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Supervisory Highlights: Advanced Technologies Special Edition

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1. Introduction

There is no "advanced technology" exception to Federal consumer financial laws.[1] Financial institutions are under an obligation to comply with these laws when using advanced computational methods, including artificial intelligence and machine learning (AI/ML), the same as if they used more traditional methods.

As part of its work to ensure that institutions using advanced technologies do not violate Federal consumer financial law, the Consumer Financial Protection Bureau (CFPB) launched a Technologist Program centered around the recognition that interdisciplinary teams—including data scientists, design experts, product managers, software engineers, and others—are critical to enhancing our work to protect consumers.[2] CFPB's technologists collaborate across the CFPB, including with our supervisory teams. Just as customer service call recordings and written customer service manuals are critical to understanding scripts and business processes are applied in real time, CFPB interdisciplinary teams work together to analyze data and test models to understand how they perform in practice.[3]

Through this collaboration between technologists, examiners, attorneys, and economists, the CFPB is well equipped to comprehensively review the entire credit decisioning process, including whether an entity's use of complex credit underwriting models complies with relevant laws. For example, as described below, in some exams, CFPB's interdisciplinary team identified potential alternative credit models that appear able to meaningfully reduce prohibited basis disparities while maintaining comparable predictive accuracy to the models the creditors used. As described below, to ensure compliance with Federal consumer financial law, including the Equal Credit Opportunity Act (ECOA)[4] examiners have directed institutions to consider a range of less discriminatory models, where appropriate, and implement them to address the risk of unlawful discrimination. This has included, for example, consideration of alternative models generated through automated testing.

[1] *CFPB and Federal partners confirm automated systems and advanced technology not an excuse for lawbreaking behavior,* April 25, 2023, is available at: cfpb_joint-statement-enforcement-against-discrimination-bias-automated-systems_2023-04.pdf

[2] *Technologist wanted*, July 7, 2022, is available at: https://www.consumerfinance.gov/about-us/blog/technologists-wanted/

[3] *Supervisory Highlights*, Issue 28, Fall 2022, is available at: cfpb_supervisory-highlights_issue-28_2022-11.pdf

[4] 15 U.S.C. §§ 1691-1691*f*.

This edition of *Supervisory Highlights* concerns select examinations of institutions that use credit scoring models, including models built with advanced technology commonly marketed as AI/ML technology, when making credit decisions. To maintain the anonymity of the supervised institutions discussed in *Supervisory Highlights*, references to institutions generally are in the plural and related findings may pertain to one or more institutions.[5] We invite readers with questions or comments about Supervisory Highlights to contact us at CFPB_Supervision@cfpb.gov.

[5] If a supervisory matter is referred to the Office of Enforcement, Enforcement may cite additional violations based on these facts or uncover additional information that could impact the conclusion as to what violations may exist.

2. Supervisory Observations

2.1 Credit scoring models and compliance with ECOA

The CFPB's fair lending supervision program includes assessing whether a supervised institution's use of credit scoring models complies with ECOA and its implementing Regulation B.[6] ECOA prohibits a creditor from discriminating against any applicant, with respect to any aspect of a credit transaction, on the basis of race, color, religion, national origin, sex (including sexual orientation and gender identity), marital status, or age (provided the applicant has the capacity to contract), because all or part of the applicant's income derives from any public assistance program, or because the applicant has in good faith exercised any right under the Consumer Credit Protection Act.[7] ECOA and Regulation B also require a creditor to provide a statement of specific reasons in writing to applicants against whom adverse action is taken.[8]

Firms increasingly understand the importance of fair lending testing that is comprehensive and commensurate with the entity's size and risk profile, whether lenders use credit scoring models developed with traditional approaches or more advanced computational methods, including technology marketed as AI or ML. The findings summarized below illustrate the importance of this testing, both when evaluating models for disparate treatment (such as whether models use prohibited basis variables or variables that may be proxies for prohibited bases) and when assessing models for disparate impact and searching for and implementing less discriminatory alternatives. In response to the circumstances summarized below, examiners directed entities to conduct searches that were comprehensive and commensurate with the entity's size and risk profile to identify models with less discriminatory impact that met the lender's legitimate business needs. This included, for example, the direction to consider alternative models generated through automated testing.

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[6] 12 C.F.R. pt. 1002.

[7] 15 U.S.C. § 1691(a).

[8] 15 U.S.C. § 1691(d)(2)(A), (B); *see also* 15 U.S.C. § 1691(d)(3); 12 C.F.R. § 1002.9. A creditor may either provide the notice or follow certain requirements to inform consumers on how to obtain such notice. 15 U.S.C. § 1691(d)(2)(B).

2.1.1 Credit card lenders' use of complex credit scoring models

In recent examinations of credit card lenders, Supervision assessed compliance with ECOA and Regulation B with respect to credit card originations. The examiners reviewed the lenders' use of credit scoring models in the underwriting and pricing of credit card applications, including models built with AI or ML technology. The exam teams found disparities in underwriting and pricing outcomes for Black or African American and Hispanic applicants, as well as deficient compliance management systems. Examiners directed the institutions to increase the rigor of testing protocols in several ways, including by using compliance tools that are commensurate with the entity's size, complexity, and risk profile to search for less discriminatory alterative credit models.

The exam teams conducted statistical analyses of the institutions' underwriting and pricing practices and found disproportionately negative outcomes for Black or African American and Hispanic applicants when compared to white applicants. Certain credit scoring models contributed to disparities in multiple card products, particularly for Black and African American applicants. The exam team's analysis suggested that the way the institutions developed or implemented their credit scoring models contributed to some of those disparities.

In response to these findings, the exam teams identified potential alternative models to the institutions' credit scoring models using open-source automated debiasing methodologies. These alternative models used the same credit strategy, machine learning algorithm, and external configuration variables as the institutions' models. For most of the credit scoring models reviewed, the exam team identified potential alternative models that appeared able to meaningfully reduce disparities while maintaining comparable predictive performance as the institutions' original models.

As this work suggested there may be appropriate less discriminatory alternative models that would meet the institutions' legitimate business needs, the exam teams directed the institutions to search for less discriminatory alternatives to the credit scoring models that produced prohibited-basis disparities. Examiners directed that searches include using methods capable of meaningfully assessing and adjusting their models to identify and evaluate potential less discriminatory alternatives to meet the documented legitimate business needs associated with use of the specific model.

Examiners also found that the institutions maintained deficient fair lending compliance management systems, including with respect to the institutions' use of complex credit scoring models for credit card originations. The institutions did not maintain fair lending controls capable of evaluating and addressing the risks associated with their credit scoring models to ensure compliance with ECOA and Regulation B. Examiners found that, when training, developing, and monitoring the credit scoring models, the institutions did not conduct adequate searches for less discriminatory alternatives. The institutions did not use compliance tools and alternatives testing techniques commensurate with the size, scope, and sophistication of their lending portfolios to identify potential alternative models that could meet the institutions' legitimate business needs.

In response to these findings, examiners directed the institutions to enhance their fair lending compliance management systems relating to testing and approving credit scoring models in several ways. For example, examiners directed the institutions to test such models for prohibited basis disparities and, when that testing revealed prohibited basis disparities, to document the specific business needs their credit scoring models serve. Examiners also directed the institutions to document how the institutions assess those disparities against the stated business needs and to establish and document the specific standards or benchmarks for assessing whether those models serve each stated business needs.

To facilitate compliance with ECOA and Regulation B, examiners also directed the institutions to develop a process for considering a range of less discriminatory models when a model produces prohibited basis disparities (for example, alternative models generated through automated testing). The methods for searching for these less discriminatory alternatives should be commensurate with the complexity of the model for which potential less discriminatory alternatives are sought. Examiners directed the institutions to document whether alternatives could reasonably meet the institutions' specific business needs with less discriminatory effects, and document the development, testing, and, when appropriate, implementation of less discriminatory alternatives. So, for example, if the institution considered accuracy in predicting default to be a business need the model meets, the institution should measure and document how potential less discriminatory alternative models affected the accuracy of the model, and document why the institution decided to use particular models.

These institutions have begun implementing these directives, including by developing processes for searching for less discriminatory alternative models.

2.1.2 Auto lenders' credit scoring models

In recent examinations at auto lenders, Supervision assessed compliance with ECOA and Regulation B with respect to the use of credit scoring models, including those built using AI/ML technology. Examiners found that the institutions used credit scoring models that, in some cases, used more than a thousand input variables, including many not traditionally used in credit scoring that may be considered “alternative data.”[9] As explained in an Interagency Statement on the Use of Alternative Data in Credit Underwriting, data not directly related to consumers’ finances and how consumers manage their financial commitments may present great consumer protection risks and warrant more robust compliance management.[10]

Examiners identified risks associated with the use of such a large number of input variables, including difficulties in being able to effectively monitor whether any variables, individually or in combination, acted as a proxy for prohibited bases under ECOA. For example, examiners found that institutions did not have a process for ensuring adequate review of input variables for fair lending risks before those variables were selected as model inputs.

Additionally, when evaluating models for disparate impact, institutions did not meaningfully identify and consider comparably accurate inputs with less discriminatory effects, nor did they adequately document the business need for the model inputs the institutions identified as contributing to prohibited basis disparities. For example, institutions lacked evidence of clear business justifications for using inputs that they had identified as being most predictive of prohibited bases or for considering alternatives with less discriminatory effects. In practice, the institutions used model inputs where their analysis identified any purported contribution to the accuracy of the model without requiring an assessment of whether and how much the variable contributed to accuracy, and without documentation of the business justifications for the model input variables. Thus, the institutions retained some model inputs even where the inputs may have been predictive of prohibited characteristics without considering alternatives that may meet accuracy requirements with less potentially discriminatory effects.

To address these findings, examiners directed institutions to comprehensively address the process for building, testing, and approving credit scoring models. The institutions also were directed to review the input variables before using those variables in models, including assessing the variable’s relationship to the creditworthiness of applicants and whether the variable may operate as a proxy for prohibited bases under ECOA. Examiners also directed the institutions to review the institution’s credit scoring models, including assessing whether there are less discriminatory alternatives that meet the institutions’ documented business needs.

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[9] *Interagency Statement on the Use of Alternative Data in Credit Underwriting*, December 13, 2019 is available at: cfpb_interagency-statement_alternative-data.pdf

[10] *Id.*

Institutions have provided proposed updated policies and procedures in response to this direction, which the exam teams are reviewing.

2.1.3 Auto lenders' adverse action notices

As the CFPB explained in recent circulars,[11] ECOA and Regulation B require creditors to provide an applicant with a statement of specific reason(s) for an adverse action and these reasons must "*accurately* describe the factors *actually* considered or scored by a creditor."[12] Some creditors may make credit decisions based on certain complex algorithms, sometimes referred to as "black-box" models, that make it difficult—if not impossible—to accurately identify the specific reasons for denying credit or taking other adverse actions. While some creditors may rely on post-hoc explanation methods to identify reasons for an adverse action, the creditors still must be able to validate the accuracy of those methods.[13] In other words, creditors cannot justify noncompliance with ECOA and Regulation B because the technology it uses is too complicated or opaque to understand.[14]

In recent examinations of auto loan originators, Supervision assessed compliance with ECOA and Regulation B requirements regarding adverse action notices. Examiners assessed institutions' use of certain credit scoring models built using AI/ML technology, including models that in some cases used more than a thousand variables. Examiners found that the institutions did not sufficiently ensure compliance with adverse action notice requirements, including how they selected the reasons given in adverse action notices when the adverse action was based on the model score. Examiners also found that the institutions had not validated that their processes for selecting reasons produced accurate results.

To address these findings, examiners directed the institutions to, among other things, test and validate the methodologies used to identify principal reasons in adverse action notices.

In response to these findings institutions have updated their policies and procedures regarding identifying adverse action reasons when the credit decision is based, at least in part, on a model

[11] *Consumer Financial Protection Circular 2022-03, Adverse action notification requirements in connection with credit decisions based on complex algorithms*, May 26, 2022; available at: cfpb_2022-03_circular_2022-05.pdf *Consumer Financial Protection Circular 2023-03, Adverse action notification requirements and the proper use of the CFPB's sample forms provided in Regulation B*, Sept. 19, 2023, available at: cfpb_adverse_action_notice_circular_2023-09.pdf

[12] 12 C.F.R. Part 1002 (Supp. I), sec. 1002.9, para. 9(b)(2)-2 (emphasis added).

[13] See: Circular 2022-03, at footnote 1.

[14] See: Circular 2022-03.

score. The institutions also have provided reports documenting their efforts to validate the methodologies used to select adverse action reasons, which the exam team is reviewing.