CRA Insights: Financial Economics

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Fair lending monitoring: Where to focus statistical analysis

It is probably an understatement to say that most compliance professionals do not naturally gravitate toward statistical analyses, especially ones that involve more than basic mathematics. Nevertheless, it is becoming an increasingly necessary component of any fair lending compliance management system (CMS). It goes hand-in-hand with the qualitative aspects of fair lending risk assessment and monitoring by helping to quantify risks and review them for trends over time. Quantifying the risk, in turn, allows for effective prioritization of risk areas for attention or corrective action.

Statistical analyses are also an integral part of how regulatory agencies examine financial institutions for fair lending compliance, and regulators expect that an institution will have a statistical testing component to their CMS that is appropriate to its size and complexity. So, compliance professionals need to understand where statistics fit into the fair lending program.

This article provides a non-technical overview of the main areas in which fair lending statistical analysis is typically applied and the sorts of analyses that can be performed in each area. The article is organized based on common risk topics in the fair lending space (underwriting, pricing and other terms, redlining, steering and servicing). Along the way, I note some analysis considerations unique to different lending lines of business.

Underwriting

Fair lending statistical analysis of underwriting decisions is conceptually similar across different lending lines of business, but can differ based on the product and business model. It is well known that raw data tends to show significant disparities in rates of denial based on race and ethnicity for some credit products. For example, the aggregate 2014 HMDA data show mortgage loan denial rates of about 40% for African Americans and 30% for Hispanics compared to about 21% for non-Hispanic whites and 20% for Asians (excluding withdrawn and incomplete applications). However, it is also well known that there are societal differences in average income, wealth, credit experience and other economic factors that come into play, so these denial rate differences do not represent differences among “similarly situated” applicants. One of the most common objectives of a fair lending underwriting analysis is to identify whether any significant prohibited basis denial rate disparities remain after adjusting for the effects of objective differences in measurable credit qualifications and loan program attributes among credit applicants.

One key distinction that should be considered is the extent of automated decision making versus manual or judgmental decision making. For example, in home mortgage, home equity, small business and unsecured personal lending, underwriting typically is not fully automated even though automated decision systems may play an important role (such as Fannie Mae’s Desktop Underwriter and Freddie Mac’s Loan Prospector in the case of first mortgages). Automobile lending may be fully automated for some lenders, but typically has both an automated and a manual component—even if only applied to a subset of applications. Credit card lending and the growing online “marketplace lending” sector tend to rely most heavily (perhaps exclusively) on fully automated underwriting and may have little or no scope for manual intervention, except perhaps in verification and fraud review processes.

The key point, though, is that it is best to examine purely automated decisions separately from judgmental decisions in order to isolate disparate impact risk from disparate treatment risk. Purely automated decisions pose no risk of disparate treatment (unless the automated process contains overtly discriminatory criteria), so the focus of analyzing automated decisions is on the potential disparate impact of the decision rules and credit scoring models used in the automated process. On the other hand, judgmental decisions have a greater potential for bias and should be analyzed separately to identify potential disparate treatment risks in addition to possible disparate impact.
At the risk of resurfacing those feelings you had in Stats classes in the past, a statistical analysis of manually underwritten applications typically involves estimating a multivariate statistical model (called “logistic regression”) of approval/denial decisions. Such models are used to test for differences in denial rates on a prohibited basis (e.g., based on race, ethnicity, gender or age group) after accounting for the influences of objective credit and loan attributes which may be incidentally correlated with prohibited basis characteristics. The specific attributes to include in the model as explanatory factors for credit decisions should be guided by the lender’s underwriting policies and guidelines, which define the factors that the lender has instructed its underwriters to consider in underwriting decisions. Depending on the product, this may include such factors as an applicant’s credit score, debt-to-income ratio, loan-to-value ratio, type of collateral, automated underwriting system recommendation, and certain detailed credit history attributes (e.g., indicators of derogatory credit, depth of credit file and credit inquiries), among other factors.

If a statistically significant difference in denial rates is found after controlling for applicable underwriting factors, the results alone should not be viewed as a sufficient basis for concluding that there is a fair lending issue. If the statistical model does not include all the non-discriminatory factors considered in underwriting, or does not correctly account for the complex ways in which compensating factors and layered risk considerations enter into credit evaluations, then prohibited basis statistical differences may still arise even though there are no fair lending compliance issues. If, after the analysis, there are indications of statistically significant differences in denial rates on a prohibited basis, the next step should be to investigate the differences through a comparative file review. A comparative file review evaluates why a difference in outcomes occurred for apparently similar individuals, and determines if the difference is attributable to inconsistent treatment or the result of consistently applied objective underwriting criteria.

A fair lending analysis of underwriting should include a specific analysis of overrides to automated system decisions and exceptions to guidelines, if applicable. As with denial rates, differences in rates of override or exception do not necessarily indicate a fair lending issue, because the ability of applicants to qualify for an override or exception may differ systematically across demographic groups. For example, it could be the case that non-minority credit applicants received overrides to a minimum credit score threshold more frequently than minority applicants because the non-minority applicants displayed compensating factors for low credit scores more often than minority applicants. To evaluate whether such a difference in overrides or exceptions truly represents differential treatment of similarly situated applicants, a comparative file review should be completed to compare non-minority applicants who received a credit score override and were approved to minority applicants who had similar credit scores and were similar in other relevant respects but were denied.

Pricing and other terms

Similar to the case of underwriting, the approach to statistically analyze pricing will depend upon the product and the lender's business model. Generally, there are two components to pricing that should be addressed when analyzing fair lending risk: the setting of the interest rate and any discretionary component of pricing (including any discretionary fees or repayment terms). How the analysis is approached will likely differ considerably across products and business models.

In home mortgage lending, we normally test for disparities in Annual Percentage Rate (because APR represents an "all-in" pricing measure) using a regression model that attempts to net out the effects of cross-borrower differences in objective credit risk and loan program characteristics. Again, if the analysis finds statistically significant differences in average APR on a prohibited basis, that may or may not indicate that there is a fair lending risk issue. It could be the case that the APR disparity is attributable to prohibited basis differences in discretionary pricing decisions. Alternatively, it could be due to measurement error: the regression model may omit some relevant pricing factors due to data limitations, there may be errors in the data or the model may not have properly accounted for all of the complex interactions among pricing factors.

For example, the pricing adjustment associated with, for example, an 80% LTV for a mortgage loan likely differs based on the borrower's credit score, occupancy status, property type and specific loan program, among other things. It may be difficult or impossible to address all of those interactions precisely in a regression model. The result could be "false positive" statistical disparities. Therefore, additional in-depth statistical analysis or manual file review is often required to evaluate whether statistical disparity in APR is truly a fair lending issue.

In mortgage lending it is also useful to specifically analyze discretionary pricing in isolation from the risk-based rate determination, because the former tends to be the main driver of fair lending risk. In this context, we typically test for disparities in an overage/underage or exception pricing measure, and analyze differences in both the incidence and the average magnitudes of discretionary pricing variations. To the extent that there are discretionary pricing disparities at the portfolio level, additional analysis by branch office and loan originator may be necessary to identify the root cause of disparities. In addition, wholesale mortgage lenders should monitor for potential prohibited basis disparities in the average level of broker compensation, both at the portfolio level and for individual brokers that have sufficient loan volume for separate analysis.

In indirect automobile lending there are two pricing measures that normally come into play for fair lending analysis: the buy rate and the contract rate. The buy rate, sometimes called the wholesale rate, is the rate charged by a bank or finance company to the auto dealership on any given loan contract. The contract rate is generally negotiated between the dealership and the borrower. The difference between these two rates is often referred to as the dealership finance reserve, or "mark-up." As in mortgage lending, analysts use multivariate regression analysis to identify potential fair lending risk issues in pricing (buy rate, contract rate and the difference between the two) after accounting for the effects of relevant differences in borrower credit and deal characteristics.
In the case of credit card lending, it is less common for lenders to establish discretionary pricing or terms within a specific product offering. Generally, the setting of APRs for newly originated accounts tends to strictly follow a risk-based pricing schedule. If this is the case, then fair lending risk assessment should focus on evaluating the factors used in pricing for potential disparate impact risk, and verifying that controls are in place to ensure that pricing truly does follow the specified rate schedule.

Although discretion in setting the rate on credit cards is less common, there is a key discretionary aspect that comes into play for credit cards: credit line amount or limit. Credit lines are typically assigned based on automated decision rules or a set line assignment schedule that is based on specified risk factors, but there is often discretion for judgmental adjustments to system-assigned credit lines. When discretion is permitted to set credit line limits, statistical analysis should be used to test for potential prohibited basis disparities in the incidence and average sizes of those adjustments—including line increases and decreases that may occur. Depending on the lender's specific policies, the analysis may require using statistical models to test for disparities that may remain after accounting for legitimate, business-justified decision factors (such as whether and how much of a balance transfer was requested by the customer, and whether the customer had elevated credit risk not fully captured by the automated line assignment criteria). If there is no provision for discretionary adjustments to a risk-based line assignment model or schedule, then the fair lending review can focus on potential disparate impact risk of the line assignment criteria and a controls assessment.

Redlining risk

The term "redlining" refers to a practice of illegal discrimination in which a lender provides unequal access to credit or unequal terms of credit because of prohibited basis characteristics of the residents of a geographic area. Historically, redlining statistical analysis and enforcement activity has focused mainly on home mortgage lending. Redlining risk assessment goes beyond confirming that a lending institution does not have an overt policy of avoiding areas on a prohibited basis. Enforcement agencies also examine whether an institution's history of lending activity suggests a tendency to avoid specific areas within its general market footprint, or to fail to serve those areas to a similar extent as it serves other areas. Statistical analysis of redlining risk analysis also considers relevant comparisons to other lenders. Publicly available Home Mortgage Disclosure Act data can be used to examine the percentage of a financial institution's lending that is in predominantly minority areas in comparison to that of other generally similar financial institutions within a given local market. If the institution's lending percentage is substantially lower than that of similarly situated "peer" lenders in the same market, that shortfall could be an indication of fair lending redlining risk.

The selection of a set of peer lenders to benchmark against can be as much art as science, but it typically focuses on lenders with generally similar characteristics (e.g., similar production volume, business model, distribution channels and/or product focus). Statistical redlining analysis can be augmented with mapping to visually analyze the locations of an institution's applications and loan originations, as well as its branch locations, in relation to census tracts.

Steering and reverse redlining risk

Fair lending "steering" risk refers to the possibility that borrowers will be placed in less favorable (e.g., more expensive) loan products on a prohibited basis when the borrower would qualify for a more favorable product. Concerns about potential discriminatory steering traditionally have focused on FHA versus conventional loans, as well as prime versus subprime loans more broadly (though non-FHA subprime lending is not a significant part of today's mortgage market).

Regulatory concern in this area derives in part from disparities in the gross HMDA statistics: in the national 2014 HMDA data, the FHA shares of home purchase originations are about 38% for both African Americans and Hispanics, but only 17% for non-Hispanic whites and 11% for Asians. An analysis of potential steering risk utilizes statistical "logistic" regression models (similar to an underwriting analysis) to test whether differences in the proportions of borrowers obtaining FHA loans can be explained by differences in relevant credit qualifications and other relevant borrower circumstances.

Steering risk analysis can also include testing for potential differences in pricing based on race/ethnicity between FHA and conventional borrowers. Specifically, statistical regression models can be used to estimate whether borrowers tend to pay more for FHA loans than they would have paid for an otherwise comparable conventional loan (if one would have been available), after accounting for the effects of objective credit risk and other characteristics that normally are considered in loan pricing.

A topic closely related to steering risk is "reverse redlining," which can be thought of as steering borrowers to products, or making different products available on an unequal basis, based on the racial or ethnic character of neighborhoods. Allegations of reverse redlining (as well as redlining) have been at the heart of numerous lawsuits filed by large municipal governments (e.g., Los Angeles, Chicago, and Miami) against major banks alleging discrimination in violation of the Fair Housing Act. The analysis of reverse redlining risk is similar to the analysis of steering, except that census tract minority status is substituted for borrower minority status in testing for potential disparities.

Loss mitigation servicing

One of the most important areas for fair lending statistical analysis in the loan servicing arena is loss mitigation work-outs, modifications and foreclosures/repossessions. This analysis tests for potential differences on a prohibited basis in outcomes for borrowers who entered the loss mitigation process. Each of the following should be considered for analysis:

a. The incidence of customers receiving a home retention outcome (i.e., payment plan, forbearance, or loan modification) versus a home liquidation outcome (i.e., foreclosure, short sale or deed in lieu of foreclosure);

b. The incidences of foreclosure versus non-foreclosure liquidations;

c. Denial rates for requests for (or incidences of offering) loan modifications;

d. Changes in terms for modified loans (i.e., amount of reduction in interest rate, payment-to-income ratio, and monthly payment; and amount of term extension or forbearance).

e. Loss mitigation processing times, such the time elapsed between entering the loss mitigation process and a loan modification decision, a referral for foreclosure or a foreclosure sale.

Analyses of loss mitigation outcomes are challenging because of the complicated nature of servicing data. Often the information must be pieced together from different computer systems and typically includes multiple workout evaluations for each loan.

Concluding comments

Finally, any attempt to statistically analyze fair lending risk in non-mortgage lending must contend with the lack of data regarding the race, ethnicity, and gender of credit applicants because the ECOA prohibits the collection of such data. Regulators have tried to circumvent this limitation by applying "proxy" methods. Such methods use demographic statistics associated with a consumer's surname and/or the area surrounding their home address to derive an estimated probability that he/she belongs to a particular racial or ethnic group, and use demographic statistics associated with first names to estimate the probability that a consumer is male or female.[1]

While proxy methods may be the only means available for attempting to quantify potential fair lending risk in non-mortgage lending, it must be recognized that they are subject to a considerable—indeed unknown—degree of error.[2] Therefore, the results of any proxy-based analysis should be interpreted with caution. Nevertheless, it is clear that regulatory agencies have established such proxies and rely upon them during examinations and enforcement actions. Therefore, financial institutions need to make a carefully considered risk decision about the use of proxy-based analyses as a way to identify potential areas of fair lending regulatory risk.

The statistical analysis topics summarized in this article include many areas in which statistical analysis can be deployed as a fair lending risk assessment tool. Other areas include marketing (especially targeted marketing such as prescreened direct mail) and the increasingly important assessment of disparate impact risk of credit scoring models and automated decision systems. Depending on the size and complexity of the lending institution, some of these topics can be addressed through fairly simple spreadsheet-based analysis or specialized fair lending software packages. And, although statistical analytical tools are necessary in some instances, they are not needed in all analyses. However, when they are needed, specialized knowledge and experience in statistical analysis provides vital information necessary to make timely and appropriate decisions. It is important for compliance professionals to be aware of where quantitative analysis may be employed to augment the more qualitative aspects of fair lending risk assessments and monitoring.

About the Financial Economics Practice at CRA

CRA's Financial Economics Practice provides economic and financial analysis and advice to financial institutions, financial regulators, and counsel representing financial institutions. Our experts are skilled in quantitative modeling and econometrics, particularly as applied to issues in credit and compliance risk in primary and secondary consumer lending markets. To learn more about the practice, visit **www.crai.com/financialeconomics**.

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[1] *See* "Using publicly available information to proxy for unidentified race and ethnicity: A methodology and assessment," Consumer Financial Protection Bureau, Summer 2014. **http://files.consumerfinance.gov/f/201409_cfpb_report_proxy-methodology.pdf**

[2] For a critique, *see* "Fair Lending: Implications for the Indirect Auto Finance Market," Prepared by Arthur P. Baines and Dr. Marsha J. Courchane for the American Financial Services Association, November 19, 2014, **http://crai.com/sites/default/files/publications/Fair-Lending-Implications-for-the-Indirect-Auto-Finance-Market.pdf**