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# Fair Lending and UDAAP Issues in Credit and Marketing Models

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Credit and marketing models are integral to lenders' businesses but they create challenges for complying with laws governing fair lending and unfair, deceptive, or abusive acts or practices ("UDAAPs"). Two economists and two lawyers spoke about these issues at the January 2016 CFSC Winter Meeting during a panel moderated by Brad Blower, VP, Principal Compliance Leader, Consumer Practices at American Express and Chair of the Fair Access to Financial Services Subcommittee.

Joining Brad on the panel were Marsha Courchane, VP and Practice Leader at Charles River Associates; Bryce Stephens, Section Chief, Compliance Analytics and Policy at the CFPB; Eric Sublett, Associate at Relman, Dane & Colfax; and Karen Barnes, Director and Senior Counsel at Discover Financial Services. This article provides a synopsis of the issues discussed, although it does not attribute any specific point to a particular panelist. To hear from the speakers themselves, I encourage you to listen to the recording posted on the committee's website.

An overarching theme of the panel, as is the case in so many fair lending discussions, was how to design and monitor marketing and credit models in a way that expands access to credit without having a disparate impact on protected classes. For background, marketing models identify potential customers, while credit models predict applicants' risk of default. To manage the risks that models will be found to discriminate against protected classes or treat consumers in a manner that could be a UDAAP, lenders must make strategic decisions about which variables to include in models and about how and when to conduct UDAAP and fair lending testing and analysis.

## Model Construction: Challenges with Big Data, Machine Learning and Third-Party Vendors

Lawyers and statisticians face relatively new challenges from the use of alternative data sources as well as from the advanced computer programming techniques used to model such data.

Alternative or non-traditional data—for example, data derived from a consumer's online behavior—can expand access to credit by providing insights into the repayment risk of the 26 million "credit invisibles" (individuals who do not have credit records maintained by any of the three nationwide credit reporting agencies) and the additional 19 million individuals lacking a credit score.[1] Yet such data also may discriminate against low-income consumers or consumers in protected classes by using information about one's social network or Internet browsing habits to target advertisements or price credit.[2] Moreover, it may perpetuate a lack of access to credit for those consumers having a limited or no digital footprint. To compound these risks, newer industry participants who rely on non-traditional data, like marketplace lenders, may not be aware of the accompanying consumer protection issues.

The use of alternative data exacerbates a longstanding tension between lenders and their vendors who supply proprietary data or scores. Where a model includes data from third party vendors, lenders must decide how far to press the third party to obtain access to the underlying variables and how they are derived. Often, vendors will be resistant to share the kind of

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1 *See* Consumer Financial Protection Bureau Office of Research, *Data Point: Credit Invisibles* (May 2015), *at* http://files.consumerfinance.gov/f/201505_cfpb_data-point-credit-invisibles.pdf.

2 *See* Federal Trade Commission, *Big Data: A Tool for Inclusion or Exclusion?* (Jan. 2016), *at* https://www.ftc.gov/system/files/documents/reports/big-data-tool-inclusion-or-exclusion-understanding-issues/160106big-data-rpt.pdf (hereinafter "FTC Report on Big Data").

information that would be meaningful for a fair lending and UDAAP analysis. Absent the ability to directly analyze vendor-provided data, lenders should obtain sufficient information about the vendor's own model development and monitoring practices.

Before transitioning fully into a discussion of monitoring and testing models, a final point related to model construction: Just as technology has expanded the data sources available for model development, it also has affected the way models read and analyze the relationships between this data. Models built with "machine learning"—which refers to algorithms that automatically adapt and update themselves when new data becomes available—can potentially increase UDAAP and fair lending risks by obscuring the relationship between model inputs and outputs. Without transparency about how models generate their predictiveness, it becomes possible that the underlying data is interacting in a way that has a disproportionately negative effect on certain groups of consumers.

Assessing Models to Manage Disparate Impact and UDAAP Risk

Combined with these relatively new evolutions in data sources and model construction, the risk of a disparate impact claim is greater today than just a few years ago. The Supreme Court has ruled that disparate impact is a cognizable claim under the Fair Housing Act,[3] and federal agencies such as the Department of Justice and CFPB, which have an active fair lending docket,[4] now regularly plead the disparate impact theory in their fair lending actions.[5]

To manage fair lending as well as UDAAP risk, lenders should assess variables for possible inclusion in a model during development and "post-test" outcomes from the use of the models to determine if there is disparate impact. The extent of fair lending assessments both before and after an institution uses a model depends on the institution's size, resources and risk management strategies.[6] As part of a lender's determination of its risk tolerance, a lender should balance (1) the need to create and preserve documentation of model testing to show the causal relationships between data and demonstrate they are using it to meet legitimate business needs that cannot be achieved by less discriminatory alternatives,[7] with (2) the chance that such documentation may be discoverable by plaintiffs and regulators, notwithstanding measures that can be taken to preserve privilege. Additionally, statistical testing involves a certain degree of estimation error due to difficulties in measuring which consumers are members of protected classes, and the conclusions may vary depending on the methodology employed by the person conducting the test.[8]

Model testing inevitably will find a disparate impact. In deciding how to deal with predictive variables that are highly correlated with protected characteristics, lenders need to determine whether removing such variables would increase credit

3 *Texas Dep't of Hous. & Cmty. Affairs v. Inclusive Comtys. Project, Inc.*, 135 S. Ct. 2507 (2015).

4 *See*, *e.g.*, Department of Justice, *The Attorney General's 2014 Annual Report to Congress Pursuant to the Equal Credit Opportunity Act Amendments of 1976* (Apr. 2015), *at* http://www.justice.gov/sites/default/files/crt/legacy/2015/04/13/ecoareport2014.pdf; *Fair Lending Report of the Consumer Financial Protection Bureau* (Apr. 2015), *at* http://files.consumerfinance.gov/f/201504_cfpb_fair_lending_report.pdf.

5 *See e.g.*, *Consumer Financial Protection Bureau and United States of America v. Hudson City Savings Bank, F.S.B.*, No. 15-7056 (D. NJ. Sept. 24, 2015).

6 For example, a statistical analysis may not be appropriate for smaller and less complex institutions. *See*, *e.g.*, *CFPB Supervisory Highlights*, Issue 9 (Fall 2015) at 28, *at* http://files.consumerfinance.gov/f/201510_cfpb_supervisory-highlights.pdf (explaining that institutions should limit the risk of ECOA violations due to disparate outcomes in underwriting by monitoring underwriting practices for potential discrimination and that, "depending on the size and complexity of the institution, [it should] consider using statistical methodologies to understand potential disparities."). Likewise, the frequency of testing depends, among other things, on the extent of growth in a lender's portfolio. A start-up that uses dummy data to build its model may find that its own performance data tells a very different fair lending story.

7 The panel noted that lenders can often effectively assess variables prior to model deployment to determine which ones will have a less discriminatory impact because they can consider development data, such as predictiveness of default. For background on the "least discriminatory alternative" defense, *see, e.g.*, Comment 6(a)-2 to Regulation B.

8 *See*, *e.g.*, Arthur P. Baines and Dr. Marsha J. Courchane, *Fair Lending: Implications for the Indirect Auto Finance Market* (Nov. 19, 2014), *at* http://www.crai.com/sites/default/files/publications/Fair-Lending-Implications-for-the-Indirect-Auto-Finance-Market.pdf (concluding that "[t]he methods commonly used by regulators to proxy race and ethnicity, including the recently applied Bayesian Improved Surname Geocoding (BISG) method, are conceptually flawed in their application and subject to significant bias and estimation error," and "[t]he use of biased race and ethnicity proxies creates significant measurement errors, which likely result in overstated disparities and overstatements of alleged consumer harm.").

risk intolerably or, conversely, whether retaining the variables poses legal risk. The key here is to be able to establish the causal relationships between model variables and model outcomes. Correlation between data and outcomes is not enough (nor, of course, is relying on one's "gut"). As the FTC Report on Big Data notes, "If companies use correlations to make decisions about people without understanding the underlying reasons for the correlations, those decisions might be faulty and could lead to unintended consequences or harm for consumers and companies."[9]

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The Fair Access to Financial Services Subcommittee's mission, as reflected in its January 2016 marketing and credit model panel, is to explore topics related to fair access to financial services, including both discrimination and UDAAP issues. At the October 2015 meeting in Chicago, the subcommittee discussed Access to Financial Services for Limited English Proficiency (LEP) communities. Please contact Brad Blower, Brad.Blower@aexp.com, with ideas for future panels or to become involved.

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[9] *See supra* note 2 at page 9.