Artificial Intelligence Discussion Draft

THE FUTURE OF CREDIT UNDERWRITING: ARTIFICIAL INTELLIGENCE AND ITS ROLE IN CONSUMER CREDIT
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Executive Summary

The Bank Policy Institute (“BPI”), and the law firm of Covington & Burling LLP (“Covington”), have developed this discussion draft to solicit input and views from relevant stakeholders on the appropriate regulatory framework for the use of artificial intelligence and machine learning (collectively, “AI”) in credit underwriting. BPI believes AI has great potential and can help banks improve access to consumer credit for underserved consumers and this discussion draft seeks to begin a dialogue among relevant stakeholders to help identify a path that regulators and industry can take to further these objectives. As a part of this effort, and based on the input provided by relevant stakeholders, BPI intends to release a final white paper with recommendations for modernizing regulatory approaches to the use of AI in credit underwriting.

AI offers a leap forward for the accuracy and fairness of decisions on consumer credit. AI can integrate and analyze richer data sets than conventional credit underwriting, and more accurately assess a consumer’s creditworthiness using factors (and combinations of factors) ordinarily not considered by conventional underwriting systems. This increased accuracy will benefit borrowers who currently face obstacles obtaining low-cost bank credit under conventional underwriting approaches.

There is no universally accepted definition of AI. In general, AI is associated with the development and implementation of computer systems to perform tasks that traditionally would have required human cognitive intelligence, such as thinking and decision making. Machine learning is a subset of AI that generally refers to the ability of a software algorithm to identify patterns and automatically optimize and refine performance from processing large data sets with little or no human intervention or programming. Although AI has existed for many years, interest in applying AI has surged as a result of increases in computing power and the availability of large data sets, including in the financial services sector, “alternative data” not traditionally collected by consumer reporting agencies or used in calculating credit scores. For simplicity, this whitepaper uses the term "AI" to refer to the evaluation of large data sets using machine learning algorithms.

THE CURRENT REGULATORY FRAMEWORK WAS DEVISED WELL BEFORE AI WAS AVAILABLE TO ASSIST CREDIT UNDERWRITING AND MAY CONSTRAIN THE TRANSFORMATIVE POWER OF AI.

BPI and Covington have prepared this discussion draft to:

- explain the regulatory framework that currently applies to the use of AI in credit underwriting;
- identify the ways in which that regulatory framework may impede broad implementation of AI in credit underwriting; and
- describe how responsible modernization of the regulatory framework would preserve core regulatory principles while removing obstacles to the use of AI to improve credit underwriting.
This discussion draft focuses principally on the regulatory frameworks relating to fair lending and model risk management, as these two areas appear to most impede banks’ efforts to implement AI systems in credit underwriting. In addition, this discussion draft describes the need for a level playing field between banks and non-banks regarding the application of the law to the use of AI in credit underwriting. Modernizing existing regulatory approaches will allow more creditors to utilize AI in credit underwriting, provide consistent consumer protection, strengthen safe and sound underwriting practices, and foster responsible and fair outcomes.

This discussion draft solicits input on identifying and addressing the regulatory obstacles to implementing AI in credit underwriting. BPI is not presently making policy recommendations. Instead, it is seeking information and analysis relevant to the following potential principles for regulatory modernization in this area:

- The Consumer Financial Protection Bureau (“CFPB”) should lead an effort to modernize the regulatory framework for the use of AI in credit underwriting in light of its authority to implement the nation’s federal consumer financial protection laws and to regulate both banks and non-banks.

- The CFPB should consider, in consultation with the relevant federal agencies:
  - developing standards tailored to prevent unlawful discrimination under the Equal Credit Opportunity Act (“ECOA”) in the use of AI credit underwriting systems;
  - clarifying that an AI credit underwriting system can qualify as an “empirically derived, demonstrably and statistically sound, credit scoring system,” just like a conventional underwriting system;
  - developing adverse action notice standards and adverse action reasons that reflect the broader factors considered in AI credit underwriting systems;
  - specifying, in consultation with the relevant federal agencies, the steps that banks and non-banks are expected to take to review AI credit underwriting systems for purposes of compliance with federal consumer financial protection laws; and
  - ensuring a coordinated approach to the oversight of AI in credit underwriting and the consistent application of the law and regulatory framework to banks and non-banks alike.

This discussion draft is organized as follows:

- **Section I** describes the promise of AI in improving credit underwriting.
- **Section II** reviews the current state of the law relating to credit underwriting.
- **Section III** outlines how responsible modernization of regulatory approaches would facilitate the use of AI in credit underwriting while preserving core regulatory principles.
AI can help banks improve access to consumer credit for underserved consumers in a manner consistent with the fair lending laws and without diminishing banks’ robust credit underwriting standards.

**THIS DISCUSSION DRAFT IS DESIGNED TO HELP IDENTIFY A PATH THAT REGULATORS AND THE INDUSTRY CAN TAKE TO ACHIEVE THESE OBJECTIVES.**
The Promise of Artificial Intelligence in Credit Underwriting

The use of AI in credit underwriting could be an important step forward in expanding the availability and reducing the cost of consumer financial services. Conventional underwriting systems, including most credit scoring models, were built prior to important changes in the availability of data, consumer demographics, consumer behavior, advanced analytics, and computing power. AI can capture and process broader and deeper data sets, and use both more sophisticated analytical tools and powerful new computing capabilities to generate more accurate credit underwriting.

Conventional credit underwriting systems were themselves innovative when first implemented, as they applied new data and technology to credit decisions. The mere collection and use of data about individuals was controversial when it began in the nineteenth century, and computerizing such data was criticized as “a threat . . . to a man’s very humanity” as recently as 1968. However, the use of expanded data and technology have reduced underwriting costs and expanded avenues for further access to credit. Those advantages, coupled with appropriate adjustments in the law to regulate the new approach, have fostered widespread acceptance of advances in consumer credit underwriting. In particular, the public and policymakers have become comfortable with the use of credit scores in addition to, and then largely in place of, subjective lending decisions.

Conventional credit underwriting systems and credit scoring systems are not, however, a panacea. They work best for consumers who have established credit histories with mainstream lenders, such as mortgage lenders and credit card issuers. They serve less well other creditworthy consumers who are unbanked or underbanked, new immigrants, young consumers, consumers with prior adverse credit history, and low-and-moderate income (“LMI”) borrowers.

Congress has recognized that AI may be the next step in the evolution of credit underwriting, and that the law and regulators need to adapt to both facilitate and regulate this development. The House Financial Services Committee recently created a bipartisan Task Force on Artificial Intelligence that will “educate Congress on the opportunities and challenges posed by these technologies and what we can do to produce the best outcomes for consumers.”

AI CREDIT UNDERWRITING SYSTEMS HAVE AT LEAST FOUR APPARENT ADVANTAGES OVER CONVENTIONAL CREDIT UNDERWRITING SYSTEMS.

First, AI has the ability to quickly capture, aggregate, and process a large volume and variety of data, yielding deeper insights into a consumer’s ability to handle credit and importantly, expanding the universe of consumers for whom relevant and accurate data is available. These data can include assets, cash flow, savings and spending behavior, digital bill payment, and other factors that predict consumer creditworthiness. AI systems also analyze alternative data to identify new patterns and correlations across data sets that are not captured by conventional models. These new paths to
credit can expand access to loans, particularly for traditionally underserved borrowers, just as the use of alternative data has led to advances in such areas as equal access to employment and healthcare for underserved communities.\textsuperscript{13}

The CFPB has recognized the benefits of alternative data, noting that:

\textit{Alternative data draws from sources such as bill payments for mobile phones and rent, and electronic transactions such as deposits, withdrawals or transfers. This information could show a track record of meeting obligations that may not turn up in a credit history. As a result, some who now cannot get reasonably priced credit may see more access or lower borrowing costs.}\textsuperscript{14}

More recently, the CFPB reiterated that:

\textit{For some consumers, the use of unconventional sources of information, or “alternative data,” to evaluate creditworthiness may be a way to increase access to credit or decrease the cost of credit. Alternative data includes information not typically found in core credit files of nationwide consumer reporting agencies and may indicate a likelihood of meeting obligations on time that a traditional credit history may not reflect.}

\textit{In addition to the use of alternative data, increased computing power and the expanded use of machine learning can potentially identify relationships not otherwise discoverable through methods that have been traditionally used in credit scoring. As a result of these innovations, some consumers who now cannot obtain favorably priced credit may see increased credit access or lower borrowing costs.}\textsuperscript{15}

Second, AI credit underwriting systems are dynamic, meaning they are continually refreshed and refined to take into account new data and the significance of such data. By comparison, conventional credit underwriting systems often remain static until the model is periodically reviewed, refreshed with a new data set, and updated on a manual basis. This dynamic updating of AI systems allows for underwriting that more accurately reflects consumers’ changing financial circumstances.

Third, because they evaluate a broader range of data and refresh their approach continuously, AI credit underwriting systems can better predict consumer performance than conventional credit underwriting systems.\textsuperscript{16} For example, a consumer may have no credit score or a low credit score but still demonstrate a probability of repayment in other ways, thereby qualifying the borrower for credit.\textsuperscript{17} Use of AI can produce a more robust and holistic assessment of a consumer’s creditworthiness and thereby expand access to low-cost mainstream credit for millions of underserved and “credit invisible” Americans.\textsuperscript{18} In this regard, AI is simply the latest phase in the expansion of credit that began when automated credit models started to replace personal experience and judgment as the basis for underwriting decisions.\textsuperscript{19} While AI-based credit underwriting will not always result in a more favorable view of the consumer’s ability to repay than a conventional credit score, it can expand access to credit for millions of Americans who simply have no credit score at all.

Fourth, AI credit underwriting systems use more diverse data sets and credit standards compared to conventional credit scores and so allow multiple approaches to assessing a consumer’s creditworthiness. Such diversification in credit underwriting should not only give underserved consumers additional opportunities to qualify for credit, but also reduce systemic risk by enabling banks to adopt different approaches to credit decisions.\textsuperscript{20}
Use of AI in credit underwriting has accelerated in the non-banking financial services sector. As described below, the relatively slow adoption of these practices by traditional banks reflects not a lack of interest or aptitude, but a regulatory, examination, and enforcement regime that overly discourages risk-taking and thwarts innovation. This difference matters to consumers because access to insured deposits makes banks the most dependable, low-cost, through-the-cycle source of credit for consumers, including LMI borrowers. It is also worth noting that non-banks and banks are subject to the same consumer protection and anti-discrimination laws, so the law does not envision this significant difference in the application of these laws.
SECTION II

The Current State of the Law

Like many innovations, the use of AI to improve credit underwriting requires modernizing the existing regulatory framework. A first step is to understand the principles and mechanisms of the current regulatory framework.

The regulatory framework for credit underwriting is designed to protect consumers from unlawful discrimination in credit decisions on the basis of race, gender, national origin, and age, among other factors. This framework applies to both human decision-making and automated decision-making. The use of technology does not excuse or justify unlawful discrimination.

Lenders and regulators play important roles in preventing credit discrimination. Lenders typically rely upon consumer reports and other common data sources that are governed by federal law and regulation and historically have been accepted by regulators as nondiscriminatory. Regulators have developed various techniques for supervising and examining lenders’ credit underwriting, including their use of automated decision-making. In addition, notices to consumers about credit decisions give a degree of transparency to credit underwriting decisions and help consumers to assert their legal rights.

This discussion draft addresses four types of regulatory frameworks most relevant credit underwriting by banks: (1) fair lending; (2) model risk management; (3) consumer reporting; and (4) unfair, deceptive, or abusive acts or practices (“UDAAP”). The current state of the law in each area is discussed below. The same regulatory framework applies to conventional credit underwriting systems and AI credit underwriting systems alike.

A. Fair Lending

ECOA, along with its implementing regulation, Regulation B, is the primary federal law prohibiting discrimination in credit transactions. ECOA and Regulation B prohibit creditors from discriminating against an applicant in any aspect of a credit transaction on a prohibited basis, including race, gender, national origin, and age, among certain other prohibited bases. It is unlawful for a creditor to treat an applicant belonging to a protected class differently from similarly situated applicants not in the protected class if the creditor lacks a legitimate nondiscriminatory reason for such action, or if the asserted reason is a pretext for discrimination. To prove such disparate treatment, a plaintiff must show that the credit decision was based at least in part on this protected characteristic.

Title X of the Dodd-Frank Wall Street Reform and Consumer Protection Act of 2010 (“Dodd-Frank Act”) transferred exclusive rulemaking and interpretive authority for ECOA and Regulation B from the Board of Governors of the Federal Reserve System (“FRB”) to the CFPB. The Dodd-Frank Act also transferred exclusive examination authority for ECOA and Regulation B to the CFPB for insured depository institutions and credit unions with assets in excess of $10 billion, as well as affiliates of such institutions, and for most non-bank lenders. Non-banks examined by the CFPB include non-bank mortgage lenders, student loan lenders, payday lenders, and other “larger participants” in markets for consumer financial products or services that the CFPB, by rule, subjects to its examination authority.
Service providers to these entities are also subject to CFPB examination authority. Accordingly, given its primary and broad authority for ECOA and Regulation B with respect to banks and non-banks, the CFPB is best positioned to interpret ECOA and Regulation B in a manner that can be applied consistently to all lenders.

The CFPB—like the FRB that previously exercised primary rulemaking and interpretive authority for ECOA and Regulation B—has determined that disparate impact may serve as a basis for a finding of discrimination under ECOA and Regulation B. Disparate impact occurs when a facially neutral creditor practice, even though applied evenly and uniformly, has a disproportionately adverse impact on applicants from a protected class, unless the practice meets a legitimate business need that cannot reasonably be achieved by means that are less disparate in impact.

There have been significant disputes regarding the application and contours of disparate impact as a basis for fair lending violations. Most recently, the Supreme Court in Texas Dep’t of Housing & Comm. Affairs v. Inclusive Communities Project, Inc. (“Inclusive Communities”) considered whether disparate impact claims are cognizable under the Fair Housing Act. In a 5-4 decision, Justice Kennedy, writing for the majority, held that disparate impact claims are cognizable under the Fair Housing Act. The four dissenting Justices, led by Justice Alito, would have reached the opposite conclusion.

Inclusive Communities did not address whether disparate impact claims are cognizable under ECOA. Lower courts have determined that disparate impact claims are permitted under ECOA, but there also are opposing views on the viability of disparate impact claims under ECOA. The debate regarding disparate impact need not delay modernizing the regulatory framework to adapt to AI credit underwriting systems, and tentative proposals in this discussion draft do not depend upon a resolution of that debate.

To avoid unlawful discrimination under ECOA and Regulation B, lenders generally must not use prohibited basis data or proxies for discrimination in their credit underwriting systems. Lenders may consider factors such as age and marital status for limited purposes, but cannot consider factors such as race, color, religion, national origin, or sex under any circumstances. Banks implement controls to ensure that their credit underwriting systems, including internal and third-party credit scoring systems, do not consider prohibited bases or proxies for prohibited bases. Banks also conduct periodic back-testing and trend analysis to validate that credit underwriting systems do not discriminate against applicants on a prohibited basis, and conduct file reviews if statistical analysis indicates that further review is warranted. In this regard, however, banks must rely on fair lending guidance that is more than twenty years old and preceded the introduction of AI and machine learning into credit underwriting.

Separately, ECOA and Regulation B require creditors to provide credit applicants with a notice of action taken within 30 days after receiving a completed application. These provisions are designed to provide applicants and regulators with information that could help identify any potential unlawful discrimination. When a creditor denies an application for credit or takes other adverse action against an applicant, it must provide an adverse action notice to the applicant and provide, or make available upon request, a statement of the specific reasons for the action taken.

The specific reasons for the action taken must be the actual factors used to deny the application—whether based on a credit scoring or a judgmental system. This is true even if the applicant may
not understand the relationship of the factor (for example, “age of automobile”) to the applicant’s creditworthiness. If a creditor bases the denial or other adverse action on a credit scoring system, no factor that was a principal reason for adverse action may be excluded from disclosure. The official interpretations to Regulation B describe two methods that may be used in a credit scoring system to determine the key factors that led to adverse action, both of which are based on deviations below an average score, although other methods that produce substantially similar results also may be used.

It is not sufficient to state that an applicant did not meet the creditor’s underwriting criteria or achieve a satisfactory score in a credit scoring system. However, a creditor need not provide a customized description of how or why a factor adversely affected an applicant.

Given the distinct attributes of AI credit underwriting systems, the methods for generating adverse action reasons and the types of reasons produced will differ from the methods used and types of reasons generated by conventional credit underwriting systems. For a discussion of potential policy responses, see Section III.E below.

B. Regulation of Credit Underwriting Systems

1. Fair Lending Regulation of Credit Underwriting Systems

Regulation B differentiates between two types of systems for evaluating applicants. The first method is an “empirically derived, demonstrably and statistically sound, credit scoring 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.” For ease of reference, this discussion draft refers to such a system an “empirically derived credit scoring system.” The second method is any system for evaluating the creditworthiness of an applicant other than an empirically derived, demonstrably and statistically sound, credit scoring system. Such a method is called a judgmental system. Regulators strongly favor the use of an empirically derived credit scoring system because these systems generally avoid disparate treatment. Accordingly, banks generally use such systems, including third-party credit scores and automated credit underwriting systems as much as possible.

An empirically derived credit scoring system must be: (i) based on data derived from an empirical comparison of sample groups or the population of creditworthy and non-creditworthy applicants who applied for credit within a reasonable preceding period of time; (ii) developed for the purpose of evaluating the creditworthiness of applicants with respect to the legitimate business interests of the creditor utilizing the system; (iii) developed and validated using accepted statistical principles and methodology; and (iv) periodically revalidated. A creditor may use an empirically derived credit scoring system obtained from a third party, or may develop a system internally based on its own credit experience, such as developing a proprietary credit scoring system. The official interpretations to Regulation B elaborate on the periodic revalidation of empirically derived credit scoring systems and the use of third-party data for initial development of such systems.

AI credit underwriting systems generally should qualify as empirically derived credit scoring systems. The specific methods used to develop and revalidate AI systems, however, may not align fully with the regulatory elements and official interpretations, which were developed decades before AI technology.
became feasible for use in credit underwriting. For a discussion of potential policy responses, see Section III.D below.

### 2. Model Risk Management Guidance

In 2011, the Office of the Comptroller of the Currency ("OCC") and the FRB issued joint Supervisory Guidance on Model Risk Management ("Model Risk Management Guidance" or the "Guidance"). The Federal Deposit Insurance Corporation ("FDIC") subsequently adopted the Guidance in 2017. The Guidance predates the advent of AI credit underwriting systems and does not mention AI, AI models, or AI systems. However, at least one member of the FRB has stated that the Guidance should apply to banks’ use of AI systems.

The Guidance includes a broad definition of “model” and covers “all aspects of model risk management.” The Guidance applies to banks supervised by the OCC, FRB, and FDIC, but does not apply to non-bank creditors, including those supervised by the CFPB. The Guidance applies to banks’ use of both internal or third-party models, but explicitly notes that the process for model risk management of vendor models may be “somewhat modified.”

The Guidance describes in detail the key aspects of an effective model risk management framework, including robust model development, implementation, and use; effective validation; and sound governance, policies, and controls. In practice, the Guidance has reportedly been applied to require banks to dedicate substantial compliance resources to anything deemed a “model,” including multiple layers of internal and regulatory review, and substantially delayed development and modification.

AI credit underwriting systems should be able to satisfy regulatory expectations for model risk management, including, for example, monitoring, periodic back-testing, and trend analysis, under consistently applied standards. For a discussion of potential policy concerns and responses, see Section III.F below.

### C. Credit Reporting

The Fair Credit Reporting Act ("FCRA") governs the communication of consumer reports from consumer reporting agencies to lenders and other users of such reports, the use of consumer reports by creditors and other parties with a permissible purpose, and the furnishing of information to a consumer reporting agency. Title X of the Dodd-Frank Act transferred most FCRA rulemaking authority and broad, but not exclusive, examination and enforcement authority for FCRA compliance to the CFPB. Credit scores developed by third-party vendors are a type of consumer report regulated by the FCRA that creditors routinely use in making credit underwriting decisions. Two such credit scores in the marketplace are the FICO® score and VantageScore.

These credit scores were developed to qualify as empirically derived credit scoring systems under Regulation B. Because these credit scores are used in making credit decisions and Regulation B generally prohibits the consideration of prohibited bases in making credit decisions, credit score developers built the algorithms used to generate these credit scores to exclude consideration of prohibited bases, such as race, national origin, or gender, or proxies for prohibited bases. In fact, third-party credit score developers warrant that their scoring systems comply with fair lending laws.
and do not consider prohibited bases. That said, the CFPB and the bank regulatory agencies do not review the algorithms that underlie the credit scoring systems used to generate credit scores which are proprietary.

The FCRA, like ECOA, has an adverse action notice requirement. When a credit denial is based in whole or in part on a consumer report, including a credit score, the creditor must provide an FCRA adverse action notice along with an ECOA adverse action notice. In an FCRA adverse action notice, the creditor must disclose, among other things, whether a credit score was used in taking the action and, if so, the key factors that adversely affected the credit score. Credit scoring systems generate the key factors that adversely affected the score to support user compliance with the FCRA. For example, a FICO® Score “comes with reason codes that indicate why the score was not higher[]” to support regulatory compliance and communication with consumers. The key factors are similar to the specific reasons that are provided or made available in connection with ECOA adverse action notices.

As with ECOA adverse action notices with specific reasons discussed in Section II.A above, generating key factors for a credit score developed through an AI algorithm may rely on methodologies and generate outputs different from those used or experienced with conventional credit scoring systems. For a discussion of potential concerns and policy responses, see Section III.E below.

D. Unfair, Deceptive, and Abusive Acts Or Practices

Sections 1031 and 1036 of Title X of the Dodd-Frank Act, prohibit UDAAP. The CFPB has exclusive UDAAP rulemaking, interpretive, and enforcement authority over banks and non-banks under Sections 1031 and 1036.

Section 5 of the Federal Trade Commission Act ("FTC Act") prohibits unfair or deceptive acts or practices ("UDAP"). The Federal Trade Commission ("FTC") has authority to promulgate regulations under Section 5 that apply to non-banks subject to its jurisdiction and to bring UDAP enforcement actions against non-bank entities subject to its jurisdiction. The federal banking agencies have asserted that they have UDAP supervisory and enforcement authority under Section 5 of the FTC Act over banks and credit unions subject to their jurisdiction.

An act or practice is unfair if it causes or is likely to cause substantial injury to consumers that consumers cannot reasonably avoid, and where the injury is not outweighed by benefits to the consumer or to competition. Likewise, an act or practice is deceptive if it involves material representations or omissions that are likely to mislead a consumer acting reasonably under the circumstances. Under the Dodd-Frank Act, an act or practice is abusive if it materially interferes with the consumer’s ability to understand a term or condition of a consumer financial product or service, or takes unreasonable advantage of a consumer’s lack of understanding of material risks, costs, or conditions; the consumer’s inability to protect his or her interests; or the consumer’s reasonable reliance on the provider to act in the consumer’s interests.

The misuse of credit underwriting systems could lead to allegations of unfair, deceptive, or abusive conduct. For example, a credit denial based on arbitrary reasons may be unfair. A UDAAP/UDAP violation also may overlap with a violation of other federal or state laws, such as ECOA or Regulation B. However, technical compliance with ECOA, Regulation B, and other federal or state laws does not shield a creditor from allegations of unfair, deceptive, or abusive conduct if, for example, the information
on which a denial is based is inaccurate. As a result, UDAAP/UDAP can provide a basis for alleging a violation of law when a regulator cannot show credit discrimination under ECOA or Regulation B. For a discussion of potential concerns and policy responses, see Section III.E below.

E. Application of the Law

A full account of the current state of the law in this area requires a discussion of how the law is applied in practice. Although the relevant federal financial services laws described above apply equally to bank and non-bank creditors, those laws are enforced quite differently. Most non-bank lenders are not regularly examined by any federal (or state) agency and therefore have greater latitude to deploy and use AI credit underwriting systems without sustained regulatory scrutiny. They run the risk (as do banks) of litigation or enforcement action, but are not required to develop multi-stage processes for internal approval or obtain pre-approval from an examination team. Conversely, banks are examined on a regular basis, in many cases by multiple agencies, and larger banks have on-site examination teams providing constant supervision. Such asymmetry means that implementation of AI in the financial services industry for credit underwriting may be both under-regulated and over-regulated at the same time.

The CFPB has the authority to bring enforcement actions against banks and non-banks alike, and examination authority over both large banks and certain types of non-bank lenders (known as “larger participants”). However, in practice, most non-bank lenders tend to face limited fair lending examination and enforcement from the CFPB. At the same time, state-level fair lending oversight and enforcement varies widely in light of the resource limitations and varied enforcement priorities of state regulators. Therefore, even non-bank lenders operating on a national scale are subject to limited and uneven scrutiny of their fair lending practices as compared to banks.

Similarly, oversight is strikingly different with respect to model risk management. Banks and other depository institutions are subject to the Model Risk Management Guidance. Non-bank lenders do not face any comparable limitations on model development and use. While the Guidance purports to be risk-based, noting that “details may vary from bank to bank,” some banks have reported that the Guidance has been applied as if it were a mandatory rule.
SECTION III

Responsible Modernization

A. Existing Standards Apply to AI Systems

ALLOWING BANKS TO USE AI IN CREDIT UNDERWRITING DOES NOT REQUIRE A WHOLLY NEW REGULATORY FRAMEWORK.

However, AI does necessitate an updated and consistent regulatory approach for applying core regulatory principles clearly and uniformly to bank and non-bank lenders in examination and enforcement. This approach can and should reflect the distinctive features and methodologies of AI credit underwriting systems.  

Regulators have long taken the position that automated decision-making processes in conventional credit underwriting tends to produce “more objective and consistent” results, with less risk of error, than judgmental underwriting. In fact, the Federal Housing Administration uses an automated program called the FHA TOTAL (Technology Open To Approved Lenders) Mortgage Scorecard to evaluate borrower credit history and application information. FHA TOTAL is a statistically derived algorithm accessed through an Automated Underwriting System that was developed by HUD.

All methods of underwriting consumer credit, including AI, carry the risk of potential for discrimination and unintentional outcomes. The fair lending controls banks employ for conventional credit underwriting systems, including documented programming decisions, monitoring, and periodic back -testing and trend analysis, are appropriate for AI credit underwriting systems, subject to certain modifications and adaptations to recognize the dynamic nature of AI.

For example, banks understand the critical importance of making [ ] informed decisions about data that should not be considered in AI credit underwriting systems and excluding data that potentially could result in discriminatory or unintended outcomes. Indeed, compliance with the law can be furthered by AI credit underwriting systems because they produce better, more predictive decisions and expand access to credit for creditworthy but underserved consumers.

Federal financial regulators have recognized how non-underwriting AI tools can assist regulated financial institutions with a range of regulatory compliance issues, including Bank Secrecy Act/ anti-money laundering compliance, and recently have encouraged such uses. Just as AI-based compliance tools provide benefits in other contexts, AI-based monitoring tools can be used with AI
credit underwriting systems to provide enhanced capabilities for back-testing and model validation, and allow institutions to more easily assess system performance and fair lending compliance.\(^\text{84}\)

The controls that minimize the potential for unlawful discrimination for conventional underwriting can be effectively applied to the use of AI credit underwriting systems.\(^\text{85}\) Such controls include modernized versions of steps taken by banks for decades with regard to conventional credit underwriting systems. Specific steps that mitigate the risk of banks or any other creditors using AI credit underwriting systems in a discriminatory manner include:

- filtering data sets so that AI credit underwriting systems do not consider prohibited bases or known proxies for discrimination;
- ensuring that data sets are representative of the population as a whole;
- including fair lending considerations in front-end testing of systems by reviewing each variable and, if appropriate, the overall system, for any prohibited bases or proxies for prohibited bases;
- programming AI credit underwriting systems so that they cannot consider prohibited bases or proxies for discrimination, such as geography;
- closely monitoring AI credit underwriting systems through supervised learning to provide conventional human oversight as a check on potentially discriminatory decision-making or unforeseen outcomes with the ability to implement overrides and course corrections as needed; and
- validating that AI credit underwriting systems are not making decisions on a discriminatory basis by conducting periodic back-testing and trend analysis of those systems, supplemented by file reviews when warranted.

In addition, as described above, creditors must be able to provide specific and accurate reasons for the action taken by credit underwriting systems in connection with adverse action notices.\(^\text{86}\) This obligation to generate specific reasons for adverse credit decisions exists regardless of the type of credit system used.

A KEY CHALLENGE FOR EARLY ADOPTION OF AI CREDIT UNDERWRITING SYSTEMS HAS INVOLVED THE ABILITY OF SUCH SYSTEMS TO GENERATE THE SPECIFIC REASONS FOR ADVERSE CREDIT DECISIONS IN ACCORDANCE WITH EXISTING STANDARDS AND WITHOUT GENERATING CONFUSION OR PROVIDING INACCURATE REASONS.

As discussed in Section III.E below, private industry is exploring a number of methods to address these challenges. The official interpretations of Regulation B outline certain basic methods for identifying
the specific reasons for adverse action when using a credit scoring system. It may be helpful for the CFPB to supplement the official interpretations to reference some of the methods used in AI credit underwriting systems for identifying reasons for adverse credit decisions.

B. The Regulatory Framework Requires Modernization

Consumers are best served by regulatory approaches that are not static and rigid, but that adapt to reflect the emergence of new technologies and new methods of providing financial products and services. Below, for further discussion, are some of the ways in which regulatory approaches could be modernized to keep pace with technological advances.

Certain aspects of today’s regulatory framework could restrict banks’ ability to fully implement AI systems in credit underwriting. The regulatory provisions, guidance, and supervisory approaches generating impediments to the use of AI, without exception, were enacted before AI became a feasible technology for use in credit underwriting. The federal banking agencies’ Model Risk Management Guidance, for example, was issued in 2011 before AI-based credit underwriting became feasible. Relevant provisions of Regulation B and related fair lending guidance have existed largely in their present form for decades without meaningful revision to reflect technological advances and the transition from paper records to a digital and mobile world. In many respects, the disconnect between current regulatory approaches and AI derives from outdated methods of applying existing regulatory standards to AI, rather than from any conflict between the use of AI and well-founded and long-standing legal standards, regulatory requirements, and policy goals.

As described more fully below, a modernized regulatory framework should fully account for the use in AI credit underwriting systems of new factors or combinations of factors not currently used in conventional underwriting systems as well as the dynamic, iterative nature of the systems. Regulators should recognize that the methods for developing, testing, and monitoring AI credit underwriting systems will differ in certain respects from the methods used in conventional credit underwriting systems. Regulators also should recognize that the specific reasons for adverse action notices will need to reflect the broader data sets and factors considered in AI credit underwriting systems. Finally, a modernized framework should apply the same standards and scrutiny to any entity using AI in credit underwriting.

Other regulatory frameworks have been incrementally modernized to reflect updates in technology and consumer behavior and may provide a roadmap for updating the regulatory framework to promote the responsible adoption of AI credit underwriting systems. A good example is the adjustment of Regulation E, which implements the Electronic Fund Transfer Act, to cover prepaid accounts. The CFPB modernized the Regulation E regulatory framework in 2016 to reflect the evolution and widespread adoption of prepaid cards. These rules evolved from targeted provisions focused on government electronic benefit transfer cards and payroll cards. Although the basic Regulation E protections remain in place, the CFPB, like the FRB before it, modified the error resolution provisions and created alternatives to mandatory periodic statements to reflect the distinct attributes of prepaid products.

Modernized regulatory approaches can allow for increased regulatory clarity, thereby prevent unlawful discrimination while allowing banks to use AI to improve the efficiency and fairness of credit underwriting. The next section describes some of the possible steps ahead.
C. Principles for Responsible Modernization

ONE STARTING POINT FOR RESPONSIBLE MODERNIZATION IS RECOGNIZING THE VITALLY IMPORTANT POLICY OBJECTIVES SERVED BY CURRENT LAW, IN PARTICULAR PREVENTING UNLAWFUL DISCRIMINATION AGAINST CONSUMERS.

The advent of AI credit underwriting systems does not diminish the importance of those policy objectives or require they be sacrificed in order to obtain the benefits of AI. Responsible modernization would complement these policy objectives by adapting regulatory and examination approaches to recognize and promote the benefits offered by AI in credit underwriting. Such reforms serve both consumers seeking access to financial services and their creditors.

Policymakers should consider whether the CFPB should take the lead on developing a modern regulatory approach for the use of AI in credit underwriting. The following four reasons would support such leadership:

First, the CFPB is the federal agency with sole rule-writing and interpretive authority over a wide range of federal consumer financial protection laws, giving it the ability to assess the current regulatory approaches to implementing those laws that raise uncertainty and friction with respect to the use of AI in credit underwriting.

Second, the CFPB is the only federal agency that examines and enforces ECOA and other consumer financial protection laws against both banks and non-banks; indeed, under the Dodd-Frank Act, it has exclusive examination authority over the consumer financial protection laws with respect to both non-banks and banks with greater than $10 billion assets. The CFPB is thus uniquely positioned to ensure that its rules are implemented effectively by bank and non-bank lenders alike. In addition, the CFPB could conduct oversight of non-bank credit underwriting practices by expanding its larger participant rules to encompass non-bank lenders in additional markets. CFPB leadership on the use of AI in credit underwriting could help to ensure that consumers are treated fairly regardless of the type of lender from whom they seek credit.

Third, the CFPB has effective tools and the requisite expertise to streamline the supervisory process by ensuring that examiners understand AI, and for sharing AI-related expertise with other regulators. Any effort should ensure sufficient support from all parts of the agency. The CFPB’s examination manual and examiner training materials are examples of tools the CFPB can use to streamline the supervisory process.

Finally, the CFPB is the federal agency best suited to ensure appropriate consumer education about the use of AI in credit underwriting, including how new types of information may be evaluated to determine creditworthiness.

In assuming leadership on these issues, the CFPB would be fulfilling objectives Congress set before it, including to ensure “that all consumers have access to markets . . . that are fair, transparent, and competitive,” and that “outdated, unnecessary, or unduly burdensome regulations are regularly identified and addressed.”

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At present, regulatory impediments to deploying AI credit underwriting systems at banks may serve as barriers to consumer credit. When borrowers have fewer choices, they face higher fees and interest rates, and other less favorable terms. In addition, consumers who rely on non-bank credit may experience more difficulty building a good credit history than a borrower who obtains bank credit. Moreover, the less favorable terms of non-bank loans may hinder consumers’ ability to repay the credit in a timely manner, and therefore depress their credit scores.

The next three subsections detail for discussion more specific paths forward for responsible modernization of the regulatory framework.

**D. Standards for Preventing Discrimination and Discriminatory Outcomes**

ECOA applies to the use of AI credit underwriting systems, just as it applies to conventional underwriting systems or any other aspect of a credit transaction. Nevertheless, because AI in credit underwriting presents novel issues, some clarification may be needed to facilitate innovation and competition, provide regulatory certainty, and reduce the litigation and enforcement risk that banks would otherwise face. The following proposals could help foster both the principles of ECOA and the benefits of AI in credit underwriting.

Any CFPB approach should consider whether the current regulatory framework—including rules, official interpretations, and examination procedures—adequately account for the dynamic nature of AI and the use by AI of new factors or combinations of factors not currently used in conventional credit underwriting systems. These new factors or combinations of factors provide innovative new ways to evaluate the creditworthiness of applicants, promote financial inclusion, and expand access to credit to underserved borrowers, including young consumers, new immigrants, and consumers with impaired credit histories.

Wherever appropriate, the standards for AI credit underwriting systems should mirror standards that apply to conventional credit underwriting systems. Regulation B standards generally prevent creditors from including prohibited bases or known proxies for prohibited bases in credit underwriting systems. Creditor best practices for applying this standard to AI credit underwriting systems may include reviewing and filtering data sets to prevent those systems from considering prohibited bases or known proxies for prohibited bases, ensuring that data sets are representative of the whole population, and programming those systems to discourage consideration of prohibited bases. In addition, it is appropriate to apply traditional standards for periodic back-testing and model validation in ex post assessments of AI credit underwriting system performance, both from a human and systems perspective, to test for and prevent discriminatory outcomes. A best practice may also include conducting fair lending testing that compares approval rates and APR results for protected classes under an AI credit underwriting system against the approval rates and APR results from a conventional credit underwriting system.

Other aspects of the ECOA regulatory framework may need adjustment to reflect AI credit underwriting
systems. For example, supervised learning is not a feature of conventional underwriting systems. The CFPB might clarify how supervised learning can contribute to the periodic revalidation of AI credit underwriting systems when used appropriately to monitor AI system performance, trigger human intervention, overrides, and course corrections when monitoring reveals potentially discrimination or unforeseen disparate outcomes, and to document system performance and adjustments for supervisory review. Even here, however, techniques used to evaluate judgmental overrides in conventional credit underwriting systems can and should be leveraged and updated to apply to the evaluation of supervised learning overrides of AI credit underwriting system outcomes.

In addition, the CFPB should clarify that an AI credit underwriting system can qualify as an empirically derived credit scoring system. In this respect, certain elements of the Regulation B definition of an “empirically derived, demonstrably and statistically sound, credit scoring system” may need to be revised, supplemented, or clarified to reflect the attributes of dynamic AI systems. For instance, the current examples of periodic revalidation may not reflect the methods used with AI credit underwriting systems.95

THE REGULATORY FRAMEWORK SHOULD FOSTER RESPONSIBLE INNOVATION IN AI CREDIT UNDERWRITING IN A MANNER THAT ACHIEVES CONSISTENT AND HIGH STANDARDS OF FAIR LENDING PROTECTION FOR CONSUMERS ACROSS ALL LENDERS.

Consistent standards, in this regard, would help ensure that the use AI credit underwriting systems with appropriate controls, such as supervised learning and periodic back-testing, would not immediately raise a fair lending or UDAAP concern if and when an AI credit underwriting system requires course correction. The CFPB has the tools and expertise that could help to drive the kinds of incremental changes and sensible approaches to oversight that could further these goals. Regulations, official interpretations, and examination procedures are among the tools available to the CFPB to modernize the regulatory framework to facilitate AI-based credit underwriting while promoting strong fair lending requirements that protect consumers regardless of the lenders from whom they obtain loans.

E. Updating Specific Reasons for Adverse Action

The CFPB efforts also should consider providing clarity with respect to adverse action notice requirements and produce an expanded list of specific reasons for adverse action to reflect the broader data sets and factors that may be considered in AI credit underwriting systems.

Creditors by law must be able to provide up to four specific and accurate reasons for the action taken in connection with providing adverse action notices.96 This obligation applies to creditors that use AI credit underwriting systems, just as it does to creditors using conventional underwriting systems.

ONE CHALLENGE FOR THE EARLY ADOPTION OF AI CREDIT UNDERWRITING SYSTEMS HAS BEEN THEIR ABILITY TO GENERATE SPECIFIC AND ACCURATE REASONS FOR CREDIT DENIALS AND OTHER ADVERSE DECISIONS.
The challenge lies in tracing the decision-making logic used by an AI credit underwriting system to identify, isolate, and weigh the importance of the factors or combinations of factors that most impacted the adverse outcome. Vendors of AI credit underwriting systems are developing or have developed a number of methods for generating reasons for the action taken. These methods may not align with the two illustrative methods for selecting reasons described in the official interpretations to Regulation B. Therefore, the CFPB should consider supplementing the official interpretations to reference newer methods used with AI credit underwriting systems. Such an approach should apply to methods for determining the key factors that adversely affected a credit score under an FCRA-regulated AI-based credit scoring system.

In addition, because AI systems analyze vastly larger data sets than conventional systems, the potential grounds for adverse credit decisions are more diverse. Therefore, the sample reasons listed in the Regulation B sample notices, even though non-exhaustive and non-binding, will not reflect the breadth of reasons that may be generated by an AI credit underwriting system. Moreover, the use of unfamiliar reasons or methods for determining reasons that are not mentioned in Regulation B or official interpretations could create an elevated risk of an allegation of unfair, deceptive, or abusive conduct.

The CFPB should consider revising or supplementing the sample notification forms in Appendix C to Regulation B to expand the illustrative list of adverse action reasons to reflect new factors or combinations of factors that may lead to credit denials in AI credit underwriting systems. The reasons for adverse action could remain short and simple, and not require customized explanations that "describe how or why a factor adversely affected" a specific applicant or application. In addition, as new reasons for credit decisions emerge, CFPB-led consumer education would be important to mitigate consumer confusion about how AI-based credit decisions can be based on unfamiliar factors or combinations of factors.

F. Reconsidering Standards for Model Risk Management

AI CREDIT UNDERWRITING SYSTEMS OFFER NEW WAYS TO EXTEND CREDIT TO UNDERSERVED POPULATIONS AND EXPAND ACCESS TO RESPONSIBLE, LOW-COST BANK CREDIT.

Certain regulatory features, including the federal banking agencies’ Model Risk Management Guidance, however, raise impediments to the implementation of AI credit underwriting systems at banks.

In some circumstances, the Guidance has reportedly been applied by bank examiners in some cases to require banks to submit models to regulators for review and approval in advance of initial use or updates (even when not required by law or regulation), and to require a multi-stage internal review as well. Such a demand for ex ante regulatory review and approval of models can result in significantly delayed updates to transaction monitoring programs. For the reasons described below, application of the Guidance to AI credit underwriting systems could adversely impact banks’ ability to use such systems, particularly given the dynamic and evolving nature of AI credit underwriting systems. Four specific concerns are set forth below.
First, the application of the Guidance to AI credit underwriting systems and updates to such systems may constrain the dynamic, constantly evolving, and data-driven nature of AI systems and limit the operational benefits at the heart of AI. The process outlined in the Guidance clearly was designed for conventional systems, not dynamic AI systems.

Second, the Guidance applies only to banks, not to non-bank lenders, and therefore results in an uneven playing field. Non-bank lenders have no obligation to follow the strictures of the Guidance, which provides these lenders with a distinct advantage over banks in implementing AI credit underwriting systems.

Third, although the Guidance gives banks flexibility to modify the model risk management framework for validating vendor and other third-party models, the federal banking agencies reportedly have not consistently afforded this flexibility to banks with regard to vendor-developed AI credit underwriting systems. By contrast, the federal banking agencies, to our knowledge, have not applied a similar review or approval process to widely-used conventional underwriting systems. A better solution would be for all credit underwriting systems—conventional or AI-based—to be subject to the same kind of regulatory review.

Fourth, as noted above, Title X of the Dodd-Frank Act shifted primary responsibility for consumer financial protection from the federal banking agencies and the FTC to the CFPB, which affords the CFPB with broad insight into the use and application of consumer lending systems and their application across banks and non-banks. However, the CFPB’s role with regard to the use of Regulation B and its official interpretations address credit scoring systems—including both AI credit underwriting systems and conventional credit underwriting systems—are now independent of the Guidance issued by the FRB and OCC. To facilitate a coordinated and consistent approach to the oversight of consumer lending systems that reflects both safety and soundness and consumer protection principles, the CFPB, in consultation with the federal banking agencies, should determine the standards for determining whether AI credit underwriting systems comply with the consumer financial protection laws.

In the long run, the same level of regulatory scrutiny should apply to both AI credit underwriting systems and conventional credit underwriting systems. Likewise, the same level of scrutiny should apply to all vendor-supplied credit underwriting systems, whether those systems are AI systems or conventional credit scoring systems. Application of the Guidance to require ex ante regulatory review of AI credit underwriting systems, but not conventional credit scoring systems, will impair innovation. Because all credit underwriting systems must abide by consumer protection laws, model oversight standards for those systems should reflect a joint and coordinated effort by the CFPB and the federal banking agencies.
THEREFORE, TO BETTER ACCOMMODATE THE USE OF AI TECHNOLOGY IN CREDIT UNDERWRITING, the CFPB and the federal banking agencies should consider undertaking a joint and coordinated approach to model oversight for systems used in credit underwriting or otherwise pertinent to consumer financial protection laws. Such an approach could, for example, specify what steps the law requires a lender to take in reviewing systems for purposes of compliance with the consumer financial protection laws and apply those steps to banks and non-banks alike. This effort may clarify, among other things, that examiner approval is not required prior to adopting or modifying an AI credit underwriting system.
Conclusion

The dynamic and iterative recalibration of decisions through AI helps creditors make better, fairer, more responsible loan decisions, promotes inclusion, and expands access to credit, particularly for underserved consumers. Regulatory approaches should be dynamic and iterative as well, adjusting to new information and technological capabilities. The advent of AI presents the CFPB and other regulators with a unique opportunity to craft a regulatory framework that enhances credit underwriting, improves credit access, and levels the playing field for all lenders and all borrowers, while simultaneously preserving and enhancing the effectiveness of the current consumer protection regulatory framework.

BPI LOOKS FORWARD TO WORKING COLLABORATIVELY WITH ITS REGULATORY PARTNERS TO ACHIEVE THESE SHARED GOALS AND HOPES THAT THIS DISCUSSION DRAFT WILL FACILITATE THAT DIALOGUE.


This discussion draft was jointly prepared by BPI and Covington. BPI is a nonpartisan public policy, research and advocacy group, representing the nation’s leading banks. BPI’s members include national banks, regional banks and major foreign banks doing business in the United States. Collectively, they employ nearly 2 million Americans, make 72% of all loans and nearly half of the nation’s small business loans, and serve as an engine for financial innovation and economic growth. Covington is an international law firm headquartered in Washington, D.C. that advises and represents a wide range of financial institutions.


See Ken Brevoort & Patrice Ficklin, New research report on the geography of credit invisibility, CFPB Blog (Sept. 19, 2018), https://www.consumerfinance.gov/about-us/blog/new-research-report-geography-credit-invisibility/ (“Creditworthy consumers can face difficulties accessing credit if they lack a credit record that is treated as “scarable” by widely used credit scoring models. These consumers include those who are “credit invisible,” meaning that they do not have a credit record maintained by one of the nationwide consumer reporting agencies (NCRA). They also include those who have a credit record that contains either too little information or information that is deemed too old to be reliable”). The CFPB’s Office of Research issued three CFPB Data Points providing important data on credit invisibility: Kenneth P. Brevoort et al., Credit Invisibles (May 2015), https://files.consumerfinance.gov/f/documents/bcfp_data-point-credit-invisibles.pdf; Kenneth P. Brevoort & Michelle Kambara Becoming Credit Visible (June 2017), https://files.consumerfinance.gov/f/documents/BecomingCreditVisible_Data_Point_Final.pdf; Kenneth P. Brevoort et al., The Geography of Credit Invisibility (Sept. 2018), https://files.consumerfinance.gov/f/documents/epc_data-point_the-geography-of-credit-invisibility.pdf.

Neil Bhutta, Steven Lauffer, & Daniel R. Ringo, The Decline in Lending to Lower-Income Borrowers by the Biggest Banks, FEDS Notes, Board of Governors of the Federal Reserve System (Sept. 28, 2017), https://www.federalreserve.gov/econres/notes/feds-notes/the-decline-in-lending-to-lower-income-borrowers-by-the-biggest-banks-20170928.htm; see also Patrice Ficklin & Paul Watkins, An update on credit access and the Bureau’s first No-Action Letter, CFPB Blog (Aug. 6, 2019), https://www.consumerfinance.gov/about-us/blog/update-credit-access-and-no-action-letter/ (noting that, as a result of one AI model, some near-prime, young, and lower income consumers “significantly expanded” access to credit) compared to a conventional model). The CFPB has found that approximately 26 million Americans are credit invisible, which means that they do not have a credit record, and another 19.4 million do not have sufficient recent credit data to generate a credit score. Kenneth P. Brevoort et al., Data Point: Credit Invisibles, CFPB Office of Research, at 12 (May 2015), http://files.consumerfinance.gov/f/201505_cfpb_data-point-credit-invisibles.pdf.


Id. The Task Force on Artificial Intelligence will examine issues including: applications of machine learning in financial services and regulation; emerging risk management perspectives for algorithms and big data; AI, digital identification technologies and combating fraud; and automation and its impact on jobs in financial services and the overall economy. See Press Release, Foster Named Chair of Artificial Intelligence Task Force (May 9, 2019), https://foster.house.gov/media/press-releases/foster-named-chair-of-artificial-intelligence-task-force.


16 See Carol Evans, Associate Director, Division of Consumer and Community Affairs, the Board of Governors of the Federal Reserve System, Keeping Fintech Fair: Thinking About Fair Lending and UDAP Risks, Consumer Compliance Outlook (Second Issue 2017), https://www.consumercomplianceoutlook.org/2017/second-issue/keeping-fintech-fair-thinking-about-fair-lending-and-udap-risks/ (“Alternative data may result in new data sources that are accurate, representative, and predictive”) (internal citations omitted).


18 See Carol Evans, Associate Director, Division of Consumer and Community Affairs, the Board of Governors of the Federal Reserve System, Keeping Fintech Fair: Thinking About Fair Lending and UDAP Risks, Consumer Compliance Outlook (Second Issue 2017), https://www.consumercomplianceoutlook.org/2017/second-issue/keeping-fintech-fair-thinking-about-fair-lending-and-udap-risks/ (“[N]ew research on alternative data may in fact improve data availability and representation for the millions of consumers who are credit invisible. Lenders currently lack good tools to evaluate these consumers’ creditworthiness. . . . Such data can increase access to credit for this population and permit lenders to more effectively evaluate their creditworthiness”) (internal citations omitted).


21 The scope of this discussion draft does not extend to the important data privacy issues raised by the use of technology, including the use of AI, in credit underwriting.

22 Similarly, the same safety and soundness considerations apply to all credit underwriting. AI systems are designed to improve the precision of underwriting decisions, and so there is little reason (and no evidence to date) that they would adversely affect banks’ safety and soundness.


24 See 15 U.S.C. § 1691(a) 12 C.F.R. § 1002.2(z), 12 C.F.R. § 1002.4(a). The Fair Housing Act also prohibits discrimination in the sale or rental of housing on the basis of certain prohibited characteristics similar to the ECOA prohibited bases. See 42 U.S.C. §§ 3601-3619.


26 See, e.g., Matthiesen v. Banc One Mortg. Corp., 173 F.3d 1242, 1247 (10th Cir. 1999); Sallion v. SunTrust Bank, Atlanta, 87 F. Supp. 2d 1323, 1329 (N.D. Ga. 2000). A plaintiff can use direct or circumstantial evidence to prove a creditor used a prohibited bases in making a credit decision. To state a prima facie case of disparate treatment through circumstantial evidence, most courts will require that a plaintiff show: (1) membership in a protected class; (2) application for credit for which the plaintiff was qualified; (3) rejection despite qualification; and (4) defendant continued to approve credit for similarly qualified applicants. See McDonnell Douglas Corp. v. Green, 411 U.S. 792, 802 (1973) (setting the standard in employment discrimination cases that is applied to most ECOA cases).


28 Dodd-Frank Act, tit. X, sec. 1025 (large bank supervision) and sec. 1024 (non-bank supervision).

29 Dodd-Frank Act, tit. X, sec. 1024(a). The CFPB does not have rulemaking, examination, or enforcement authority over auto dealers. Dodd-Frank Act, tit. X, sec. 1029.

30 Dodd-Frank Act, tit. X, secs. 1024(e), 1025(d).

12 C.F.R. § 1002.6(b). Some consumer information such as geography and education can be used both legitimately and as a proxy for discrimination. Geography can be used appropriately when, for example, a creditor limits its geographic footprint to certain states. Education also can appropriately be used as an additional factor in evaluating a consumer’s creditworthiness.

See also 12 C.F.R. pt. 1002, suppl. I, § 1002.6(b). Creditors are permitted to use an applicant’s age as a predictive factor in an empirically derived, demonstrably and statistically sound, credit scoring system so long as applicants age 62 years or older are treated at least as favorably as applicants who are under age 62. 12 C.F.R. § 1002.6(b)(2)(ii). 12 C.F.R. pt. 1002, suppl. I, § 1002.6(b)(2)-1 and -2. In a judgmental system of credit underwriting, a creditor may consider age only for the purpose of determining a pertinent element of creditworthiness. 12 C.F.R. § 1002.6(b)(2)(iii). 12 C.F.R. pt. 1002, suppl. I, § 1002.6(b)(2)-3. Marital status may be used for the limited purpose of ascertaining the creditor’s rights and remedies applicable to the particular extension of credit. See 12 C.F.R. pt. 1002, suppl. I, § 1002.6(b)(8).


See, e.g., Carroll v. Exxon Co., 434 F. Supp. 557, 562-63 (E.D. La. 1977). Sometimes a denial is based on an “automatic-denial-factor,” that is a

See, e.g., Francesca Lina Procaccini, Stemming the Rising Risk of Credit Inequality: The Fair and Faithful Interpretation of the Equal Credit Opportunity Act’s Disparate Impact Prohibition, 9 Harv. L. & Pol’y Rev. S43, S44 (2015) (“Although no court has yet to accept their argument, creditors continue to defend against disparate impact claims by arguing that the text of the ECOA, read in light of recent Supreme Court precedent, compels the conclusion that the ECOA neither prescribes disparate impact discrimination nor permits private plaintiffs to bring disparate impact claims to challenge lending practices that create or perpetuate unequal access to credit.”). The continuing debate over disparate impact is apparent from HUD’s recent proposal to modify its disparate impact rule, and consumer advocates’ opposition to the proposal. 83 Fed. Reg. 42,854 (Aug. 19, 2019); c.f., e.g., National Fair Housing Alliance, NFHA and Other Civil Rights Leaders Fight Trump’s Attempt to Gut Core Civil Rights Protection (Aug. 16, 2019), https://nationalfairhousing.org/2019/08/16/nfha-and-other-civil-rights-leaders-fight-trump%E2%80%99s-attempt-to-gut-core-civil-rights-protection/.


See id. at 2522.

12 C.F.R. pt. 1002, suppl. I, § 1002.6(b). Creditors are permitted to use an applicant’s age as a predictive factor in an empirically derived, demonstrably and statistically sound, credit scoring system so long as applicants age 62 years or older are treated at least as favorably as applicants who are under age 62. 12 C.F.R. § 1002.6(b)(2)(ii). 12 C.F.R. pt. 1002, suppl. I, § 1002.6(b)(2)-1 and -2. In a judgmental system of credit underwriting, a creditor may consider age only for the purpose of determining a pertinent element of creditworthiness. 12 C.F.R. § 1002.6(b)(2)(iii). 12 C.F.R. pt. 1002, suppl. I, § 1002.6(b)(2)-3. Marital status may be used for the limited purpose of ascertaining the creditor’s rights and remedies applicable to the particular extension of credit. See 12 C.F.R. pt. 1002, suppl. I, § 1002.6(b)(8).

Banks generally rely on interagency fair lending guidance that was released in 1994, and endorsed by the CFPB in 2012. See CFPB Bulletin 2012-04 (Fair Lending), Lending Discrimination at 2 (Apr. 18, 2012), https://files.consumerfinance.gov/f/documents/201709_cfpb_upstart-no-action-letter.pdf (stating that the CFPB staff did not intend to recommend initiation of supervisory or enforcement action with respect to ECOA against Upstart, a firm that considers applicant’s educational information including, but not limited to, the school attended and degree obtained, in addition to traditional underwriting factors such as income and credit score).


See, e.g., Francesca Lina Procaccini, Stemming the Rising Risk of Credit Inequality: The Fair and Faithful Interpretation of the Equal Credit Opportunity Act’s Disparate Impact Prohibition, 9 Harv. L. & Pol’y Rev. S43, S44 (2015) (“Although no court has yet to accept their argument, creditors continue to defend against disparate impact claims by arguing that the text of the ECOA, read in light of recent Supreme Court precedent, compels the conclusion that the ECOA neither prescribes disparate impact discrimination nor permits private plaintiffs to bring disparate impact claims to challenge lending practices that create or perpetuate unequal access to credit.”). The continuing debate over disparate impact is apparent from HUD’s recent proposal to modify its disparate impact rule, and consumer advocates’ opposition to the proposal. 83 Fed. Reg. 42,854 (Aug. 19, 2019); c.f., e.g., National Fair Housing Alliance, NFHA and Other Civil Rights Leaders Fight Trump’s Attempt to Gut Core Civil Rights Protection (Aug. 16, 2019), https://nationalfairhousing.org/2019/08/16/nfha-and-other-civil-rights-leaders-fight-trumps-attempt-to-gut-core-civil-rights-protection/.

See id. at 2522.
factor that always results in a denial of credit no matter what else is contained in the application (e.g., minors). Such automatic-denial-factors must always be disclosed as a reason for denial. 12 C.F.R. pt. 1002, suppl. I, § 1002.9(b)(2)-8.

49 12 C.F.R. § 1002.2(p)(1).
50 12 C.F.R. § 1002.2(t).
52 12 C.F.R. § 1002.2(p)(1), (2).
53 12 C.F.R. § 1002.2(p)(2). Some proprietary credit scoring systems incorporate and use FICO® scores and other scoring systems obtained from another person.
58 Model Risk Management Guidance at 2.
59 Id. at 15.
63 12 C.F.R. § 1002.6.
68 15 U.S.C. § 45(a)(1) (UDAAP). Many states have adopted similar laws related to UDAP, which are commonly referred to as “mini-FTC Acts.”
69 15 U.S.C. §§ 45, 57a(a)(1). Under its UDAP rulemaking authority, the FTC’s has promulgated its Credit Practices Rule, codified in 16 C.F.R. part 444. The Rule is applicable to all persons, partnerships, and corporations within the FTC’s jurisdiction, but is not applicable to banks, savings associations, and Federal credit unions. See 15 U.S.C. § 45(a)(2) for the types of entities to which the FTC’s Credit Practices Rule does not apply. The CFPB has authority to enforce the FTC’s Credit Practices Rule to the extent it applies to creditors within the CFPB’s enforcement authority. See Identification of Enforceable Rules and Orders, 76 Fed. Reg. 43,569, 43,571 (July 21, 2011); 12 U.S.C. § 5581(b)(5)(B)(ii).


75 Dodd-Frank Act, tit. X, sec. 1024-1025.


77 Model Risk Management Guidance at 2.


81 See Douglas Merrill, CEO ZestFinance, Testimony to the House Committee on Financial Services AI Task Force (June 26, 2019), https://docs.house.gov/meetings/BA/BA00/20190626/109735/HHRG-116-BA00-Wstate-McWatersR-20190626.pdf.

82 See Carol Evans, Associate Director, Division of Consumer and Community Affairs, the Board of Governors of the Federal Reserve System, Keeping Fintech Fair: Thinking About Fair Lending and UDAP Risks, Consumer Compliance Outlook (Second Issue 2017), https://www.consumercomplianceoutlook.org/2017/second-issue/keeping-fintech-fair-thinking-about-fair-lending-and-udap-risks/ (“Better calibrated models can help creditors make better decisions at a lower cost, enabling them to expand responsible and fair credit access for consumers”).


84 See Financial Stability Board, Artificial intelligence and machine learning in financial services - Market developments and financial stability implications, at 15 (Nov. 1, 2017), https://www.fsb.org/wp-content/uploads/201111.pdf (“Financial institutions can use AI and machine learning tools for a number of operational (or back-office) applications [including] . . . model risk management (back-testing and model validation)”; KPMG, AI / Compliance In Control, Financial services regulatory challenges 7, (2019), https://advisory.kpmg/us/content/dam/advisory/en/pdfs/2019/ai-compliance-in-control.pdf (“AI and automation present opportunities to incorporate digital transformation into compliance challenges including “real-time” compliance risk management and reporting in areas such as...consumer lending. . .AI tools can facilitate faster, more comprehensive, and more accurate monitoring and testing...”); Bart van Liebergen, Machine Learning: A Revolution in Risk Management and Compliance?, Capco Inst. J. Fin. Transformation at 60 (April 2017), https://www.iif.com/portals/0/Files/private/32370132_van_liebergen_-_machine_learning_in_compliance_risk_management.pdf (“the ability of machine learning methods to analyze very large amounts of data, while offering a high granularity and depth of predictive analysis, can improve analytical capabilities across risk management and compliance areas in FIs. Examples are the detection of complex illicit transaction patterns on payment systems and more accurate credit risk modeling”).

85 AI developers are already taking these steps. See, e.g., Jay Budzik, Chief Technology Officer at ZestFinance, Explainable Machine Learning
in Credit, What is it and why you should care, https://www.zestfinance.com/hubs/Underwriting/Explainable-Machine-Learning-in-Credit.pdf?hsLang=en ("ZestFinance’s Automated Machine Learning (ZAML) solution offers unique tools that allow you to benefit from the power of machine learning while meeting the transparency requirements required to ensure your models are safe, fair, and compliant with the law. . . . These same customers produce adverse actions, perform disparate impact analysis, and create model risk management documentation that allows them to remain compliant with ECOA, FCRA, and OCC/Fed guidance for Model Risk Management").

86 12 C.F.R. § 1002.9(a), (b).
89 CFPB, Prepaid Accounts Under the Electronic Fund Transfer Act (Regulation E) and the Truth In Lending Act (Regulation Z), 81 Fed. Reg. 83,934 (Nov. 22, 2016).
91 CFPB, Prepaid Accounts Under the Electronic Fund Transfer Act (Regulation E) and the Truth In Lending Act (Regulation Z), 81 Fed. Reg. 83,934 (Nov. 22, 2016).
92 12 U.S.C. § 5511(a), b(3).
93 See 12 C.F.R. pt. 1002, suppl. I, § 1002.2(p)-4 (noting that an empirically derived credit scoring system may not use any prohibited basis as a variable, aside from age).
94 See Patrice Ficklin & Paul Watkins, An update on credit access and the Bureau’s first No-Action Letter, CFPB Blog (Aug. 6, 2019), https://www.consumerfinance.gov/about-us/blog/update-credit-access-and-no-action-letter/ (reporting that the results of such a test of an AI model compared to a conventional model showed no disparities requiring further fair lending analysis).
96 See 12 C.F.R. § 1002.9(b)(2); 12 C.F.R. pt. 1002, suppl. I § 1002.9(b)(2)-1 (noting that more than four reasons is not likely to be helpful to an applicant).
102 See Model Risk Management Guidance at 15-16.
103 See Dodd-Frank Act, tit. X.