already determine what input traits have the highest causal effect on the decision-making process. While traditional adverse action notices often fail to explain the reason for rejecting an applicant, QII modeling can increase that transparency and fill in the gaps.[30]

Lenders should be required to use QII or similar modeling, which would help enable lenders to identify meaningful data points to report to applicants and separate the signal from the noise. This information could then be communicated to credit applicants through adverse action notices. The improved adverse action notices can equip applicants with the information they need to investigate and

[29] White & Case, *Algorithms and Bias: What Lenders Need to Know*, 7 (2017). https://www.whitecase.com/publications/insight/algorithms-and-bias-what-lenders-need-know.
[30] Anupam Datta et. al., *Algorithmic Transparency via Quantitative Input Influence*, 2016 IEEE Symp. on Sec. and Priv. 598 (2016).

challenge their rejections. Without anti-bias modeling, the fintech lenders are at much higher risk of using discriminatory data points that violate ECOA.

C. Allow Consumers to Request Manual Review and Third Party Auditing of Adverse Action Notices.

The Bureau should strongly consider requiring firms to provide consumers who have been denied credit through the use of ML algorithms the right to request manual review of adverse determinations. To compensate for the high risk of statistical error and discriminatory outcomes that comes with using "black box" algorithms, lenders should be required to maintain teams, either in house or through a third-party auditor, dedicated to manual review. In addition, lenders should be required to undergo regular audits by third-party firms to certify that their algorithmic determinations are not resulting in disparate impact discrimination.

IV. Conclusion

Ultimately, the Bureau may need to reconsider its current framework for preventing discrimination in consumer lending to meet the challenges of AI/ML-powered decision making.[31] Relying on algorithms to make bias-free determinations will not work. Allowing firms to convey adverse action notices containing incomprehensible explanations of algorithmic determinations provides no benefit to consumers – and violates the express requirements of both ECOA and FCRA. Instead, transparency is vital. Adverse action notices must disclose in clear, understandable detail which factors were most significant in the decision-making process. Only then can the Bureau begin to break open the "black-box" of fintech and critically examine data points that may serve as proxies for discrimination in credit lending.

[31] Aaron D. Klein, *Fair-lending laws haven't caught up to AI*, American Banker (May 1, 2019), https://www.americanbanker.com/opinion/fair-lending-laws-havent-caught-up-to-ai.

With strong regulations in place, fintech lending may increase affordable credit options without violating critical anti-discrimination laws. Without such robust rules, fintech lending threatens to create an automated process of rampant discrimination against protected groups, and widen the gap between those consumers who can access affordable financial products and those who cannot.

We are grateful for your time and the opportunity to participate in this process.

Respectfully submitted,

Eliza Duggan
Jared Madnick
Angela Zhao
Ted Mermin
Center for Consumer Law & Economic Justice
UC Berkeley School of Law
ejduggan@law.berkeley.edu
(510) 393-8254

Kara Acevedo
East Bay Community Law Center
kacevedo@ebclc.org
(510) 548-4040