

AI and Machine Learning-Based Credit Underwriting and Adverse Action Under the ECOA

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ABSTRACT

In the rapidly evolving retail financial services market, new technologies, including artificial intelligence and machine learning, are challenging the premises of existing laws and revolutionizing the process of loan and credit underwriting. These technologies allow creditors to consider a wide range of alternative factors which are untapped by traditional credit scoring models, with research suggesting that they can allow companies to extend affordable credit to members of underserved communities who currently lack the credit history necessary to fully participate in the financial system. Using these tools, businesses can increase efficiency while potentially maintaining or lowering risk levels and delinquency rates.

Despite the potential benefits of these methods of credit decision making, they are difficult to fit neatly into the framework of existing fair lending laws like the Equal Credit Opportunity Act which, among other things, requires creditors to provide applicants with a statement of specific reasons for adverse action taken in connection with a credit application. These notices are intended to give consumers the information necessary to contest unfair credit decisions, dispute incorrect information in their credit report, and improve their creditworthiness for future transactions.

In a world in which credit decisions are based on a potentially vast and evolving set of factors, some of which have no intuitive relationship to creditworthiness, it is hard to see how these public policy goals can be achieved under existing frameworks. If they are forced to comply with existing law, creditors may be compelled to forego use of these new technologies, with limited countervailing benefits to consumers.

This Note seeks to resolve fundamental conflicts between existing law and these developing technologies. I advocate for a light regulatory touch to adverse action notices, with the goal of fostering innovative approaches to credit decision-making while remaining mindful of the consumer protection goals of the Equal Credit Opportunity Act. I will attempt to outline the basic principles of AI and machine learning-based credit scoring, how consumers and businesses alike stand to benefit from their implementation, how they fit (or do not fit) within the current legal regime, and a potential solution for this new frontier of credit decision

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INTRODUCTION

As innovations in technology are changing the way business is conducted in all sectors of the economy, financial services providers are exploring the ways in which emerging technologies and strategies can help to revolutionize their business practices. One example of this phenomenon is the increasing use of artificial intelligence (“AI”) and machine learning in loan and credit underwriting.¹

A recent World Trade Organization report defines artificial intelligence as “the ability of a digital computer or computer-controlled robot to perform tasks commonly associated with humans, such as the ability to reason, discover meaning, generalize or learn from past experience.”² While most artificial intelligence currently in use can perform basic tasks such as facial recognition or playing chess, AI researchers believe that in the long term such technologies will be able to outperform humans at most, if not all, cognitive tasks.³ Accordingly, AI has the potential to provide massive increases in efficiency in the provision of goods and services and thus revolutionize the way businesses operate.⁴

Machine learning, a subset of AI, “rel[ies] on computing power to

¹ See U.S. DEP’T OF TREASURY, NONBANK FINANCIALS, FINTECH, AND INNOVATION 12 (2018).

² WORLD TRADE ORGANIZATION, THE FUTURE OF WORLD TRADE: HOW DIGITAL TECHNOLOGIES ARE TRANSFORMING GLOBAL COMMERCE 6 (2018).

³ *Id.*

⁴ *Id.*

sift through big data to recognize patterns and make predictions without being explicitly programmed to do so."⁵ Over time, machine learning algorithms use previous experience to “self-evolve” and improve the manner in which they perform their assigned task.⁶ This technology⁷ is promising for banks, mortgage companies, and other businesses who engage in loan and credit underwriting because it can efficiently consider alternative data that is untapped by current lending and credit scoring models.⁸ Through this process, companies can “improve nationwide access to financial opportunity by making more consumers ‘scorable’ within the mainstream financial system,” acquiring new customers in the process while theoretically maintaining or lowering risk levels and delinquency rates.⁹

While these technologies have the potential to greatly benefit businesses and consumers, as with many innovative technologies the existing legal and regulatory regime is ill-equipped to deal with the upheaval of new ways of doing business. Governments and regulators face the difficult balancing act of weighing the potential benefits of innovation against “the risks to consumers, investors and the broader financial systems”¹⁰ posed by these new technologies. When faced with such a choice, the role of the government should be to promote socially beneficial innovation while placing limited, reasonable constraints on businesses in order to protect consumers and the broader financial system.

In view of this dynamic, it is readily apparent that the drafters of existing statutes which promote fair lending and seek to prevent unlawful discrimination in credit decisions, such as the Equal Credit Opportunity Act (“ECOA”),¹¹ did not anticipate a world in which the factors used to make credit decisions are theoretically limitless and ever evolving.

Scholarly discussion regarding the ECOA and AI-based credit decision making has largely focused on assessing the effect of AI on the Act’s substantive discrimination rules. The ECOA states that “a creditor shall not discriminate against an applicant on a prohibited basis regarding any aspect of a credit transaction.”¹² Prohibited basis is defined to include:

- (a) race, color, religion, national origin, sex, marital status, or age (provided that the applicant has the capacity to enter into a binding contract); (b) the fact that all or part of the

⁵ *Id.* at 30.

⁶ *Id.*

⁷ In general, this Note uses the terms “artificial intelligence” and “AI” to subsume machine learning.

⁸ See U.S. DEP’T OF TREASURY, *supra* note 1, at 12.

⁹ ROBINSON & YU, KNOWING THE SCORE: NEW DATA, UNDERWRITING, AND MARKETING IN THE CONSUMER CREDIT MARKETPLACE A GUIDE FOR FINANCIAL INCLUSION STAKEHOLDERS 21 (2014).

¹⁰ Lev Bromberg, Andrew Godwin & Ian Ramsay, *Cross-Border Cooperation in Financial Regulation: Crossing the Fintech Bridge*, 13 CAP. MKTS. L.J. 59, 59 (2018).

¹¹ 15 U.S.C. § 1691–1691f.

¹² 12 C.F.R. § 1002.4(a).

applicant's income derives from any public assistance program; or (c) the fact that the applicant has in good faith exercised any right under the Consumer Credit Protection Act or any state law upon which an exemption has been granted by the Consumer Financial Protection Bureau (“CFPB”).¹³

Under the ECOA, Plaintiffs can bring discrimination claims based either on an intentional discrimination theory, or a disparate impact theory, where a facially neutral policy “has the *effect* but not the *intent* of discriminating against” a protected class.¹⁴ Disparate impact may occur in a credit scoring system under the ECOA when:

(1) a variable used in the credit scoring system is facially neutral; (2) that variable is applied evenly, without regard to any prohibited basis; (3) that variable disproportionately adversely affects a segment of the population that shares a common characteristic that may not be considered legally; and (4) that variable cannot be justified by business necessity, or the business necessity can be achieved by substituting a comparably predictive variable that will allow the credit scoring system to continue to be validated, but also operate with a less discriminatory result.¹⁵

While it seems unlikely that companies will explicitly direct their models to discriminate based on any of the aforementioned categories, these tools “risk creating a system of ‘creditworthiness by association’ in which consumers’ familial, religious, social, and other affiliations determine their eligibility for an affordable loan.”¹⁶ As some have noted, various factors considered by automated credit scoring may at first glance appear objective but may actually reflect systematic bias.¹⁷ “Algorithms may place a low score on occupations like migratory work or low-paying service jobs. This correlation may have no discriminatory intent, but if a majority of those workers are racial minorities, such variables can unfairly impact consumers’ loan application outcomes.”¹⁸ There is also the risk of disparate impact

¹³ 12 C.F.R. § 1002.2(z).

¹⁴ Joseph A. Seiner, *Disentangling Disparate Impact and Disparate Treatment: Adapting the Canadian Approach*, 25 YALE L. & POL’Y R. 95, 96 (2006).

¹⁵ OFFICE OF THE COMPTROLLER OF THE CURRENCY, OCC BULL. NO. 97-24, CREDIT SCORING MODELS: EXAMINATION GUIDANCE app. at 11 (1997).

¹⁶ Mikella Hurley & Julius Adebayo, *Credit Scoring in the Era of Big Data*, 18 YALE J.L. & TECH. 148, 149 (2018).

¹⁷ *Id.*

¹⁸ Danielle Citron & Frank A. Pasquale, *The Scored Society: Due Process for Automated Predictions*, 89 WASH. L. REV. 1, 14 (2014) (citing Kenneth G. Gunter, *Computerized Scoring’s Effect on the Lending Industry*, 4 N.C. BANKING INST. 443, 445, 451–52 (2000)).

resulting from the subconscious bias of the programmers who develop these algorithms. These problems are exacerbated by the fact that companies currently treat their algorithms as "closely-guarded trade secrets, making it impossible to offer a comprehensive picture of the industry."¹⁹

However, while AI-based credit underwriting may conflict in some ways with the ECOA's anti-discrimination goals, it is fundamentally irreconcilable with ECOA adverse action notice requirements. The ECOA requires that creditors provide notice to applicants regarding adverse actions taken in connection with credit applications and either the specific reasons for such adverse action or the applicant's right to request a statement of specific reasons.²⁰ Adverse action includes:

- (a) a refusal to grant credit in substantially the amount or on substantially the terms requested in an application unless the creditor makes a counteroffer (to grant credit in a different amount or on other terms) and the applicant uses or expressly accepts the credit offered; (b) the termination of an account or an unfavorable change in the terms of an account that does not affect all or substantially all of a class of the creditor's accounts; and (c) a refusal to increase the amount of credit available to an applicant who has made an application for an increase.²¹

Adverse action notices are intended to give consumers the information necessary to (1) contest unfair credit decisions; (2) correct inaccurate information in their credit report; and (3) understand how to improve their credit for future transactions.²²

While disclosure under traditional models, which consider basic factors such as income, employment history, and credit card payment history is simple, disclosure under so called "alternative" and AI driven models which consider a much wider range of factors pose complicated problems for businesses, consumers, and regulators alike.²³ AI underwriting models may "integrate thousands of data points, most of which are collected without consumer knowledge."²⁴ As a result, "[c]onsumers have limited ability to identify and contest unfair credit decisions, and little chance to understand what steps they should take to improve their credit."²⁵

This dynamic is exacerbated by the fact that many of the factors considered by AI-based credit scoring models are complex and may appear unrelated to creditworthiness. No matter how much time and effort a creditor

¹⁹ Hurley & Adebayo, *supra* note 16, at 158.

²⁰ 12 C.F.R. § 1002.9.

²¹ 12 C.F.R. § 1002.2(c)(1)(i-iii).

²² See Sarah Ammermann, *Adverse Action Notice Requirements Under The ECOA And The FCRA*, 1 CONSUMER COMPLIANCE OUTLOOK 4 (2013).

²³ See ROBINSON & YU, *supra* note 9, at 2.

²⁴ Hurley & Adebayo, *supra* note 16, at 149.

²⁵ *Id.*

spends attempting to outline the specific reasons for an AI-based adverse action, the average consumer would likely find the operative set of reasons utterly incomprehensible. Accordingly, as discussed in greater detail below, the principles behind adverse action notices fundamentally conflict with these emerging methods of credit underwriting.

Because the ECOA is ill-equipped to deal with the rapidly growing and evolving use of these technologies in credit and lending decisions, some of the requirements of the existing legal framework should be relaxed or eliminated altogether, at least as it relates to AI and machine learning-based credit decisions. At the same time, regulators should place limited constraints on businesses utilizing these technologies to ensure transparency in the methods used in loan and credit underwriting and to ensure that the principles of fair lending and credit reporting promoted by the current law are not eroded.

I. BACKGROUND

Consumer Financial Protection Bureau (“CFPB”) regulations define a credit scoring system as

a system that evaluates an applicant's creditworthiness mechanically, based on key attributes of the applicant and aspects of the transaction, and that determines, alone or in conjunction with an evaluation of additional information about the applicant, whether an applicant is deemed creditworthy.²⁶

In essence, credit scoring systems enable companies to use statistical regression analysis to estimate the probability that a borrower will show some undesirable behavior in the future in relation to an extension of credit.²⁷ “In application scoring, for example, lenders employ predictive models, called scorecards, to estimate how likely an applicant is to default.”²⁸

Lenders use these scores, “as an important factor — often the only factor — in making lending decisions . . . includ[ing] whether to extend credit, the rates at which credit will be extended, and other terms of repayment.”²⁹ As the CFPB states, “[a] good credit score can mean access to a wide range of credit products at the better rates available in the market, while a bad credit score can lead to greatly reduced access to credit and much

²⁶ 12 C.F.R. § 1002.2(p)(1).

²⁷ See Stefan Lessman, Bart Baesens, Hsin-Vonn Seow & Lyn C. Thomas, *Benchmarking State-of-the-Art Classification Algorithms for Credit Scoring: An Update of Research*, 247 EUROPEAN J. OPERATIONAL RES. 124, 124 (2015).

²⁸ *Id.*

²⁹ ROBINSON & YU, *supra* note 9, at 8.

higher borrowing costs.”³⁰

People generally need credit and access to other financial services to buy homes, finance businesses, and send their children to college.³¹ Accordingly, a good credit score is “a prerequisite for full participation in the mainstream U.S. financial system.”³² Studies have shown that large numbers of Americans lack the credit score necessary to “fully participate” in the financial system. The CFPB estimated in a study published in May 2015 that about 26 million Americans (about 11 percent of the adult population) were “credit invisible”, meaning they lack credit records compiled by a nationwide credit reporting agency.³³ In addition, 19 million consumers (about 8.3 percent of the adult population) were unscorable by a commercially-available credit scoring model because they either had an insufficient credit history or lacked a recent history.³⁴

The report also suggests a considerable correlation between race and credit invisibility and unscorability. The study found that about 15 percent of African-Americans and Hispanic people are credit invisible as compared to 9 percent of Whites and Asians, while 13 percent of African-Americans and 12 percent of Hispanics have unscorable records as compared to 7 percent of Whites.³⁵ This is but one of many studies outlining the problems many Americans have in accessing affordable credit.

One possible solution to this problem is to simply expand the universe of data considered in credit scoring to bring some of these potential consumers into the orbit of commercial credit scoring models.³⁶ Businesses are increasingly developing and adopting models which consider alternative data, including utility payments and other regular payments like cell phone and internet bills, in determining creditworthiness.³⁷ Some are even developing models which consider “fringe alternative data” like rental payments, shopping activity, and social media habits, among others.³⁸ Models which consider these alternative factors could benefit all consumers, but specifically young people, the poor, and historically disadvantaged minorities, who are more likely to lack the traditional credit history necessary to acquire affordable loans and reasonably priced credit.³⁹

While many lenders have shown a willingness to use alternative credit data in their lending models, the predictive power of this alternative data is not widely known because studies of its effectiveness have rarely been

³⁰ CONSUMER FINANCIAL PROTECTION BUREAU, THE IMPACT OF DIFFERENCES BETWEEN CONSUMER- AND CREDITOR-PURCHASED CREDIT SCORES 1 (2011).

³¹ ROBINSON & YU, *supra* note 9, at 7.

³² *Id.*

³³ CONSUMER FINANCIAL PROTECTION BUREAU, DATA POINT: CREDIT INVISIBLES 6 (2015).

³⁴ *Id.*

³⁵ *Id.*

³⁶ ROBINSON & YU, *supra* note 9, at 11.

³⁷ *Id.* at 10.

³⁸ *Id.* at 13–15.

³⁹ CONSUMER FINANCIAL PROTECTION BUREAU, *supra* note 33, at 19–20.

made public.⁴⁰ To test the efficacy of their models, lenders first generate “alternative credit scores” for each consumer approved under the lender’s conventional underwriting methods as of the time of their original credit application.⁴¹ Then, lenders retroactively apply the alternative score produced by their model to approved consumers to determine whether it would have improved the lender’s ability to evaluate and manage risk.⁴² This methodology allows lenders to “determine how well the score that would have been assigned at the time of application correlates with actual [borrower] behavior.”⁴³

One such study conducted by LexisNexis demonstrates the potential benefit of alternative credit scoring for historically underserved groups. The study found that 41 percent of historically underserved minority groups are unscorable using traditional credit scores, as compared to just 24 percent of the general population.⁴⁴ When the researchers applied LexisNexis’ RiskView alternative credit scoring model, however, 81 percent of these groups became scorable and 43 percent of them had a RiskView score of 680 or higher.⁴⁵

Another study conducted by the Policy and Economic Research Council reviewed more than four million credit files and found that, “if both positive and negative utility and telecom payments were included, over 70 percent of the unscorable files would become scorable and 64 percent of the ‘thin files’ (files with very little other credit history) would see improved scores.”⁴⁶ In addition, the study found that the improvement especially benefited low-income borrowers.⁴⁷ The results of these and other studies

⁴⁰ Rachel Schneider & Arjan Schutte, *The Predictive Value of Alternative Credit Scores*, CENTER FOR FINANCIAL SERVICES INNOVATION 8 (Nov. 1, 2007), <https://cfsinnovation.org/research/the-predictive-value-of-alternative-credit-scores/>.

⁴¹ *Id.*

⁴² *Id.*

⁴³ *Id.*

⁴⁴ The study also concluded that “[d]epending on a lenders risk strategy, we see that between 6% and 23% of all applicants from underserved minority groups can be offered credit when alternative data is used as part of an underwriting strategy. Put differently as many as 1-in-4 of all minority applicants could transition from unscorable to scorable and can be eligible for reasonably priced credit.” Jeffrey Feinstein, *Alternative Data and Fair Lending*, LEXISNEXIS, at 4 (August 2013), <http://insights.lexisnexis.com/creditrisk/wp-content/uploads/2013/09/alternative-data-and-fair-lending-wp.pdf>.

⁴⁵ While the numerical credit score generated by a given model is meaningless without context, the researchers in the study used a score of 680 “as a threshold to indicate a customer that should be considered for a lower cost non-subprime credit product.” *Id.* at 6.

⁴⁶ EXEC. OFFICE OF THE PRESIDENT, BIG DATA: A REPORT ON ALGORITHMIC SYSTEMS, OPPORTUNITY, AND CIVIL RIGHTS 12 (2016) (citing Michael A. Turner, Patrick D. Walker, Sukanya Chaudhuri & Robin Varghese, *A New Pathway to Financial Inclusion: Alternative Data, Credit Building, and Responsible Lending in the Wake of the Great Recession*, POL’Y & ECON. RES. CTR. (June 2012), <http://www.perc.net/wp-content/uploads/2013/09/WEB-file-AD15-layout1.pdf>.)

⁴⁷ Michael A. Turner, Patrick D. Walker, Sukanya Chaudhuri & Robin Varghese, *A New Pathway to Financial Inclusion: Alternative Data, Credit Building, and Responsible*

show that the implementation of alternative credit models could help businesses accurately determine the creditworthiness of a much wider swath of consumers.

The highest levels of the federal government have explicitly recognized the value of these technologies and have begun to work with businesses to shepherd their responsible development. In February of 2017, the CFPB published a request for comment in the Federal Register seeking input on alternative data and modeling techniques which “are changing the way that some financial service providers conduct business.”⁴⁸ The request noted that, while “[t]hese changes hold the promise of potentially significant benefits for some consumers” they also “present certain potentially significant risks.”⁴⁹

The request, among other things, noted the complex and troublesome issues that these technologies raise with regard to ECOA adverse action notices.⁵⁰ As stated above, the ECOA requires, among other things, that creditors provide notice to applicants regarding adverse actions taken in connection with credit applications and either the specific reasons for such adverse action or the applicant’s right to request a statement of specific reasons.⁵¹ Adverse action includes (a) a refusal to grant credit in substantially the amount or on substantially the terms requested in an application; (b) the termination of an account or an unfavorable change in the terms of an account that does not affect all or substantially all of a class of the creditor’s accounts; and (c) a refusal to increase the amount of credit available to an applicant who has made an application for an increase.⁵²

Under the ECOA, a statement of reasons for adverse action, “must be specific and indicate the principal reason(s) for the adverse action. Statements that the adverse action was based on the creditor’s internal standards or policies or that the applicant, joint applicant, or similar party failed to achieve a qualifying score on the creditor’s credit scoring system are insufficient.”⁵³

As discussed above, the main purposes of the ECOA adverse action notice provisions are to give consumers a chance to contest inappropriate credit decisions, to rectify incorrect information in their credit report, and to give them the information necessary to improve their credit in the future. It is difficult to see how these policy goals can be accommodated in a world where the universe of factors pertinent to credit decisions is vast, self-evolving, and involves elements not traditionally correlated to

Lending in the Wake of the Great Recession, POL’Y & ECON. RES. CTR. (June 2012), <http://www.perc.net/wp-content/uploads/2013/09/WEB-file-ADI5-layout1.pdf>.

⁴⁸ Request for Information Regarding Use of Alternative Data and Modeling Techniques in the Credit Process, 82 Fed. Reg. 11,183, 11,183 (Feb. 21, 2017).

⁴⁹ *Id.*

⁵⁰ *Id.* at 11,187.

⁵¹ 12 C.F.R. § 1002.9.

⁵² 12 C.F.R. § 1002.2(c)(1)(i-iii).

⁵³ 12 C.F.R. § 1002.9 (b)(2).

creditworthiness.

As the CFPB explained in its request for comment, “[t]he more factors that are integrated into a consumer’s credit score or into decisions in the credit process, or the more complex the modeling process in which the data are used, the harder it may be to explain to a consumer what factors led to a particular decision.”⁵⁴ According to the CFPB, this dynamic will make it more difficult for lenders and financial educators “to improve consumers’ understanding of the factors that impact their credit standing” and “make it more difficult for consumers to exercise control in their financial lives, such as by learning how to improve their credit rating.”⁵⁵

The factors considered by LendUp, a fintech company which provides loans and credit cards, are illustrative of this problem. Some criteria considered by LendUp’s alternative credit scoring model, “veer into the esoteric. Social-media posts about a car breakdown could indicate a risky borrower. So can filling out an application in capital letters.”⁵⁶ The underwriting model even “looks at how quickly a user scrolls through the lender’s website,” because “[u]sers who jump to large loan amounts, without reading materials on the site, may be high-risk borrowers.”⁵⁷ As LendUp CEO Sasha Orloff states, “It’s like walking into a bank and screaming, ‘I need money now!’”⁵⁸

Despite its concerns with these and other issues, in September of 2017, the CFPB issued a no-action letter to Upstart Network, Inc., a company that uses non-traditional or alternative data and modeling techniques in credit underwriting.⁵⁹ Among other things, the letter states that the agency’s staff, “has no present intention to recommend initiation of an enforcement or supervisory action against Upstart with regard to application of the Equal Credit Opportunity Act (ECOA) and its implementing regulation, Regulation B, to Upstart’s automated model for underwriting applicants for unsecured non-revolving credit.”⁶⁰ The letter shows the government’s desire to support consumer-friendly innovations in the financial services marketplace and is a promising sign for the regulatory landscape moving forward.

On August 6, 2019, the CFPB issued an update on the results of its coordination efforts with Upstart. As the update noted, over the 22 months since the issuance of the letter, Upstart worked with the CFPB to answer several key questions, including: (1) “whether the tested model’s use of alternative data and machine learning expands access to credit, including lower-priced credit . . . compared to the traditional model;” and (2) “whether the tested model’s underwriting or pricing outcomes result in greater

⁵⁴ 82 Fed. Reg. 11,183, 11,187 (Feb. 21, 2017).

⁵⁵ *Id.*

⁵⁶ Elizabeth Dwoskin, *Global Finance: 'Big Data' Doesn't Yield Better Loans*, WALL ST. J., Mar. 18, 2014, at C3.

⁵⁷ *Id.*

⁵⁸ *Id.*

⁵⁹ CFPB No-Action Letter, Upstart Network, Inc. (Sept. 14, 2017).

⁶⁰ *Id.*

disparities than the traditional model with respect to race, ethnicity, sex, or age, and if so, whether applicants in different protected class groups with similar model-predicted default risk actually default at the same rate.”⁶¹

According to the CFPB, the results were almost overwhelmingly positive. First, studies of Upstart’s model found that “the tested model approves 27% more applicants than the traditional model and yields 16% lower average APRs for approved loans” and that this expansion in access to reasonably priced credit was reflected “across all tested race, ethnicity, and sex segments.”⁶² Furthermore, the analysis found that “[n]ear prime’ consumers with FICO scores from 620 to 660 are approved approximately twice as frequently...applicants under 25 years of age are 32% more likely to be approved [and] [c]onsumers with incomes under \$50,000 are 13% more likely to be approved.”⁶³ Finally, with regard to fair lending testing, the results for minority, female, and elderly applicants showed “no disparities that require further fair lending analysis under the compliance plan.”⁶⁴

In view of the above discussion, the increasing use of alternative credit scoring models presents both considerable promise and potential risks for businesses and consumers alike. Under the current ECOA legal framework, however, businesses that implement these alternative credit models will face substantial regulatory burdens because the specific reasons for adverse credit actions will often be unclear and ill-defined. Similarly, without significant regulatory reform, consumers will be largely uninformed with regard to the accuracy of their credit profile and how to improve their credit scores, especially for models that consider “fringe alternative” data which, at first glance, appear utterly unrelated to creditworthiness.⁶⁵ Therefore, while AI and machine learning have the potential to revolutionize vast swaths of our society, “this won’t happen - or shouldn’t happen - unless we find ways of making [these] . . . techniques more understandable to their creators and accountable to their users.”⁶⁶

II. ANALYSIS

A. Overview of Alternative Credit Data & Modeling Approaches

As briefly discussed above, companies are increasingly developing and implementing models which use AI and machine learning to incorporate a wider range of factors into credit decisions in order to more efficiently and expediently evaluate creditworthiness while maintaining or lowering risk

⁶¹ Patrice Ficklin & Paul Watkins, *An Update on Credit Access and the Bureau’s First No-Action Letter*, CONSUMER FINANCIAL PROTECTION BUREAU (Aug. 6, 2019), <https://www.consumerfinance.gov/about-us/blog/update-credit-access-and-no-action-letter/>.

⁶² *Id.*

⁶³ *Id.*

⁶⁴ *Id.*

⁶⁵ ROBINSON & YU, *supra* note 9, at 22.

⁶⁶ Will Knight, *The Dark Secret at the Heart of AI*, 120 MIT TECH REV. 55, 56 (2017).

levels and delinquency rates. Credit scoring is, in general, a multi-stage process which involves: (1) development of a statistical model from historical data; (2) application of that model to calculate potential borrowers' risk scores; (3) measurement of the accuracy of the model; and finally (4) monitoring of business performance indicators.⁶⁷ Historically, data on transaction and payment history from financial institutions was the main source of information for credit scoring models,⁶⁸ but that is no longer necessarily the case.

Increasingly, companies are developing models which incorporate “additional, unstructured and semi-structured data sources, including social media activity, mobile phone use and text message activity, to capture a more nuanced view of creditworthiness, and improve the rating accuracy of loans.”⁶⁹ This ability to leverage additional sources of information allows for “greater, faster, and cheaper segmentation of borrower quality and ultimately leads to a quicker credit decision.”⁷⁰ However, while traditional credit models have been extensively studied and have withstood regulatory scrutiny due to their reliable predictive ability, alternative credit models have not been as rigorously or widely studied.⁷¹ Early returns from many analyses have been promising, but the body of research remains in its relative infancy. In the world of traditional credit scoring, many customers simply lack the historical credit history necessary for companies to accurately evaluate their creditworthiness.⁷² Accordingly, “a credit score cannot be generated, and a potentially creditworthy borrower is often unable to obtain credit and build a credit history.”⁷³ Through the use of alternative data sources and the application of machine learning algorithms, lenders may be able to extend affordable credit to those who were previously unable to obtain the credit necessary to fully participate in the financial system.⁷⁴ In addition, aside from the obvious benefits to the consumers who are made scorable by these new models, businesses who use them can reap the benefits of a sizeable crop of newly creditworthy consumers.⁷⁵

Generally, when developing their models and weighing the benefits and drawbacks of certain modeling strategies, researchers focus on three factors: comprehensibility, resource efficiency, and predictive accuracy.⁷⁶

⁶⁷ Artem Beque & Stefan Lessman, *Extreme Learning Machines for Credit Scoring: An Empirical Evaluation*, 86 EXPERT SYS. WITH APPLICATIONS 42, 42 (2017).

⁶⁸ FINANCIAL STABILITY BOARD, ARTIFICIAL INTELLIGENCE & MACHINE LEARNING IN FINANCIAL SERVICES 12 (2017).

⁶⁹ *Id.*

⁷⁰ *Id.* (citing Stefan Lessman, Bart Baesens, Hsin-Vonn Seow & Lyn C. Thomas, *Benchmarking State-of-the-Art Classification Algorithms for Credit Scoring: An Update of Research*, 247 EUROPEAN J. OPERATIONAL RES. 124, 124–36 (2015)).

⁷¹ ROBINSON & YU, *supra* note 9, at 21.

⁷² CONSUMER FINANCIAL PROTECTION BUREAU, *supra* note 33, at 6.

⁷³ FINANCIAL STABILITY BOARD, *supra* note 68, at 12.

⁷⁴ *Id.*

⁷⁵ ROBINSON & YU, *supra* note 9, at 21.

⁷⁶ Beque & Lessman, *supra* note 67, at 42.

Comprehensibility is important because it ensures correct interpretation of the scorecard generated by a model, reduces the cost of implementing, monitoring, and updating the model, and mitigates the cost of regulatory compliance.⁷⁷ Resource efficiency ensures that an algorithm is able to process the vast amounts of data available, while simultaneously producing timely risk predictions and applicant scores.⁷⁸ Finally, predictive accuracy is necessary for any predictive decision model, because a comprehensible and efficient model is only useful to the extent that it accurately predicts and mitigates risk.⁷⁹

While researchers and businesses are still experimenting and developing models that attempt to strike the correct balance between these and other important factors, studies of the predictive ability of alternative scoring models have shown promising results. One recent study concludes, among other things, that several of the alternative scoring algorithms studied predict credit risk significantly more accurately than the industry standard and that there is some evidence that more accurate scoring facilitates “sizeable financial returns.”⁸⁰

As the benefits that these technologies can provide come into focus and they become more readily and widely applicable, it will become apparent that they have the potential to truly revolutionize the financial services industry.

B. *AI, Alternative Credit Models, & ECOA Discrimination Issues*

While this Note mainly focuses on the implications of AI and machine learning-based credit decision making on the disclosure and notice provisions of the ECOA, it is worth noting and outlining the discrimination concerns raised by these technologies. While fair lending issues are certainly important to consider, the anti-discrimination provisions of the ECOA are, at the very least, not facially contradictory with AI and machine learning-based credit scoring.

As discussed above, the ECOA prohibits discrimination based on a variety of factors, including race, color, religion, national origin, sex, marital status, or age, among others, with regard to any part of a credit transaction.⁸¹ Under the ECOA, plaintiffs can bring discrimination claims based either on an intentional discrimination theory or a disparate impact theory.⁸²

In this new credit underwriting regime, because credit decisions are made through a complex algorithm which considers a myriad of factors

⁷⁷ *Id.*

⁷⁸ *Id.*

⁷⁹ *Id.*

⁸⁰ Stefan Lessman, Bart Baesens, Hsin-Vonn Seow & Lyn C. Thomas, *Benchmarking State-of-the-Art Classification Algorithms for Credit Scoring: An Update of Research*, 247 EUROPEAN J. OPERATIONAL RES. 124, 134 (2015).

⁸¹ 12 C.F.R. § 1002.2(z).

⁸² Seiner, *supra* note 14, at 96.

entirely unrelated to any of the prohibited bases for discrimination under the ECOA, it will likely be difficult for potential claimants to bring intentional discrimination suits. However, if an AI or machine learning-based credit model considers factors that serve as a proxy for a protected class, it may be easier for plaintiffs to prove disparate impact discrimination. In view of these concerns, we should be mindful and work proactively to ensure that companies are not unlawfully discriminating against consumers under the guise of facially neutral and objective algorithms.

While this problem is obviously an important one for regulators to plan for and resolve, unlike the notice issues described below, this dynamic does not represent a fundamental and seemingly unsolvable contradiction between new methods of underwriting and compliance with the current fair lending framework. In fact, it is entirely possible that new methods of underwriting will be *better* than traditional models at promoting fair lending and preventing discriminatory credit decisions, as they can, to some extent, insulate the decision-making process from conscious human action. Furthermore, even if that is not the case, historically disadvantaged populations stand to benefit overall from the expansion of creditworthiness that these technologies can provide.⁸³ In any event, it is not a foregone conclusion that the implementation of these new methods of underwriting will lead to increases in unlawful discrimination.

The issues that these technologies raise with regard to ECOA adverse action notices, on the other hand, are facially problematic and fundamentally incompatible with existing law. Accordingly, before we can tackle the substantive discrimination issues posed by these advances in technology, we must first consider and resolve the facial contradictions between these new methods of underwriting and the principles behind ECOA adverse action notices. For that reason, this Note will focus primarily on the latter.

C. AI, Alternative Credit Models, & ECOA Adverse Action Notices

The challenges posed by these radical technological changes occurring in loan and credit underwriting are numerous and manifest. While one could spend a staggering amount of time and effort considering and analyzing the various nuances and legal problems posed by these technologies, this Note focuses on the challenges that businesses implementing them will face with regard to ECOA adverse action notices.

Before going further, it is worth noting that the Fair Credit Reporting Act (“FCRA”) also requires companies to issue adverse action notices in connection with credit applications. Specifically, the FCRA requires that a creditor issue an adverse action notice when it takes adverse action that is based (a) in whole or in part on any information contained in a consumer

⁸³ CONSUMER FINANCIAL PROTECTION BUREAU, *supra* note 33, at 6.

report;⁸⁴ or (b) on information obtained from third parties other than Consumer Reporting Agencies.⁸⁵

The requirements of adverse action notices under the FCRA and the policy goals behind them dovetail significantly with those of ECOA adverse action notices. In fact, creditors can, and generally do, issue a combined notice to comply with the adverse action requirements of both laws when applicable.⁸⁶ Because of the similar and overlapping requirements of both laws, many of the concerns and issues described herein apply to FCRA notices as well. However, because I will deal primarily with the ECOA, further discussion of FCRA adverse action notices is beyond the scope of this Note.

As stated above, the ECOA requires that creditors provide notice to applicants regarding adverse actions taken in connection with credit applications and either the specific reasons for such adverse action or the applicant's right to request a statement of specific reasons.⁸⁷ A statement of specific reasons for adverse action must, "indicate the principal reason(s) for the adverse action. Statements that the adverse action was based on the creditor's internal standards or policies or that the applicant, joint applicant, or similar party failed to achieve a qualifying score on the creditor's credit scoring system are insufficient."⁸⁸

The official CFPB staff commentary to Regulation B, the ECOA's implementing regulation, states that, "[i]f a creditor bases the denial or other adverse action on a credit scoring system, the reasons disclosed must relate only to those factors actually scored in the system. Moreover, no factor that was a principal reason for adverse action may be excluded from disclosure."⁸⁹ "The regulation does not mandate that a specific number of reasons be disclosed, but disclosure of more than four reasons is not likely to be helpful to the applicant."⁹⁰

By imposing these requirements, Congress sought to give consumers the information necessary to contest unfair credit decisions, dispute inaccurate information in their credit reports, and to improve their creditworthiness in the future.⁹¹ Because these new methods of underwriting potentially involve an unendingly vast and constantly updating set of factors, some of which have no intuitive relation to creditworthiness, it is difficult to

⁸⁴ 15 U.S.C. § 1681m(a).

⁸⁵ 15 U.S.C. § 1681m(b).

⁸⁶ Ammermann, *supra* note 21, at 4.

⁸⁷ 12 C.F.R. § 1002.9.

⁸⁸ 12 C.F.R. § 1002.9 (b)(2).

⁸⁹ BUREAU OF CONSUMER FINANCIAL PROTECTION, COMMENT 9(B)(2)–4 OF THE OFFICIAL STAFF COMMENTARY FOR REGULATION B (Jan. 1, 2018), <https://www.consumerfinance.gov/policy-compliance/rulemaking/regulations/1002/Interp-9/>.

⁹⁰ BUREAU OF CONSUMER FINANCIAL PROTECTION, COMMENT 9(B)(2)–1 OF THE OFFICIAL STAFF COMMENTARY FOR REGULATION B (Jan. 1, 2018), <https://www.consumerfinance.gov/policy-compliance/rulemaking/regulations/1002/Interp-9/>.

⁹¹ See Ammermann, *supra* note 22, at 1.

see how companies can comply with the letter or the intent of existing law.

For credit providers and consumers alike, the “specific reasons” for credit decisions rendered by AI-powered alternative credit scoring models may be a moving target which is constantly changing and adapting. Accordingly, the scores produced by these models could theoretically treat two applicants with the same credit profile and the same inputs to the model differently simply because they applied for credit at different times. Unlike relatively simplistic methods of traditional credit scoring, in alternative scoring models, “[a]ny given score may be based on hundreds of shifting variables.”⁹² Accordingly, creditors, “may not be capable of predicting exactly how any given action will be scored in a week, a month, or a year.”⁹³ Therefore, consumers and creditors alike lack the stability that the existing legal framework relies upon.

Furthermore, even if companies can provide consumers with specific reasons for adverse actions in connection with credit applications, consumers will have a limited ability to improve their credit score, especially if one of those reasons could be that they scrolled through the lender’s website too quickly or have a sub-optimal level of social media activity. This inability of consumers to improve their credit represents a fundamental tension between the policies underlying the current legal regime and the manner in which these technologies operate.

If companies are required to outline in painstaking detail the myriad reasons for an individual credit decision, they will be forced to spend considerable amounts of time and labor and will be subjected to significant regulatory risk should they fail to sufficiently outline the reasons for an adverse action. These companies will need to sift through a potentially massive number of interrelated factors for an adverse action and then, according to existing guidance, disclose to the consumer no more than four reasons for the action. Furthermore, even if companies do furnish an adverse action notice regarding an AI-based credit decision, consumers will be hard pressed to find ways to improve their credit and to comprehend how these complicated models operate. Accordingly, the legal framework surrounding credit scoring must bend to accommodate these innovative approaches to credit decision-making.

D. To Assimilate (or Not To Assimilate) AI-Based Alternative Credit Models Into the Existing Legal Regime

When grappling with the question of how to regulate this emerging method of underwriting we are faced with a situation in which, to use a colloquial phrase, something has to give. For a variety of reasons, it would be best for both consumers and businesses if regulators were to relax or

⁹² Citron & Pasquale, *supra* note 18, at 30.

⁹³ *Id.*

eliminate altogether the ECOA's adverse action notice requirement, at least as it relates to AI and machine learning-based alternative credit models.

First and foremost, the widespread use of sophisticated AI-based models in loan and credit underwriting will allow businesses to evaluate creditworthiness, approve or deny credit applications, and price credit more efficiently than previously thought possible. Considering the massive amount of money that is involved in consumer credit and lending transactions,⁹⁴ this will be beneficial not only for individual credit providers' bottom lines, but also for the economy as a whole.⁹⁵

As many have noted, to fully participate in the financial system, consumers must have ready access to affordable credit.⁹⁶ Current methods of credit decision making may adequately serve some customers, namely those with long, consistent credit and payment histories, but millions of others, namely young people and historically disadvantaged minorities, are left out in the cold.⁹⁷ These emerging technologies will give businesses the opportunity to expand the universe of creditworthy applicants to bring these underserved groups into the fold.⁹⁸

One of the main benefits of credit scoring systems generally is that while they involve significant fixed costs to develop, their operating cost is extremely low.⁹⁹ That is to say, "it costs a lender little more to apply the system to a few million cases than it does to a few hundred."¹⁰⁰ The highly "scalable" nature of credit-scoring systems enhances the lending process by "allowing lenders to compete for a wider range of customers and by making their management of existing account relationships more efficient."¹⁰¹

This dynamic is especially true in alternative credit scoring systems.¹⁰² Because the factors considered by these systems are much more complex and wide-ranging than traditional scoring systems, requiring credit providers who use them to furnish adverse action notices would have a significant detrimental effect on their ability to increase access to credit and promote market efficiency. Accordingly, interfering with this process by requiring these credit providers to fully comply with existing law would be imprudent.

Some will argue that allowing companies to dispense with the

⁹⁴ A recent Federal Reserve report indicated that total outstanding consumer credit exceeded \$4 trillion in fiscal year 2018, an almost 5% increase over 2017. BOARD OF GOVERNORS OF THE FEDERAL RESERVE SYSTEM, FEDERAL RESERVE STATISTICAL RELEASE: CONSUMER CREDIT G.19 (2019).

⁹⁵ See U.S. DEP'T OF TREASURY, *supra* note 1, at 10.

⁹⁶ ROBINSON & YU, *supra* note 9, at 7.

⁹⁷ CONSUMER FINANCIAL PROTECTION BUREAU, *supra* note 33, at 6.

⁹⁸ ROBINSON & YU, *supra* note 9, at 21.

⁹⁹ BOARD OF GOVERNORS OF THE FEDERAL RESERVE SYSTEM, REPORT TO CONGRESS ON CREDIT SCORING AND ITS EFFECTS ON THE AVAILABILITY AND AFFORDABILITY OF CREDIT 11 (Aug. 2007),

<https://www.federalreserve.gov/boarddocs/rptcongress/creditscore/creditscore.pdf>.

¹⁰⁰ *Id.*

¹⁰¹ *Id.*

¹⁰² ROBINSON & YU, *supra* note 9, at 21.

adverse action notice requirement will insufficiently protect consumers from the evils that Congress sought to combat when passing the ECOA. However, the potential benefits that the upheaval of the current system of credit scoring could usher in are simply too promising to restrict by mandating inflexible compliance with an outdated legal framework. Accordingly, while consumers may be, to some extent, in the dark about what factors contributed to a denial or an unfavorable rate on an extension of credit, this will be significantly outweighed by the millions of new consumers who will potentially be made creditworthy through the adoption of these technologies.

In addition, the plain text of the ECOA and Congress' underlying intent shows that it was never intended to serve as an absolute bar to specific methods of credit underwriting, but merely as a notice and disclosure mechanism. Applying the existing adverse action framework to AI-based alternative credit models would contradict Congressional intent, as it could serve as a constructive bar for the use of these technologies. The scope of factors considered by alternative credit models is so vast that many companies would simply not want to wade into this murky and uncertain territory.

This point is further illustrated by the official CFPB staff commentary to Regulation B, which states that, "[t]he creditor must disclose the actual reasons for denial...even if the relationship of that factor to predicting creditworthiness may not be clear to the applicant."¹⁰³ This language would impose a substantial burden on companies who use AI-based scoring models, because it would require them to both identify and disclose the actual reasons why their algorithm denied a credit application or issued credit with less favorable terms, with little to no countervailing benefit to the consumer.

Also, the regulation does not require that any one method be used for selecting which reasons should be disclosed to explain a given adverse action.¹⁰⁴ Various methods of selecting reasons will meet the requirements of the regulation.¹⁰⁵

One method is to identify the factors for which the applicant's score fell furthest below the average score for each of those factors achieved by applicants whose total score was at or slightly above the minimum passing score. Another method is to identify the factors for which the

¹⁰³ BUREAU OF CONSUMER FINANCIAL PROTECTION, COMMENT 9(B)(2)-4 OF THE OFFICIAL STAFF COMMENTARY FOR REGULATION B (Jan. 1, 2018), <https://www.consumerfinance.gov/policy-compliance/rulemaking/regulations/1002/Interp-9/>.

¹⁰⁴ BUREAU OF CONSUMER FINANCIAL PROTECTION, COMMENT 9(B)(2)-5 OF THE OFFICIAL STAFF COMMENTARY FOR REGULATION B (Jan. 1, 2018), <https://www.consumerfinance.gov/policy-compliance/rulemaking/regulations/1002/Interp-9/>.

¹⁰⁵ *Id.*

applicant's score fell furthest below the average score for each of those factors achieved by all applicants. These average scores could be calculated during the development or use of the system. Any other method that produces results substantially similar to either of these methods is also acceptable under the regulation.¹⁰⁶

As with many of the other provisions of Regulation B, this highlights the fundamental conflicts between the existing legal regime and these emerging methods of underwriting. The above language clearly contemplates a traditional 1-100 scale, in which credit decisions can be understood simply by the fact that, for example, more income is better than less income. Credit decisions rendered by alternative scoring models, on the other hand, are based on potentially limitless factors, many of which are unrelated to one another and divorced from traditional conceptions of creditworthiness.

As a creditor, it would be difficult if not impossible to select specific reasons that comply with the above portion of the regulation. Certain factors, such as social media activity, simply cannot be evaluated on a 1-100 scale. Little to no social media activity might indicate a risky borrower. An excessive amount of social media activity might indicate the same. For these and many other alternative factors, creditors would be hard pressed to determine which reasons to disclose and, more importantly, which reasons would be most meaningful and helpful to the consumer.

It is clear that, regardless of how much time and effort creditors spend compiling comprehensive adverse action notices, they will find it difficult to comply with the letter or intent of existing law. Due to this lack of regulatory certainty, companies could decide that developing and implementing these technologies is more trouble than it is worth and simply maintain the status quo. This would perpetuate the credit access issues that plague the current system and would deny consumers and businesses the potential benefits that an expansion of creditworthiness could provide.

Furthermore, even if companies are required to provide consumers with a comprehensive notice specifying the reasons for adverse action taken in connection with a credit application, the results would in many cases be incomprehensible for the average consumer. Many factors considered by alternative models, including social media activity, the length of time taken to fill out an application, and whether or not the applicant filled out the application in all capital letters, have no intuitive relationship to creditworthiness. The average consumer would likely find any notice of an adverse credit decision on this basis perplexing and, more importantly, would find it hard to change their behavior to improve their creditworthiness in the future.

The staff commentary to Regulation B again brings this point into

¹⁰⁶ *Id.*

relief. It states that, “[a] creditor need not describe how or why a factor adversely affected an applicant. For example, the notice may say ‘length of residence’ rather than ‘too short a period of residence.’”¹⁰⁷

Therefore, under current law, an adverse action notice based on an alternative credit scoring system could list a specific reason for such action as “social media activity” or “time of application submission.” Applicants receiving such a notice would be left with many questions. Am I too active on social media or not active enough? What time *should* I have submitted the application? It is easy to see how adverse action notices listing these and other similarly vague reasons would raise more questions than they answer.

Also, as stated above, the Official Staff Commentary to Regulation B acknowledges that the disclosure of more than four reasons for an adverse action is not likely to be helpful to consumers.¹⁰⁸ Disclosure of each and every possible reason for an adverse action is not desirable, because the more reasons a creditor provides, the less meaningful each reason will be to the consumer. Creditors that implement alternative credit scoring models will be faced with the difficult task of narrowing down a universe of potentially thousands of factors to explain an adverse action using four or fewer reasons. Because many of the factors involved are complex and may be based as much on the interrelationship of factors as opposed to the factors viewed in isolation, and lack an intuitive relationship to creditworthiness, average consumers receiving these notices will be no better off than if the adverse action notice was not provided at all.

Furthermore, if credit providers are required to disclose the behavioral aspects of their models, like time spent filling out an application, consumers can “game the system” the next time they apply for credit by simply taking more time to apply. Consumers who do so will appear more creditworthy without actually being more creditworthy. Accordingly, disclosure of these types of easily changeable behavioral factors could harm the predictive ability of alternative credit scoring models in the long term.

The foregoing dynamic shows that requiring compliance with the current legal regime would impose myriad costs on credit issuers with limited countervailing benefits to consumers. It would be irrational and detrimental to society as a whole to impede progress in the name of a public policy goal that, while laudable, is essentially impossible to accomplish. Accordingly, the ECOA adverse action requirement should give way to these

¹⁰⁷ BUREAU OF CONSUMER FINANCIAL PROTECTION, COMMENT 9(B)(2)–3 OF THE OFFICIAL STAFF COMMENTARY FOR REGULATION B (Jan. 1, 2018), <https://www.consumerfinance.gov/policy-compliance/rulemaking/regulations/1002/Interp-9/>.

¹⁰⁸ BUREAU OF CONSUMER FINANCIAL PROTECTION, COMMENT 9(B)(2)–1 OF THE OFFICIAL STAFF COMMENTARY FOR REGULATION B (Jan. 1, 2018), <https://www.consumerfinance.gov/policy-compliance/rulemaking/regulations/1002/Interp-9/>.

innovative technologies.

E. AI-Based Credit Scoring Model Disclosure

This is not to say that the use of artificial intelligence and machine learning in loan and credit underwriting should be entirely unregulated. To ensure financial stability and the responsible use of such technologies, Congress should enact legislation or the CFPB should promulgate regulations which require companies to disclose certain basic information about their alternative credit decision making processes.

Because the companies issuing credit have the most information about their models and the reasons behind the decisions rendered by their models, any new rules or regulations should require companies to disclose to regulators: (1) the basic factors considered by their models; (2) the relative weight given to various factors by their models; (3) the rationale behind their inclusion of the specified factors; and (4) how their model adapts and updates based on changing inputs. To ensure that the fair lending principles underlying the ECOA are not undermined, the CFPB should also require companies using these technologies to furnish statistics regarding minority inclusion, similar to those provided by Upstart pursuant to the no action relief described above.

Because of the complexity of these methods of loan and credit underwriting, any potential rule or regulation should not require comprehensive disclosure, but merely require companies to provide sufficient information to allow regulators to analyze the methods by which various models determine creditworthiness in order to detect potentially discriminatory underwriting techniques and to protect and ensure the stability of the financial system. Because these new methods of underwriting represent a moving target, companies should be required to update their disclosures to the CFPB annually, to reflect the ever-evolving nature of the underlying technology.

The companies subject to these regulations may argue that these requirements will deter innovation and will be an onerous hurdle to clear to get their models to market. These concerns are, at best, overblown.

As a matter of corporate best practices, most of the companies developing these technologies are constantly and thoroughly analyzing their predictive ability to minimize delinquency rates and thus minimize the potential for financial harm to their businesses. Companies have a strong incentive to extend credit only to those who are capable of meeting their obligations and a company that failed to analyze and document the results produced by their models would be truly irresponsible. Accordingly, most of the information that would be required by the proposed disclosure regime is readily available to companies and simply requiring them to disclose basic information considered by their models and the mechanisms behind their models imposes little additional cost or burden.

While the potential benefits that these technologies can provide makes requiring inflexible compliance with the current legal framework

improper, this basic disclosure system will ensure market stability and will protect consumers and businesses alike from the potential problems that could arise when AI and machine learning-based credit decision making models become the norm, rather than the exception.

CONCLUSION

The issues discussed herein are a microcosm of the broader issues surrounding AI and its complex nature and opacity. Many observers have argued that as AI gains prominence, those who develop and implement it in their businesses must ensure that it is explainable.¹⁰⁹ In fact, “there is an emerging computer science field developing ‘explainable AI’ methods” that seeks to bridge the gap between these developing technologies and broader societal understanding.¹¹⁰ Absent considerable progress in this space, however, AI and machine learning-based algorithms will continue to be “black boxes” to the general public.

For the reasons set forth above, the current legal framework is ill-equipped to deal with the massive technological changes to the financial services market that will come with AI and machine learning-based credit underwriting models. Instead of attempting to shoehorn these new methods of credit decision making into existing law designed for more basic, traditional models of loan and credit underwriting, Congress and the relevant federal agencies should utilize a light regulatory touch to accommodate and shepherd the widespread development and implementation of alternative credit underwriting methods.

While current laws like the ECOA seek to achieve laudable and important public policy goals, requiring companies which are developing innovative and ground-breaking technologies to comply with various provisions thereof, namely the adverse action notice requirement, will retard progress and even serve as a constructive bar to the development and implementation of alternative credit models. The ECOA adverse action requirement was never intended to bar any specific method of credit decision making, but simply to require lenders to provide consumers with the information necessary to detect discriminatory lending decisions and to improve their creditworthiness in the future. Accomplishing these goals in the new frontier of loan and credit underwriting would be difficult, if not impossible, for businesses and incomprehensible to consumers.

The government’s role in the coming years, as these technologies become more fully developed and more widely implemented, should be to refrain from restricting societally beneficial innovation while, at the same time, requiring companies to share basic information which will allow

¹⁰⁹ See Carsten Jung & Philippe Bracke, *Tell Me Why! Looking Under the Bonnet of Machine Learning Models*, BANK UNDERGROUND (Nov. 26, 2019), <https://bankunderground.co.uk/2019/11/26/tell-me-why-looking-under-the-bonnet-of-machine-learning-models/#more-5797>.

¹¹⁰ *Id.*

regulators to evaluate their models and ferret out discriminatory or unfair lending decisions. As with any new technology which has the potential to benefit wide swaths of consumers and the businesses who utilize them, the relevant laws should be flexible and bend to accommodate their responsible use, while at the same time seeking to maintain and strengthen some of the principles underlying existing law to the extent that it is possible.

To this end, while we should take every feasible measure to promote and shepherd the responsible development of these technologies, the government cannot allow companies to operate in a totally unregulated space and in the process run roughshod over the goals of consumer protection embodied in existing laws and norms. The approach this Note advocates for strikes the correct and responsible balance between these two competing goals and argues that where, as in the case of AI and machine learning-based underwriting methods, something has to give, the government should err on the side of fostering societally beneficial innovation.