Artificial Intelligence

RECOMMENDATIONS FOR PRINCIPLED MODERNIZATION OF THE REGULATORY FRAMEWORK

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Executive Summary

This report contains recommendations for financial services policymakers for a principled modernization of the regulatory framework to facilitate the responsible use of artificial intelligence in credit underwriting.

Artificial intelligence ("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 can more accurately assess a consumer's creditworthiness using factors (and combinations of factors) 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.[1] 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.[2] 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.[3] 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.[4] For simplicity, this white paper uses the term "AI" to refer to the evaluation of large data sets using machine learning algorithms.

Much of the current regulatory framework was devised well before AI was used to assist credit underwriting. Unsurprisingly, that framework is now outdated in ways that constrain the transformative power of AI. The Bank Policy Institute ("BPI") and the law firm of Covington & Burling LLP ("Covington")[5] have prepared this white paper to:

- explain the regulatory framework that currently applies to the use of AI in credit underwriting;
- identify the ways in which that regulatory framework impedes broad implementation of AI in credit underwriting; and
- provide BPI's recommendations for a regulatory process designed to modernize the regulatory framework in a way that preserves core regulatory principles while removing unnecessary obstacles to the use of AI to improve credit underwriting.

This white paper focuses principally on the regulatory frameworks relating to fair lending and model risk management, as these two areas bear significantly on banks' efforts to implement AI systems in credit underwriting. Although this paper focuses on credit underwriting, the proposed regulatory modernization would also facilitate the use of AI systems in related areas, such as marketing, customer service, and collections.

BPI recommends that the Consumer Financial Protection Bureau ("CFPB") and the federal banking agencies[6] work together to identify obstacles to the responsible use of AI in credit underwriting and

implement a principled modernization of the existing regulatory framework to eliminate those obstacles. To succeed and foster the responsible use of AI in credit underwriting, principled modernization should include each of the following six elements:

- **Coordination.** Principled modernization should involve a coordinated, interagency effort to develop a consistent set of expectations for the use of AI in credit underwriting. Such an effort would promote both consumer protection and the safety and soundness of financial institutions.

- **Preservation of Regulatory Principles.** Principled modernization should preserve critical regulatory principles, such as the prohibition against unlawful discrimination, while critically examining and updating regulatory practices that may unintentionally discourage bank adoption of new technologies.

- **Recognition of the Distinct Features of AI.** Principled modernization should include targeted changes to regulatory practices to take into account the distinct features of AI models and to place AI and traditional models on an equal regulatory footing. Such changes should create substantial flexibility going forward in light of the pace of technological change and the risk that prescriptive changes may have unintended consequences.

- **Level Playing Field.** Principled modernization should create a regulatory framework that applies equally to banks and non-banks. A level playing field gives consumers the broadest possible opportunities to obtain credit and promotes fair treatment of consumers by all creditors.

- **Consistency.** Principled modernization should result in a uniform regulatory framework that is applied consistently by all federal financial regulatory agencies.

- **Transparency.** Principled modernization should yield a regulatory framework that is made wholly transparent through one or more regulatory publications, whether issued jointly or in consultation and coordination among the agencies, so that all stakeholders understand how AI may be used in credit underwriting.

Consistent with the foregoing elements, BPI also recommends that the CFPB and the federal banking agencies follow the principles set forth in the Memorandum issued by the Office of Management and Budget ("OMB") in January 2020 containing proposed Guidance for Regulation of Artificial Intelligence Applications, and submit to OMB plans for achieving consistency with the Guidance.[7] Modernizing existing regulatory approaches as described above would 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 white paper 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 provides recommendations for modernization of the regulatory framework to facilitate

the responsible use of AI in credit underwriting while preserving core regulatory principles and outlines potential regulatory areas that may be candidates for modernization.

I. 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 can 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.[8] 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.[9] 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.[10]

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.[11] Last year, the House Financial Services Committee 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."[12]

AI credit underwriting systems have at least four 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.[13] 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.[14] These new paths to credit can expand access to credit, 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.[15]

The federal banking agencies and the CFPB jointly recognized the benefits of using alternative data in credit underwriting in their Interagency Statement on the Use of Alternative Data in Credit Underwriting, issued in December 2019.[16] The agencies found that the use of alternative data may improve the speed and accuracy of credit decisions, help firms evaluate the creditworthiness of consumers who may not be able to obtain credit in the mainstream credit system, and enable consumers to obtain additional products or more favorable pricing or terms based on enhanced assessments of repayment capacity.[17] Recognizing "alternative data's potential to expand access to credit and produce benefits for consumers," the agencies sought to "encourage responsible use of such data."[18] For example, the agencies pointed to the use of cash flow data that "may present no greater risks than data traditionally used in the credit evaluation process."[19] The Interagency Statement echoes prior CFPB recognition of the benefits of alternative data in filling gaps in credit history, expanding credit access, and lowering borrowing costs.[20]

The CFPB has also spoken directly to the combined potential of using alternative data with AI systems:

> 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.
>
> 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.[21]

Second, AI credit underwriting systems have the potential to be dynamic, meaning they may be 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. The 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.[22] 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 for credit.[23] 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.[24] 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.[25] 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 the 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.[26]

Use of AI in credit underwriting has accelerated in the non-banking financial services sector. However, 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 may unintentionally discourage bank innovation. The hurdles placed before banks matter 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.

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 white paper addresses four types of regulatory frameworks most relevant to credit underwriting by banks: (1) fair lending; (2) model risk management; (3) consumer reporting; and (4) unfair, deceptive, or abusive acts or practices ("UDAAP").[27] 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.[28]

A. FAIR LENDING

ECOA, along with its implementing regulation, Regulation B, is the primary federal law prohibiting discrimination in credit transactions.[29] 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.[30] 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.[31] To prove such disparate treatment, a plaintiff must show that the credit decision was based at least in part on this protected characteristic.[32]

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 FRB to the CFPB.[33] 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.[34] 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.[35] Service providers to these entities are also subject to CFPB examination authority.[36] 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.[37] 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.[38]

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 Department of Housing & Community Affairs v. Inclusive Communities Project, Inc.* ("Inclusive Communities") considered whether disparate impact claims are cognizable under the Fair Housing Act.[39] In a 5-4 decision, Justice Kennedy, writing for the majority, held that disparate impact claims are cognizable under the Fair Housing Act.[40] The four dissenting Justices, led by Justice Alito, would have reached the opposite conclusion.[41]

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,[42] but there also are opposing views on the viability of disparate impact claims under ECOA.[43] The debate regarding disparate impact need not delay modernizing the regulatory framework to adapt to AI credit underwriting systems, and proposals in this white paper 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.[44] 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.[45] 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 testing

of models and their results 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.[46]

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.[47] 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.[48]

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.[49] 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.[50] 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.[51] 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.[52] 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.[53] However, a creditor need not provide a customized description of how or why a factor adversely affected an applicant.[54]

Given the distinct attributes of AI credit underwriting systems, the methods for generating adverse action reasons and the types of reasons produced may 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.C.3 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."[55] For ease of reference, this white paper refers to such a system as 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.[56] 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.[57] Accordingly, banks 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: (1) 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; (2) developed for the purpose of evaluating the creditworthiness of applicants with respect to the legitimate business interests of the creditor utilizing the system; (3) developed and validated using accepted statistical principles and methodology; and (4) periodically revalidated.[58] 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.[59] 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.[60]

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.C.2 below.

2. MODEL RISK MANAGEMENT GUIDANCE

In 2011, the OCC and the FRB issued joint Supervisory Guidance on Model Risk Management ("Model Risk Management Guidance" or the "Guidance").[61] The FDIC subsequently adopted the Guidance in 2017.[62] 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.[63]

The Guidance includes a broad definition of "model" and covers "all aspects of model risk management."[64] 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 and third-party models, but explicitly notes that the process for model risk management of vendor models may be "somewhat modified."[65]

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, in certain circumstances, 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, which has resulted, in these cases, in 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 testing of models, and trend analysis, under consistently applied standards. For a discussion of potential policy concerns and responses, see Section III.C.4 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.[66] 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.[67] 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.[68] 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,[69] 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 proprietary algorithms that underlie the credit scoring systems used to generate credit scores.

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.[70] 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.[71] 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.[72] 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.C.2 below.

D. Unfair, Deceptive, and Abusive Acts or Practices

Sections 1031 and 1036 of Title X of the Dodd-Frank Act prohibit unfair, deceptive or abusive practices ("UDAAP").[73] 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").[74] 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.[75] 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.[76]

An act or practice is unfair if it causes or is likely to cause substantial injury to consumers that consumers cannot reasonably avoid, and the injury is not outweighed by benefits to the consumer or to competition.[77] 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.[78] 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.[79]

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.[80] 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 even when a regulator cannot show credit discrimination under ECOA or Regulation B.

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 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 the 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,[81] and examination authority over both large banks and certain types of non-bank lenders (known as "larger participants").[82] 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.

Regulatory oversight is also 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,"[83] some banks have reported that the Guidance has been applied as if it were a mandatory rule.

III. Principled Modernization

A. The Elements of Principled Modernization

As noted above, BPI recommends that the CFPB and the federal banking agencies undertake an interagency process to evaluate and remove unwarranted regulatory obstacles to the responsible use of AI in credit underwriting. This effort should preserve essential regulatory principles, such as the prevention of unlawful discrimination, while aligning regulatory practices with the technological innovations that are reshaping the landscape of consumer financial services. The resulting framework should encompass, as appropriate, regulations, supervisory guidance, and examination procedures. Such principled modernization will allow for "thoughtfully designed" regulation and supervision that "ensure[s] risks are appropriately mitigated but do[es] not stand in the way of responsible innovations that might expand access and convenience for consumers."[84]

In undertaking such a process of principled modernization, BPI recommends that the CFPB and the federal banking agencies follow the Memorandum issued by the Office of Management and Budget ("OMB") in January 2020 containing proposed Guidance for Regulation of Artificial Intelligence Applications, and submit to OMB plans for achieving consistency with the Guidance.[85]The OMB Memorandum makes clear that fostering innovation and growth of AI requires "reducing unnecessary barriers to the development and deployment of AI" by, among other things, avoiding regulatory actions that "needlessly hamper AI innovation and growth," assessing the effect of potential regulations on AI innovation and growth, and "avoid[ing] a precautionary approach that holds AI systems to such an impossibly high standard that society cannot enjoy their benefits."[86] These guiding principles, along with the ten principles of stewardship of AI applications outlined in the OMB Memorandum, align with the recommendations set out in this white paper.[87]

To succeed, principled modernization in credit underwriting should satisfy each of the following six elements:

- **Coordination.** Principled modernization requires a coordinated, interagency effort to develop a consistent set of expectations for using AI in credit underwriting.[88] These expectations can and should advance both consumer protection and safety and soundness considerations.
    - Interagency coordination among the federal banking agencies and the CFPB is essential because potential obstacles to the use of AI systems in credit underwriting may result from consumer protection regulation, safety and soundness regulation, or both.
    - In particular, the standards for evaluating AI credit underwriting algorithms currently are fragmented between consumer protection standards found in ECOA and safety and soundness standards reflected in the Model Risk Management Guidance. This fragmented approach to model evaluation hinders the adoption of AI credit underwriting systems by banks.

- **Preservation of Regulatory Principles.** Principled modernization should reflect the difference between regulatory principles and regulatory practices. Regulatory principles should abide as technology changes, but regulatory practices can and should evolve to meet new challenges and opportunities.

  - Existing regulatory principles that should be preserved include the prohibition of unlawful credit discrimination, transparency through the provision of reasons for adverse action, and appropriate standards for the development, implementation, and use of credit underwriting models.[89]

  - Existing regulatory practices that should be modernized include updated standards for model risk management and for adverse action reasons that were written before the advent of AI in credit underwriting, and so may pose unintended and unnecessary obstacles to its flexibility and ingenuity.

- **Recognition of the Distinct Features of AI.** Principled modernization should identify and retain those regulatory practices that work well for both AI and traditional credit underwriting models, while expanding or changing other regulatory practices to take into account the distinct features of AI models and place AI and traditional models on an equal regulatory footing.

  - AI involves larger data sets and more complex forms of data analysis than traditional credit underwriting. Moreover, AI models are dynamic, rather than static, and so will grow in sophistication between regulatory reviews. These innovations help drive credit underwriting that is fairer and more accurate, and so should be matched by innovation in the regulatory framework.

  - In adopting targeted changes, preserving flexibility is critical given the pace of technological innovation and the risk that prescriptive changes may have unintended consequences.[90]

- **Level Playing Field.** Principled modernization should result in a regulatory framework that applies equally to banks and non-banks, and so creates a level playing field for banks and non-banks using AI in credit underwriting.

  - Consumers benefit when banks and non-banks have the same opportunity to innovate with AI credit underwriting systems. Without modernization, banks will continue to face intense scrutiny under the Model Risk Management Guidance while non-banks face little or no model risk oversight.

  - As Federal Reserve Governor Lael Brainard has said: "[I]t is important not to drive responsible innovation away from supervised institutions and toward less regulated and more opaque spaces in the financial system."[91]

- **Consistency.** Principled modernization should result in a uniform regulatory framework that is applied consistently by all federal financial regulatory agencies and agency staff.

  - Consistent application of the updated regulatory framework by all of the relevant regulatory

agencies is essential to create a level playing field for banks and non-banks and to give all banks the same opportunities to implement AI systems in credit underwriting, regardless of charter.

  - For example, standards for developing, implementing, and using AI credit underwriting models in a manner designed to prevent unlawful credit discrimination could be developed to apply equally to both bank and non-bank lenders and to recognize that "[m]odels are never perfect"[92] and that with proprietary vendor models, "not all aspects of a model may be fully transparent."[93]

- **Transparency.** Principled modernization requires transparency through regulatory publications, whether issued jointly or in consultation and coordination among the agencies, so that all stakeholders can understand the rules regarding the use of AI systems in credit underwriting.

  - Transparency can take many forms depending upon the issues identified and the solutions best suited to addressing those issues.[94]

  - Options for providing regulatory transparency include: an interagency policy statement regarding the use of AI systems for credit underwriting; revised model risk management guidance; joint federal banking agency-CFPB guidance on AI model evaluation standards for fair lending and safety and soundness purposes; revised examination procedures tailored to AI credit underwriting models; and/or revisions to Regulation B or the model forms. Such changes should be subject to public notice and comment whenever feasible, and to some form of industry and other input in all cases.

Modernizing existing regulatory approaches as described above should 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.

Subsection B describes issues where banks' compliance experience is already being applied to the use of AI in credit underwriting. Subsection C discusses issues where principled modernization may be needed to advance the use of AI in credit underwriting.

B. Building upon Existing Standards

Principled modernization to facilitate the use of AI in credit underwriting does not require writing on a blank slate. In fact, it has been a longstanding regulatory 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. [95] For example, 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.[96]

Given regulators' longstanding partiality toward automated credit underwriting, banks' substantial experience with managing the fair lending risk associated with conventional credit underwriting systems provides them with tools that can be adapted to manage the fair lending risks associated with AI credit underwriting systems.

The fair lending controls already used by banks for conventional credit underwriting systems, including documented programming decisions, monitoring, and periodic testing of models and trend analysis, are already being adapted to AI credit underwriting systems. Banks also understand the critical importance of 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.[97]

Federal financial regulators have recognized that 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.[98] Just as banks are already using AI-based compliance tools to address a range of regulatory compliance issues, AI-based monitoring tools can be used with AI credit underwriting systems to provide enhanced capabilities for testing and model validation, and allow institutions to more easily assess system performance and fair lending compliance.[99]

Substantial progress has already been made in adapting the controls that minimize the potential for unlawful discrimination for conventional underwriting to the use of AI credit underwriting systems. Such controls include modernized versions of steps taken by banks for decades with regard to conventional credit underwriting systems.[100] Specific steps that mitigate the risk of banks or any other creditors using AI credit underwriting systems in a discriminatory manner can include:

- filtering data sets so that AI credit underwriting systems do not consider prohibited bases or known proxies for discrimination;
- identifying and addressing clear indications that data sets are not representative of protected classes;
- 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 narrow geographic areas;
- closely monitoring AI credit underwriting systems to check for potentially discriminatory decision-making or unforeseen outcomes, which may include modern techniques for detection and mitigation of algorithmic bias or conventional human oversight; and
- validating that AI credit underwriting systems are not making decisions on a discriminatory basis by conducting periodic testing of models and their results and trend analysis of those systems, supplemented by file reviews when warranted.

With the help of these or other controls, the goals of fair lending can be advanced by AI credit underwriting systems, which serve to produce better, more predictive decisions and expand access to credit for creditworthy but underserved consumers.[101]

C. Potential Areas for Principled Modernization of the Regulatory Framework

Consumers are best served by regulatory approaches that are not static or rigid, but are sufficiently flexible and adaptable to the emergence of new technologies and new methods of providing financial products and services. With regard to the use of AI in credit underwriting, there are a host of 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 that impede the use of AI were all 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 – including the transition from paper records to a digital and mobile world. In many respects, the disconnect between current regulatory approaches and the use of AI derives from outdated methods of applying existing regulatory standards to AI, rather than from any conflict between the use of AI and long-standing legal standards, regulatory requirements, and policy goals.

As described more fully below, a modernized regulatory framework should account for the use in AI credit underwriting systems of new factors or combinations of factors not currently used in conventional underwriting systems. Regulators 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. Recent CFPB statements about the flexibility of the existing adverse action notice framework are encouraging in this regard.[102] Similarly, a modernized framework should reflect the dynamic, iterative nature of the systems. This will require that regulators think anew about how to devise appropriate methods for developing, testing, and monitoring a different kind of credit underwriting.

In the past, other regulatory frameworks have been modernized to reflect changes in technology and consumer behavior, and so provide a roadmap for updating the regulatory framework to promote the responsible use 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.[103] The CFPB modernized the Regulation E regulatory framework in 2016 to reflect the evolution and widespread adoption of prepaid cards.[104] These rules evolved from targeted provisions focused on government electronic benefit transfer cards and payroll cards.[105] Although the basic Regulation E protections remain in place, and the same policy goals are being served, 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.[106]

The same kind of principled modernization can protect consumers, prevent unlawful discrimination, and promote bank safety and soundness while allowing banks to use AI to improve the efficiency and fairness of credit underwriting. The next section describes some of the steps ahead.

1. COORDINATION AND CONSISTENCY

Interagency coordination and consistency are critical components of principled modernization.[107] The advent of AI credit underwriting systems does not diminish the importance of longstanding policy objectives or require they be sacrificed in order to obtain the benefits of AI. But this use of AI does serve to illustrate the differences in the intensity of regulatory scrutiny between banks and non-banks. The reduced regulatory scrutiny on non-bank credit underwriting models and lending practices has allowed non-bank lenders to jump ahead of banks in adopting AI for credit underwriting. This asymmetry does not serve the policy objectives of current law.

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, would avoid regulatory imbalances. Reducing such imbalances would both benefit competition in the credit markets and provide consistent protections to consumers. Because AI systems implicate both consumer protection and safety and soundness concerns, the creation of such a level playing field requires a coordinated and consistent effort by both the federal banking agencies and the CFPB.

Leadership from the CFPB will be essential to developing a modern regulatory approach for the use of AI in credit underwriting. To begin, the CFPB has a mandate from the Congress 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."[108] Moreover, the CFPB has exclusive rule-writing and interpretive authority over a wide range of federal consumer financial protection laws. Accordingly, the CFPB has the mission and means to modernize many of the rules that raise uncertainty and friction with respect to the use of AI in credit underwriting.

Similarly, 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 in assets. The CFPB is thus uniquely positioned to ensure that its rules are implemented effectively by bank and non-bank lenders alike. This supervisory process can be strengthened by updating CFPB examination manual and examiner training materials to ensure that examiners understand the use of AI in credit underwriting.

The CFPB has additional tools at its disposal here. The CFPB could further regulatory consistency by expanding its larger participant rules to encompass non-bank lenders in additional markets. Such 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. Furthermore, the CFPB is the federal agency best suited to ensure appropriate consumer education about the use of AI in credit underwriting, including helping consumers understand how new types of information may be evaluated to determine creditworthiness.

Consumers will benefit if the CFPB and other federal regulators work together to level the regulatory playing field for AI-based credit underwriting. 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, and 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. Coordination and consistency in the regulation of the use of AI in credit underwriting would promote lending to the benefit of consumers who presently lack access to bank credit.

2. PREVENTING DISCRIMINATION

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 regulatory innovation may be needed. Such changes would be designed to provide regulatory certainty and reduce the litigation and enforcement risk that banks would otherwise face in adopting AI. Such principled modernization could help foster both the regulatory principles of ECOA and the benefits of AI in credit underwriting.

The CFPB, for example, should consider whether the current regulatory framework for ECOA—including its rules, official interpretations, and examination procedures—adequately takes into account 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 new ways to evaluate the creditworthiness of applicants, and so promote financial inclusion. The beneficiaries of this increased access to credit would include underserved borrowers, including young consumers, new immigrants, and consumers with impaired credit histories.

Where possible, 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.[109] 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, identifying and addressing clear indications that data sets are not representative of the whole population, and programming those systems to discourage consideration of prohibited bases. In addition, traditional standards for periodic fair lending testing, model testing and model validation in *ex-post* assessments may continue to make sense for an AI credit underwriting system performance to test for and prevent discriminatory outcomes. Other best practices may 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.[110]

Other aspects of the ECOA regulatory framework may need some adjustment to reflect AI credit underwriting systems. For example, modern techniques for detection and mitigation of algorithmic bias are not a feature of conventional underwriting systems and are not addressed in examination procedures or other supervisory guidance.[111] The CFPB should clarify how these techniques can contribute to: (1) periodically revalidating AI credit underwriting systems; (2) monitoring AI system performance; (3) triggering human intervention and course corrections when monitoring reveals potential discrimination or unforeseen disparate outcomes; and (4) documenting system performance and adjustments for supervisory review. Here too, techniques used to evaluate judgmental overrides in conventional credit

underwriting systems can and should be leveraged and updated to apply to the evaluation of how these modern techniques engage in overrides of AI credit underwriting system outcomes.

In addition, the CFPB should consider clarifying 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.[112] A further discussion of empirically derived credit scoring systems is found below.

A modernized regulatory framework can foster responsible innovation in AI credit underwriting while achieving consistent and high standards of fair lending protection for consumers across all lenders. Consistent standards should help ensure that the use AI credit underwriting systems with appropriate controls, such as modern techniques intended to mitigate algorithm bias and periodic testing, would not immediately raise fair lending or UDAAP concerns if and when an AI credit underwriting system requires course correction.

3. UPDATING ADVERSE ACTION NOTICES

Principled modernization must also address the rules that require a statement of specific reasons for an adverse credit decision in an adverse action notice.

Under Regulation B, creditors must be able to provide up to four specific and accurate reasons for the action taken in connection with providing adverse action notices.[113] This obligation applies to creditors that use AI credit underwriting systems, just as it does to creditors using conventional underwriting systems. The official interpretations of Regulation B outline certain basic methods for identifying the specific reasons for adverse action when using a credit scoring system.[114]

The CFPB's 2019 Fair Lending Report, released in April 2020, provides clarifications regarding adverse action notice. The report states that the regulatory framework "has built-in flexibility that can be compatible with AI algorithms" where, for example, "the variables and key reasons are known, but which may rely upon non-intuitive relationships."[115] The report also notes that a creditor "need not describe how or why a disclosed factor adversely affected an application" or a credit score, and does not mandate the use of "any particular list of reasons."[116] BPI appreciates the CFPB's constructive and timely guidance. BPI believes the CFPB's 2019 Fair Lending Report provides an excellent foundation and building block for additional guidance related to adverse action.

A key challenge for the early adoption of AI credit underwriting systems has involved the ability of such systems to generate the 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. Academic work on AI has led to the development of new methods for explaining AI decisions that vendors of AI credit underwriting systems may use to generate reasons for the action taken.[117]

Building upon its 20190 Fair Lending Report, the CFPB should consider how well these methods

developed for AI models align with the illustrative methods for selecting reasons described in the official interpretations to Regulation B and whether additional methods should be added as examples.[118] The CFPB, for example, might consider whether to supplement the official interpretations to reference the methods used in AI credit underwriting systems for identifying reasons for adverse credit decisions. Here, it is particularly important to maintain the "built-in flexibility" the CFPB has acknowledged exists in ECOA and Regulation B, as research into methods for generating reasons or explanations is ongoing and new methods may evolve as work in this area progresses. Likewise, the CFPB might consider whether these new methods can be used to generate the key factors that adversely affected a credit score produced by an FCRA-regulated AI-based credit scoring system.

With AI credit underwriting systems, the potential reasons for adverse credit decisions are more diverse because AI systems analyze vastly larger data sets than conventional systems. As a result, the sample reasons listed in the Regulation B sample notices, even though non-exhaustive and non-binding, may not reflect the breadth of reasons that may be generated by an AI credit underwriting system.[119] In addition, 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. For these reasons, the adoption of additional sample reasons for adverse action that capture reasons generated by AI models would be useful for both industry and consumers.

The CFPB, therefore, should consider providing an expanded list of sample adverse action reasons in the sample notification forms in Appendix C to Regulation B. These additional reasons should reflect new factors or combinations of factors that may lead to credit denials in AI credit underwriting systems. The reasons for adverse action should remain short and simple, and continue to not require customized explanations that "describe how or why a factor adversely affected" a specific applicant or application.[120] In addition, as new reasons for credit decisions emerge, 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.

4. RECONSIDERING MODEL RISK MANAGEMENT STANDARDS

The federal banking agencies' Model Risk Management Guidance could raise potential impediments to the implementation of AI credit underwriting systems at banks, and the application of that Guidance may magnify those impediments. In some circumstances, the Guidance has reportedly been applied by bank examiners 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.[121]

For the reasons described below, application of the current Model Risk Management Guidance to AI credit underwriting systems could adversely impact banks' ability to deploy and use such systems in a timely manner to meet consumer credit needs and compete with non-bank lenders using AI systems.

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.

Second, the Guidance applies only to banks, not 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,[122] the federal banking agencies reportedly have not consistently granted this flexibility to banks with regard to vendor-developed AI credit underwriting systems. By contrast, the federal banking agencies appear not to require a similar process for 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.

Regulation B and its official interpretations address credit scoring systems—including both AI credit underwriting systems and conventional credit underwriting systems—independent of the Guidance issued by the FRB and OCC. While the federal banking agencies apply the Guidance for safety and soundness purposes, the CFPB through Regulation B evaluates AI credit underwriting systems in terms of consumer protection using the standards for empirically derived credit scoring systems.

To better accommodate the use of AI technology in credit underwriting and facilitate a coordinated and consistent approach to the oversight of consumer lending systems, the federal banking agencies and the CFPB should consider adopting a joint and coordinated approach to model oversight standards for systems used in credit underwriting or otherwise pertinent to consumer financial protection laws, such as AI credit underwriting systems.[123] Such an approach could reflect safety and soundness, fair lending, and consumer protection principles. Joint guidance related to developing, implementing, and using AI credit underwriting models could:

- 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;
- harmonize relevant standards derived from the Guidance with Regulation B standards for empirically derived credit scoring systems for application to AI credit underwriting systems; and
- clarify, among other things, that examiner approval is not required prior to adopting or modifying an AI credit underwriting system.

An interagency standard could promote a level playing field by applying equally to both bank and non-bank lenders and outline the steps that both banks and non-banks are expected to take to review AI credit underwriting systems for purposes of compliance with federal consumer financial protection laws. Any such standard should reflect a recognition that "[m]odels are never perfect,"[124] and that, with proprietary vendor models, "not all aspects of a model may be fully transparent."[125]

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.

5. TRANSPARENCY

The federal banking agencies and the CFPB have a wide range of tools to drive the kinds of incremental changes and sensible approaches to oversight that could further the goals outlined in this white paper. Regulations, official interpretations, examination procedures, and interagency guidance or statements are among the tools available to modernize the regulatory framework. The agencies should use these and other tools to ensure that lenders and borrowers alike understand the rules regarding credit underwriting. A transparent process that actively encourages public participation will best serve the interests of all stakeholders and create public trust in AI credit underwriting systems and the regulatory framework established to provide oversight of those systems.[126] Of course, transparency to consumers is impeded if there are inconsistent rules depending upon the type of credit underwriting system or the lender making the loan.

IV. 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 the federal banking agencies with a unique opportunity to modernize the current regulatory framework to enhance credit underwriting, improve credit access, and level the playing field for all lenders while preserving and enhancing the effectiveness of core regulatory principles of consumer protection, fair lending, and safety and soundness. **BPI looks forward to working collaboratively with its regulatory partners to achieve these shared goals and hopes that the recommendations contained in this white paper will move the process forward.**

ENDNOTES

1. *See* National Institute of Standards and Technology, *U.S. Leadership in AI: A Plan for Federal Engagement in Developing Technical Standards and Related Tools* at 7-8 (Aug. 9, 2019), https://www.nist.gov/system/files/documents/2019/08/10/ai_standards_fedengagement_plan_9aug2019.pdf (noting that "definitions of AI vary"); Executive Office of the President National Science and Technology Council Committee on Technology, *Preparing for the Future of Artificial Intelligence*, at 6 (Oct. 2016), https://obamawhitehouse.archives.gov/sites/default/files/whitehouse_files/microsites/ostp/NSTC/preparing_for_the_future_of_ai.pdf.

2. *See* U.S. Dep't of the Treasury, *A Financial System That Creates Opportunities: Nonbank Financials, Fintech, and Innovation*, at 53 (July 2018), https://home.treasury.gov/sites/default/files/2018-07/A-Financial-System-that-Creates-Economic-Opportunities---Nonbank-Financi....pdf; Financial Stability Board, *Artificial intelligence and machine learning in financial services - Market developments and financial stability implications*, at 4 (Nov. 1, 2017), https://www.fsb.org/wp-content/uploads/P011117.pdf.

3. *See* U.S. Dep't of the Treasury, *A Financial System That Creates Opportunities*, at 53 (July 2018), https://home.treasury.gov/sites/default/files/2018-07/A-Financial-System-that-Creates-Economic-Opportunities---Nonbank-Financi....pdf; Financial Stability Board, *Artificial intelligence and machine learning in financial services - Market developments and financial stability implications*, at 4 (Nov. 1, 2017), https://www.fsb.org/wp-content/uploads/P011117.pdf; Governor Lael Brainard, *What Are We Learning about Artificial Intelligence in Financial Services?*, speech at Fintech and the New Financial Landscape, Philadelphia, Pennsylvania (Nov. 13, 2018), https://www.federalreserve.gov/newsevents/speech/brainard20181113a.htm.

4. *See* Financial Stability Board, *Artificial intelligence and machine learning in financial services - Market developments and financial stability implications*, at 3-4 (Nov. 1, 2017), https://www.fsb.org/wp-content/uploads/P011117.pdf; see also CFPB, *Request for Information Regarding Use of Alternative Data and Modeling Techniques in the Credit Process*, 82 Fed. Reg. 11,183, 11,184 (Feb. 21, 2017), https://www.govinfo.gov/content/pkg/FR-2017-02-21/pdf/2017-03361.pdf ("Alternative data" refers to any data that are not "traditional." We use "alternative" in a descriptive rather than normative sense and recognize there may not be an easily definable line between traditional and alternative data"); U.S. Government Accountability Office, *Financial Technology: Agencies Should Provide Clarification on Lender's Use of Alternative Data*, GAO-19-111 at 33 (Dec. 2018), https://www.gao.gov/assets/700/696149.pdf (". . . alternative data is any information not traditionally used by the three national consumer reporting agencies when calculating a credit score").

5. This white paper 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 and other clients.

6. The federal banking agencies are the Board of Governors of the Federal Reserve System ("FRB"), Federal Deposit Insurance Corporation ("FDIC"), National Credit Union Administration ("NCUA"), and Office of the Comptroller of the Currency ("OCC").

7. Office of Management and Budget, Memorandum for the Heads of Executive Departments and Agencies, *Guidance for Regulation of Artificial Intelligence Applications* (Jan. 7, 2020), https://www.whitehouse.gov/wp-content/uploads/2020/01/Draft-OMB-Memo-on-Regulation-of-AI-1-7-19.pdf (hereafter "*OMB Memorandum*"); *see also* 85 Fed. Reg. 1825 (Jan. 13, 2020) (requesting public comment on the draft Memorandum).

8. *See* Sean Trainor, The Long, Twisted History of Your Credit Score, Time (July 22, 2015), https://time.com/3961676/history-credit-scores/.

9. *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 "scorable" 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 (NCRAs). 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/201505_cfpb_data-point-credit-invisibles.pdf; Kenneth P. Brevoort & Michelle Kambara B*ecoming 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/bcfp_data-point_the-geography-of-credit-invisibility.pdf.

10. Neil Bhutta, Steven Laufer, & 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 expand[ed] 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.

11. *See, e.g.,* Press Release, *Waters Announces Committee Task Forces on Financial Technology and Artificial Intelligence* (May 9, 2019), https://financialservices.house.gov/news/documentsingle.aspx?DocumentID=403738.

12. *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 combatting 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.

13. *See* Executive Office of the President, *Big Data: Seizing Opportunities, Preserving Values* at 2 (May 2014), https://obamawhitehouse.archives.gov/sites/default/files/docs/big_data_privacy_report_may_1_2014.pdf. Big datasets are "large, diverse, complex, longitudinal, and/or distributed datasets generated from instruments, sensors, Internet transactions, email, video, click streams, and/or all other digital sources available today and in the future." *Id.* at 3 (citing National Science Foundation, Solicitation 12-499: *Core Techniques and Technologies for Advancing Big Data Science & Engineering (BIGDATA)*, 2012, http://www.nsf.gov/pubs/2012/nsf12499/nsf12499.pdf).

14. *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/.

15. *See* FTC Report, Big Data – A Tool for Inclusion or Exclusion? Understanding the Issues at 6-7 (Jan. 2016), https://www.ftc.gov/system/files/documents/reports/big-data-tool-inclusion-or-exclusion-understanding-issues/160106big-data-rpt.pdf.

16. FRB, CFPB, FDIC, NCUA, and OCC, *Interagency Statement on the Use of Alternative Data in Credit Underwriting* (Dec. 3, 2019) https://files.consumerfinance.gov/f/documents/cfpb_interagency-statement_alternative-data.pdf.

17. *Id.* at 1.

18. *Id.* at 2.

19. *Id.*

20. CFPB, Press Release, *CFPB Explores Impact of Alternative Data on Credit Access for Consumers Who Are Credit Invisible* (Feb. 16, 2017), https://www.consumerfinance.gov/about-us/newsroom/cfpb-explores-impact-alternative-data-credit-access-consumers-who-are-credit-invisible/. *See also* CFPB, *Request for Information Regarding Use of Alternative Data and Modeling Techniques in the Credit Process*, 82 Fed. Reg. 11,183 (Feb. 21, 2017), https://www.govinfo.gov/content/pkg/FR-2017-02-21/pdf/2017-03361.pdf.

21. 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/.

22. *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).

23. *See* Richard Cordray, *Prepared Remarks of CFPB Director Richard Cordray at the Alternative Data Field Hearing*, Charleston, W. Va. (Feb. 16, 2017), https://www.consumerfinance.gov/about-us/newsroom/prepared-remarks-cfpb-director-richard-cordray-alternative-data-field-hearing/.

24. *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).

25. *See* Sean Trainor, The Long, Twisted History of Your Credit Score, Time (July 22, 2015), https://time.com/3961676/history-credit-scores/.

26. *See* Financial Stability Board, *Artificial intelligence and machine learning in financial services - Market developments and financial stability implications* (Nov. 1, 2017), https://www.fsb.org/wp-content/uploads/P011117.pdf; Brian Browdie, *Can Alternative Data Determine a Borrower's Ability to Repay?*, Am. Banker (Feb. 24, 2015), https://www.americanbanker.com/news/can-alternative-data-determine-a-

borrowers-ability-to-repay.

27. 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.

28. 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.

29. *See* 15 U.S.C. § 1691 *et seq.;* 12 C.F.R. pt. 1002.

30. *See* 15 U.S.C. § 1691(a) 12 C.F.R. § 1002.2(z), .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.

31. 12 C.F.R. pt. 1002, suppl. I, § 1002.4(a)-1, -2.

32. *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).

33. Pub. L. No. 111-203, tit. X, sec. 1085, 124 Stat. 1376 (2010); *see generally* Dodd-Frank Act, tit. X, sec. 1022 and 1061. The one exception is that rulemaking authority over auto dealers did not transfer to the CFPB. Dodd-Frank Act, tit. X, sec. 1029.

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

35. 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.

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

37. 12 C.F.R. pt. 1002, suppl. I , § 1002.6(a)-2; CFPB Bulletin 2012-04 (Fair Lending), *Lending Discrimination* at 1 (Apr. 18, 2012), https://files.consumerfinance.gov/f/201404_cfpb_bulletin_lending_discrimination.pdf ("[T]he CFPB reaffirms that the legal doctrine of disparate impact remains applicable as the Bureau exercises its supervision and enforcement authority to enforce compliance with the ECOA and Regulation B."); *see also* Interagency Task Force on Fair Lending, *Policy Statement on Discrimination in Lending*, 59 Fed. Reg. 18,266 (Apr. 15, 1994), https://www.occ.treas.gov/news-issuances/federal-register/94fr9214.pdf (policy statement from all of the federal banking agencies).

38. See 12 C.F.R. pt. 1002, suppl. I, § 1002.6(a)-2; Interagency Task Force on Fair Lending, Policy Statement on Discrimination in Lending, 59 Fed. Reg. 18,266 (Apr. 15, 1994), https://www.occ.treas.gov/news-issuances/federal-register/94fr9214.pdf.

39. 576 U.S. ___, 135 S. Ct. 2507, 2523 (2015). Subsequent to *Inclusive Communities*, the Department of Housing and Urban Development ("HUD") announced that it was reconsidering the disparate impact standard under its Fair Housing Act rules. HUD published an advance notice of proposed rulemaking in June 2018 soliciting comments on the disparate impact standard set forth in HUD's 2013 final rule and issued a proposed rule in August 2019. 83 Fed. Reg. 42,854 (Aug. 19, 2019); *see generally* 24 C.F.R.

§ 100.500; 78 Fed. Reg. 11,460 (Feb. 15, 2013).

40. *See* Inclusive Communities, 576 U.S. ___, 135 S. Ct. at 2523.

41. *See id.* at 2522.

42. *See, e.g., Garcia v. Country Wide Fin. Corp.,* No. EDCV 07-1161-VAP, 2008 WL 7842104, at *3 (C.D. Cal. Jan. 17, 2008) ("A plaintiff can establish an ECOA claim under a theory of disparate treatment or disparate impact."); *Golden v. City of Columbus*, 404 F.3d 950, 963 (6th Cir. 2005) (observing that "it appears" that disparate impact claims are permissible under ECOA); *Miller v. American Express Co.,* 688 F.2d 1235, 1240 (9th Cir. 1982) (holding that ECOA permits disparate impact liability); *Haynes v. Bank of Wedowee,* 634 F.2d 266, 269 n.5 (5th Cir. 1981) ("ECOA regulations endorse use of the disparate impact test to establish discrimination").

43. *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 proscribes 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 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/.

44. 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* FTC Report, *Big Data – A Tool for Inclusion or Exclusion? Understanding the Issues* at 6 (Jan. 2016), https://www.ftc.gov/system/files/documents/reports/big-data-tool-inclusion-or-exclusion-understanding-issues/160106big-data-rpt.pdf (noting that LexisNexis created an alternative credit score called RiskView that considers educational history, professional licensure data, and personal property ownership data, among other things); *see also* CFPB, No-Action Letter to Upstart Network, Inc. (Sept. 14, 2016), 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).

45. 12 C.F.R. § 1002.6(b). *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).

46. 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/201404_cfpb_bulletin_lending_discrimination.pdf (concurring with Interagency Task Force on Fair Lending, *Policy Statement on Discrimination in Lending*, 59 Fed. Reg. 18,266 (Apr. 15, 1994), https://www.occ.treas.gov/news-issuances/federal-register/94fr9214.pdf). National banks also rely on OCC Bulletin 1997-24, *Credit Scoring Models: Examination Guidance* (May 20, 1997), https://www.occ.treas.gov/news-issuances/bulletins/1997/bulletin-1997-24.html.

47. 15 U.S.C. § 1691(d)(1); 12 C.F.R. § 1002.9(a)(1)(i).

48. 12 C.F.R. § 1002.9(a), (b).

49. 12 C.F.R. pt. 1002, suppl. I, § 1002.9(b)(2)-4, -6.

50. 12 C.F.R. pt. 1002, suppl. I, § 1002.9(b)(2)-4.

51. 12 C.F.R. pt. 1002, suppl. I, § 1002.9(b)(2)-4.

52. 12 C.F.R. pt. 1002, suppl. I, § 1002.9(b)(2)-5 (describing two methods for identifying factors that fall furthest below average scores for those factors).

53. *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 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.

54. 12 C.F.R. pt. 1002, suppl. I, § 1002.9(b)(2)-3.

55. 12 C.F.R. § 1002.2(p)(1).

56. 12 C.F.R. § 1002.2(t).

57. 12 C.F.R. pt. 1002, suppl. I, § 1002.2(p)-4.

58. 12 C.F.R. § 1002.2(p)(1), (2).

59. 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.

60. 12 C.F.R. pt. 1002, suppl. I, § 1002.2(p)-2 (periodic revalidation) and -4 (use of third-party data for development).

61. FRB, SR 11-7, *Supervisory Guidance on Model Risk Management* (Apr. 4, 2011), https://www.federalreserve.gov/supervisionreg/srletters/sr1107a1.pdf; OCC, Bulletin 2011-12, *Supervisory Guidance on Model Risk Management* (Apr. 4, 2011), https://occ.gov/news-issuances/bulletins/2011/bulletin-2011-12a.pdf.

62. FDIC, FIL-22-2017, *Adoption of Supervisory Guidance on Model Risk Management* (June 7, 2017), https://www.fdic.gov/news/news/financial/2017/fil17022.pdf.

63. *See* Governor Lael Brainard, *What Are We Learning about Artificial Intelligence in Financial Services?* at 5, speech at Fintech and the New Financial Landscape, Philadelphia, Pennsylvania (Nov. 13, 2018), https://www.federalreserve.gov/newsevents/speech/brainard20181113a.htm.

64. Model Risk Management Guidance at 2.

65. Id. at 15.

66. 15 U.S.C. § 1681 *et seq.*

67. Dodd-Frank Act, tit. X, sec. 1088.

68. See 15 U.S.C. § 1681g(f)(2); FTC, *40 Years of Experience with the Fair Credit Reporting Act: An FTC Staff Report with Summary of Interpretations* at 21 (July 2011), https://www.ftc.gov/sites/default/files/documents/reports/40-years-experience-fair-credit-reporting-act-ftc-staff-report-summary-interpretations/110720fcrareport.pdf.

69. 12 C.F.R. § 1002.6.

70. 15 U.S.C. § 1681m(a).

71. 15 U.S.C. §§ 1681g(f)(1)(C), 1681g(f)(2)(B), 1681m(a)(2)(B).

72. See FICO web site, Product Details, Product Architecture, https://www.fico.com/en/products/fico-score (last visited Sept. 4, 2019).

73. 12 U.S.C. §§ 5331, 5536.

74. 15 U.S.C. § 45(a)(1) (UDAP). Many states have adopted similar laws related to UDAP, which are commonly referred to as "mini-FTC Acts."

75. 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).

76. See FRB, CFPB, FDIC, NCUA, OCC, *Interagency Guidance Regarding Unfair or Deceptive Credit Practices* (Aug. 22, 2014), https://www.occ.gov/news-issuances/bulletins/2014/bulletin-2014-42a.pdf.

77. See Dodd-Frank Act, tit. X, sec. 1031(c); CFPB Supervision and Examination Manual, V.2, UDAAP 1-UDAAP 5 (Oct. 2012), https://files.consumerfinance.gov/f/201210_cfpb_supervision-and-examination-manual-v2.pdf; CFPB Bulletin 2013-07, *Prohibition of Unfair, Deceptive, or Abusive Acts or Practices in the Collection of Consumer Debts* (July 10, 2013), https://files.consumerfinance.gov/f/201307_cfpb_bulletin_unfair-deceptive-abusive-practices.pdf; OCC, Advisory Letter, AL 2002-3, *Guidance on Unfair or Deceptive Acts or Practices* (Mar. 22, 2002), https://www.occ.gov/news-issuances/advisory-letters/2002/advisory-letter-2002-3.pdf; FTC, *Policy Statement on Unfairness* (Dec. 17, 1980), https://www.ftc.gov/public-statements/1980/12/ftc-policy-statement-unfairness.

78. See CFPB Supervision and Examination Manual, V.2, UDAAP 5-UDAAP 8, (Oct. 2012), https://files.consumerfinance.gov/f/201210_cfpb_supervision-and-examination-manual-v2.pdf; CFPB Bulletin 2013-07, *Prohibition of Unfair, Deceptive, or Abusive Acts or Practices in the Collection of Consumer Debts* (July 10, 2013), https://files.consumerfinance.gov/f/201307_cfpb_bulletin_unfair-deceptive-abusive-practices.pdf; OCC, Advisory Letter, AL 2002-3, *Guidance on Unfair or Deceptive Acts or Practices* (Mar. 22, 2002), https://www.occ.gov/news-issuances/advisory-letters/2002/advisory-

letter-2002-3.pdf; FTC, *Policy Statement on Deception* (Oct. 14, 1983), https://www.ftc.gov/system/files/documents/public_statements/410531/831014deceptionstmt.pdf.

79. 12 U.S.C. § 5531(d)(2). An abusive act or practice may also materially interfere with a consumer's ability to understand a term or condition of a consumer financial product or service. 12 U.S.C. § 5531(d)(1). *See also* CFPB Supervision and Examination Manual, V.2, UDAAP 9 (Oct. 2012), https://files.consumerfinance.gov/f/201210_cfpb_supervision-and-examination-manual-v2.pdf; CFPB Bulletin 2013-07, *Prohibition of Unfair, Deceptive, or Abusive Acts or Practices in the Collection of Consumer Debts* (July 10, 2013), https://files.consumerfinance.gov/f/201307_cfpb_bulletin_unfair-deceptive-abusive-practices.pdf.

80. CFPB Supervision and Examination Manual, V.2, UDAAP 10 (Oct. 2012), https://files.consumerfinance.gov/f/201210_cfpb_supervision-and-examination-manual-v2.pdf.

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

82. Dodd-Frank Act, tit. X, sec. 1024-25; 12 C.F.R. § 1090.

83. Model Risk Management Guidance at 2.

84. Governor Lael Brainard, *What Are We Learning about Artificial Intelligence in Financial Services?* at 4, speech at Fintech and the New Financial Landscape, Philadelphia, Pennsylvania (Nov. 13, 2018), https://www.federalreserve.gov/newsevents/speech/brainard20181113a.htm.

85. Office of Management and Budget, Memorandum for the Heads of Executive Departments and Agencies, *Guidance for Regulation of Artificial Intelligence Applications* (Jan. 7, 2020), https://www.whitehouse.gov/wp-content/uploads/2020/01/Draft-OMB-Memo-on-Regulation-of-AI-1-7-19.pdf (hereafter "OMB Memorandum").

86. *OMB Memorandum* at 2.

87. The ten principles of stewardship for AI applications are: (1) public trust in AI; (2) public participation; (3) scientific integrity and information quality; (4) risk assessment and management; (5) benefits and costs; (6) flexibility; (7) fairness and non-discrimination; (8) disclosure and transparency; (9) safety and security; and (10) interagency coordination. *Id.* at 2-6.

88. *Id.* at 6 (citing interagency coordination as a principle for AI regulation).

89. *Id.* at 5-6 (citing fairness and non-discrimination and disclosure and transparency as principles for AI regulation).

90. *Id.* at 5 (citing flexibility and the ability to adapt to rapid changes to AI applications as a principle for AI regulation).

91. Governor Lael Brainard, *What Are We Learning about Artificial Intelligence in Financial Services?* at 4-5, speech at Fintech and the New Financial Landscape, Philadelphia, Pennsylvania (Nov. 13, 2018), https://www.federalreserve.gov/newsevents/speech/brainard20181113a.htm.

92. Model Risk Management Guidance at 3.

93. Governor Lael Brainard, *What Are We Learning about Artificial Intelligence in Financial Services?* at 6, speech at Fintech and the New Financial Landscape, Philadelphia, Pennsylvania (Nov. 13, 2018), https://www.federalreserve.gov/newsevents/speech/brainard20181113a.htm.

94. *OMB Memorandum* at 3 (citing public trust in AI and public participation in regulatory actions as principles for AI regulation).

95. *See, e.g.,* Federal Reserve Bank of St. Louis, *How Mortgage Lenders Are Using Automated Credit Scoring* (Jan. 1, 1998), https://www.stlouisfed.org/publications/bridges/winter-1998/how-mortgage-lenders-are-using-automated-credit-scoring (citing "more objective and consistent decisions" as one of the benefits of an automated credit scoring system); OCC Bulletin 1997-24, *Credit Scoring Models: Examination Guidance* at 6 (May 20, 1997), https://www.occ.treas.gov/news-issuances/bulletins/1997/bulletin-1997-24.html (stating the OCC's concerns that an excessive level of overrides negates the use of scoring models, and should be used with considerable caution if the scoring model properly reflects the bank's risk parameters). *See also* Doug Peterson, Moody's Analytics, Whitepaper, *Maximize Efficiency: How Automation Can Improve Your Loan Origination Process* at 2 (Dec. 2017), https://www.moodysanalytics.com/articles/2018/maximize-efficiency-how-automation-can-improve-your-loan-origination-process ("Manual and paper-based underwriting practices lack consistency, auditability, and accuracy, and are above all, time consuming. Automation can allow for the streamlining of disparate systems, provide reliable and consistent dataflow for any stage of the loan origination process and quicken the overall process, while delivering solid audit and control benefits").

96. *See* Hud.Gov, FHA TOTAL, https://www.hud.gov/program_offices/housing/sfh/total (last visited Sept. 4, 2019); FHA Single Family Housing Policy Handbook, Handbook 4000.1 at 177, https://www.hud.gov/sites/documents/40001HSGH.PDF#page=179.

97. *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").

98. *See* Financial Stability Board, *Artificial intelligence and machine learning in financial services - Market developments and financial stability implications*, at 1 (Nov. 1, 2017), https://www.fsb.org/wp-content/uploads/P011117.pdf (noting that use cases for AI and machine learning by regulated institutions include regulatory compliance and observing that "applications of AI and machine learning can help improve regulatory compliance and increase supervisory effectiveness"); FRB, FDIC, Financial Crimes Enforcement Network, NCUA, OCC, *Joint Statement on Innovative Efforts to Combat Money Laundering and Terrorist Financing* at 2 (Dec. 3, 2018), https://www.fincen.gov/sites/default/files/2018-12/Joint%20Statement%20on%20Innovation%20Statement%20%28Final%2011-30-18%29.pdf (recognizing the benefits of banks using AI to "strengthen BSA/AML compliance approaches, as well as enhance transaction monitoring systems. The Agencies welcome these types of innovative approaches to further efforts to protect the financial system against illicit financial activity").

99. *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/P011117.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").

100. See, e.g., Jay Budzik, Zest AI Blog, *Explainable Machine Learning in Credit, What is it and why you should care*, https://www.zest.ai/article/explainable-ml-credit-blog ("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").

101. 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").

102. CFPB, *Fair Lending Report of the Bureau of Consumer Financial Protection*, April 2020, 85 Fed. Reg. 27395, 27396-97 (May 8 2020) (hereafter "*CFPB 2019 Fair Lending Report*") (noting that the existing adverse action notice regulatory framework "has built-in flexibility that can be compatible with AI algorithms").

103. 15 U.S.C. § 1693 *et seq.;* 12 C.F.R. pt. 1005.

104. 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).

105. See 12 C.F.R. § 1005.2(b), .15, .18; 59 Fed. Reg. 10,678 (Mar. 7, 1994) (adding provision covering government electronic benefit transfers); 71 Fed. Reg. 51,437 (Aug. 30, 2006) (adding provision covering payroll cards).

106. 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).

107. See OMB Memorandum at 6.

108. 12 U.S.C. § 5511(a), b(3).

109. 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).

110. 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).

111. Such modern techniques may include AI Fairness Toolkits, such as the following: https://aif360.mybluemix.net/.

112. See 12 C.F.R. pt. 1002, suppl. I, § 1002.2(p)-2.

113. 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).

114. 12 C.F.R. pt. 1002, suppl. I, § 1002.9(b)(2)-5.

115. CFPB 2019 Fair Lending Report, 85 Fed. Reg. at 27396-97.

116. Id.

117. See, e.g., Jay Budzik, Zest AI Blog, *Explainable Machine Learning in Credit, What is it and why you should care*, https://www.zest.ai/article/explainable-ml-credit-blog; Bob Birmingham, *3 Questions Compliance Pros Have To Ask Before Adopting Machine Learning In Underwriting*, Zest AI Blog (June 1, 2018), https://zest.ai/article/3-questions-compliance-pros-have-to-ask-before-adopting-machine-learning-in-underwriting; Mukund Sundararajan, Ankur Taly, & Qiqi Yan, *Axiomatic Attribution for Deep Networks* (June 13, 2017), https://arxiv.org/pdf/1703.01365.pdf; Fiddler.ai Blog, 2nd *Explainable AI Summit* (2019), https://blog.fiddler.ai/; Github Blog, https://github.com/slundberg/shap/issues/624.

118. See 12 C.F.R. pt. 1002, suppl. I § 1002.9(b)(2)-5 (describing two methods for identifying factors that fall furthest below average scores for those factors).

119. See 12 C.F.R. pt. 1002, App. C.

120. 12 C.F.R. pt. 1002, suppl. I, § 1002.9(b)(2)-3; 12 C.F.R. pt. 1002, App. C.

121. See Testimony of William J. Fox, Managing Director, Global Head of Financial Crimes Compliance, Bank of America, on behalf of The Clearing House, Before the U.S. House Financial Services Subcommittees on Financial Institutions and Consumer Credit and Terrorism and Illicit Finance, At the Hearing Legislative Proposals to Counter Terrorism and Illicit Finance at 9 (Nov. 29, 2017), https://financialservices.house.gov/uploadedfiles/11.29.2017_william_j._fox_testimony.pdf.

122. See Model Risk Management Guidance at 15-16.

123. See Dodd-Frank Act, tit. X.

124. Model Risk Management Guidance at 3.

125. Governor Lael Brainard, *What Are We Learning about Artificial Intelligence in Financial Services?* at 6, speech at Fintech and the New Financial Landscape, Philadelphia, Pennsylvania (Nov. 13, 2018), https://www.federalreserve.gov/newsevents/speech/brainard20181113a.htm.

126. See OMB Memorandum at 3.