FICO Decisions

WHITE PAPER

To Score or Not to Score?

Research explores the minimum amount of data required to build accurate, reliable credit scores

FICO research showed that over 70% of traditionally unscorable consumers could be assigned a statistically meaningful credit score by using alternative data.

According to studies by the Federal Reserve[1] and others, the widespread adoption of credit scoring by financial institutions over the last 25 years has made credit available and affordable to more people than ever before. Credit scores have enabled financial institutions to more precisely measure credit risk, and as a result, there has been a democratization of credit in the US.

However, millions of US consumers currently don't receive credit scores, making it difficult for them to establish credit. Indeed, an estimated 15% of US consumer credit reports do not have sufficient information to calculate a FICO® Score. The impacted consumers, who frequently include new immigrants, recent college graduates and people recovering from earlier financial missteps, are often excluded from the mainstream financial system.

FICO recently completed research on how to provide a robust and accurate assessment of credit risk for a broader set of consumers than is available today. This white paper will examine:

- The pitfalls of credit scores based on biased, limited, insufficient or old data.
- What factors and data must be considered to ensure that any expansion of the scorable universe still supports responsible lending.
- The use of alternative data to assess risk for currently unscorable consumers.

[1]Report to Congress on Credit Scoring and Its Effects on the Availability and Affordability of Credit, August 2007

Purpose of Minimum Score Criteria

To make any key decision, there's a minimum amount of information required to make an informed judgment. Consider an airplane pilot readying for takeoff. Suppose that her radar is out, or her instruments are flickering, or her cockpit windows are dirty. As a responsible pilot, she won't proceed down the runway until she has all the information required to assure a safe takeoff.

Similarly, a prudent lender seeks a minimum amount of relevant data about a prospective customer before making a credit decision. Thus, the FICO® Score algorithm requires a minimum amount of information from a consumer's credit file to calculate a score. Some consumers may not receive scores because their credit files are considered too "thin" due to little or no credit history; for instance, files with only collections or public records do not receive FICO® Scores. Also, credit files without any reported account activity in over six months are considered "stale" by the FICO® Score algorithm and thus are not scored.

Carefully constructed "minimum score criteria" ensure that the credit scoring algorithm has sufficient and sufficiently recent information from the consumer credit file to generate a score that is an accurate assessment of that individual's credit risk. The FICO® Score's current minimum score criteria are as follows:

- The consumer cannot be deceased.
- The credit file needs one trade line reported by a creditor within the last six months.
- The credit file needs one trade line that is at least six months old.

Note that the second and third conditions can be satisfied by two different trade lines.

While scorable rates may vary by lender, account type, consumer segment and data provider, roughly 91% of applicants of US consumer credit files meet the above minimum score criteria, allowing for the calculation of FICO® Scores. The resulting challenge, which we tackle in this paper, is how to fairly and accurately assess credit risk for the remaining 9% of credit files that exist but do not currently receive FICO® Scores—the "unscorables."[2]

[2]This white paper does not address the equally important question of how to assess risk for consumers who do not have credit files—the so-called "no hits"—though we may address that question in future research.

Pitfalls of Imprudent Minimum Score Criteria

An obvious answer to the challenge of how to score more consumers is to simply eliminate or reduce the minimum score criteria. But the recent economic crisis showed what can happen when important credit criteria are ignored or overlooked. Before making a wholesale change in the minimum score criteria to score more people, it's critical to scientifically analyze what those changes would mean with respect to the score's predictiveness. Not doing so could present huge problems for investors and consumers.

Why? Lenders rely on various pieces of information to make a credit decision, and credit scores are often a key component of this decision process. Accurate and predictive credit scores can help match consumers to credit products and terms in line with their ability to pay. Credit card issuers frequently set initial credit line limits based on the consumer's risk level. Auto lenders may set a maximum loan amount based on the applicant's credit score. A credit score should reliably reflect each consumer's true level of risk, and a score that doesn't do this could impact investors and consumers in potentially negative ways.

Suppose a credit scoring algorithm has lax minimum score criteria, and thus the score it generates is less reliable, inaccurate or even misleading. This could result in consumers getting a smaller credit limit than merited, unfairly limiting their credit usage. Alternatively, if consumers default due to being granted a larger loan than they can handle, this is harmful to both consumers and investors. The negative effects can impact the broader economy, as we saw during the recent economic crisis.

Bottom line: No one benefits when faulty risk assessment results in credit decisions that don't reflect someone's true ability to repay debt.

Challenges in Expanding the Scorable Universe

Revising the minimum score criteria requires rigorous analytic analysis to assess whether previously unscorable consumers can safely be included in the current scorable universe. We recently conducted such research, looking to answer three key questions:

- Is the available credit information sufficiently predictive of a person's repayment risk?
- Is there sufficient credit repayment history to predict future repayment behavior?
- Is the odds-to-score relationship appropriately aligned? In other words, does a 700 score represent the same risk level for both potential newly scorable and traditionally scorable groups?

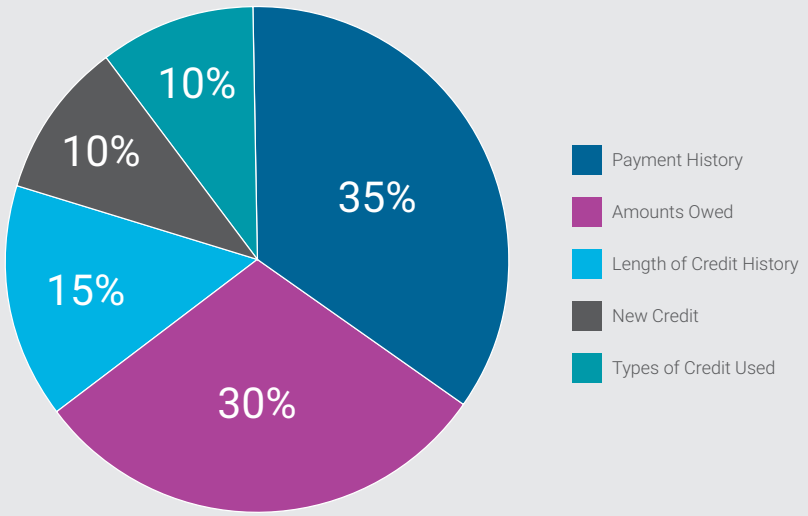
Is the available credit information sufficiently predictive of a person's repayment risk?

When looking at adding consumers to the scorable universe, it's important to assess whether there is enough data for a robust, reliable assessment of future credit risk. For example, can a meaningful credit score be calculated for a consumer with a credit file containing only a single collection item? How about if the file has no credit information reported in the last two years?

Consider Figure 1, which shows the five categories of predictive credit information that are used to calculate a FICO® Score. Some unscorable consumers have information in as few as one of these five categories. Any score calculated on such limited data could be misleading or inaccurate.

Figure 1

Categories of Predictive Credit Data in the FICO® Score



The FICO® Score is calculated from several categories of predictors based on information in the credit report. The percentages reflect the relative importance of each category for the national population in calculating the score. Some currently unscorable consumers have files with as few as one data category. A score calculated on such limited data could be misleading or inaccurate.

Our research shows that, for consumers with significantly limited credit data, the attainable risk discrimination is equally weak. For instance, we developed a research score for consumers with one or more collections or adverse public records but no other account information. We then calculated several standard predictive measures to evaluate the performance of this score on these consumers. For them, the Gini index[3] of the score was 0.147, significantly less than the 0.600 to 0.800 Gini indices for scorable consumers. A lower Gini index means the score is less predictive of future behavior.

Our research consistently shows that for certain potential new scorable consumers, the risk discrimination from the extremely sparse data was considerably weaker than for currently scorable consumers. Having sufficient credit data to predict future repayment risk is essential to any credit score that lenders and regulators rely on as a tool for safe and sound lending decisions.

Is there sufficient credit repayment history to predict future repayment behavior?

The core function of a credit score is to evaluate past behavior as a predictor of future activity. To do that, we look at credit behavior at two different points in time, 24 months apart, to determine if a consumer repaid a loan as agreed (a "good" payer) or not (a "bad" payer).

As Figure 2 shows, the consumer credit file at Snapshot A is used to calculate the score's predictive variables. The same consumer's credit file at Snapshot B is used to categorize the consumer as a good payer or a bad payer based on how he paid his credit obligations during the 24-month window.

Figure 2

Sufficient Repayment History Is Needed to Predict Future Repayment

Only consumers with actual credit repayment history between Snapshots A and B—what we call "classifiable performance"—can be included in the development sample. Many unscorable consumers don't have classifiable performance during the defined time period.

Consider again the consumers with one or more collections or adverse public records on file at Snapshot A, but no prior credit account history. How many of them would be able to open a new credit account and show some payment history over the subsequent 24 months?

[3] A Gini index or coefficient is a statistic used to measure the effectiveness of a predictive model. Gini indices range from 0 to 1; the higher the number, the stronger the model. A Gini index of 1 represents perfect risk discrimination.A Gini index of 0 is equivalent to a random decision or completely imperfect risk discrimination.

In fact, our research revealed that only 18.8% of these consumers had classifiable performance during the subsequent 24 months. That means 81.2%, or four out of five records, would be excluded from the model development process. Generating a score for the 81.2% based on the 18.8% with classifiable performance amounts to assuming that the risk patterns of a minority hold true for the larger group. This is unlikely to be a reasonable assumption.

We know that at the time of application (Snapshot A), consumers in this segment would not have had a FICO® Score, and the only information on their credit file would be negative (i.e., collections and/or adverse public records). To be approved for credit, they probably had to meet a lender's "no FICO® Score" underwriting criteria. This would have likely involved verifying substantial income or assets, and/or being offered credit products with tight risk controls such as secured cards.

Consequently, it seems unlikely that the repayment behavior of these 18.8% "cherry-picked" consumers would align closely with the behavior and risk of the other 81.2%. Putting it in modeler's terms, the development sample drawn from this small sample of consumers would be heavily truncated and strongly biased.

A credit score built from such a sample is likely to be at risk for significantly overstating the credit quality of these newly scorable consumers. The model would be based on the cherry-picked underwriting and repayment performance of a small, favored, non-representative slice of the group. In addition, a model based on such a questionable sample is likely to be much less robust—across industries (e.g., auto vs. mortgage), across applications (e.g., originations vs. account management) and over time. It would be similar to our pilot deciding to take off with only one instrument working on her control panel.

Is the odds-to-score relationship of the potential new scorable group appropriately aligned?

A key consideration during FICO® Score development is the relationship between the score and risk, and the consistency of that relationship across different types of consumers. Investors expect that a FICO® Score of 700 equates to the same level—or odds—of repayment risk, regardless of whether the consumer has a thick (mature) credit file or a thin (young) credit file.

Our research shows that this consistent "odds-to-score" alignment doesn't hold true for some currently unscorable consumers when compared with the larger traditionally scorable population.

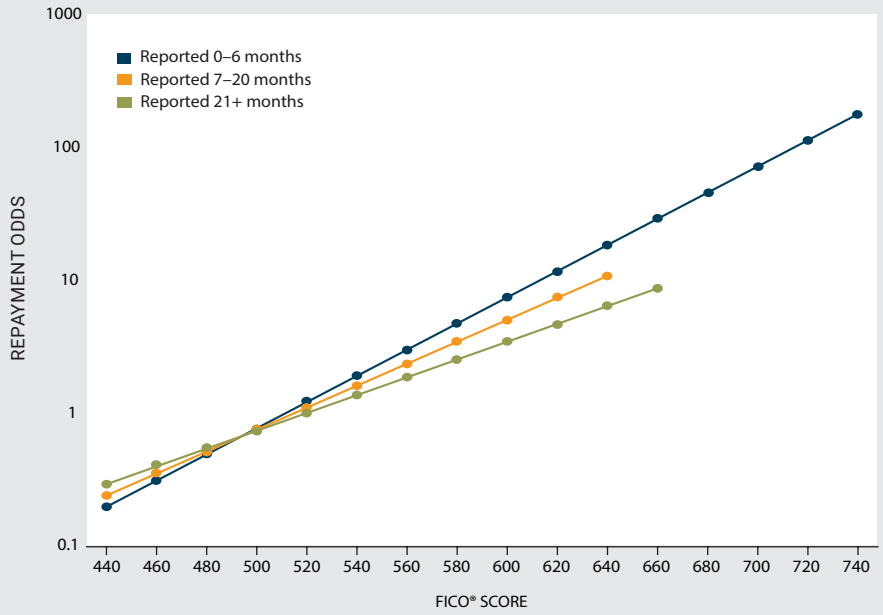
Take, for example, credit files with no trade line reported in the last six months. We compared the odds-to-score relationship of consumers with these "stale" files to traditionally scorable consumers and saw a troubling pattern. Consumers with stale files typically show a flatter odds-to-score relationship; this means the score generated is less effective at rank-ordering[4] risk. And the staler the credit file, the flatter the odds-to-score line.

[4] Credit scores are designed to rank-order risk—that is, sort accounts so that higher scorers perform better (or have less risk) than lower scorers. For example, a credit risk model rank-orders accounts such that those scoring 680 have better repayment odds (or fewer future delinquencies) as a whole than those scoring 640, but worse repayment odds (or more future delinquencies) than those scoring 720.

Figure 3

Rank-Ordering Flattens as Staleness Increases

Booked Auto Loans



Results of this study are shown in Figure 3. We used a recent national credit bureau sample to assign consumers with stale credit records a provisional FICO® Score based on the actual FICO® Score table, in order to compare them to traditionally scorable consumers.

The odds-to-score relationship for traditionally scorable consumers—with at least one trade line updated in the prior six months—is shown in the graphic as "Reported 0–6 months." For consumers with credit records last reported 7–20 months prior, the odds-to-score relationship is flatter than the baseline. For consumers with credit records 21 months and above, the odds-to-score relationship is flatter still. While Figure 3 shows results for auto loans, we saw similar odds-to-score patterns for bankcard and mortgage loans.

Conceptually these results are not surprising. Consider our fictional aircraft pilot approaching an airport for landing. A few miles out, weather conditions look favorable; her radar shows a clear airspace for her landing path; and air traffic control reports she is next in line to land. Now suppose that all her instruments and her radio go out for 120 seconds, and the pilot must decide whether to land the plane as scheduled. Her likelihood for a safe landing is still possible because everything looked fine two minutes ago. But things may have changed during the intervening period. As time passes, her available data becomes staler and less reliable.

Similarly, over time a consumer's financial situation may change. Some consumers will see their financial status improve, some will experience problems, and some will remain stable. For traditionally scorable consumers, we have relatively fresh data available at the time of scoring, and strong evidence to trust its reliability.

But for consumers where no activity has been reported for six months or longer, any possible change in financial status has gone unreported, and the data associated with the corresponding credit scores have become unreliable. As Figure 3 shows, the older the data, the less reliable the score.

An astute modeler knows that another option would be to build specialized scorecards for currently unscorable consumers. This approach could possibly yield better odds-to-score alignment with the traditionally scorable population.

However, our research showed that this approach was also not analytically sound. Let's look once again at consumers with stale files. Only 13% of them had classifiable performance during the subsequent 24-month performance window. That means nearly 9 out of 10 of these consumers would be excluded from the development of the scorecard. As discussed in the previous section, it is not reasonable to assume that the risk patterns of such a minority would hold true for the larger group.

This highlights the difficulty of the problem: Neither a flatter odds-to-score relationship nor the considerable risks associated with building models on such a truncated (and likely biased) sample are desirable.

A Smarter Way to Expand the Consumer Credit Market

Many in the financial services industry have expressed interest in better serving unscorable consumers, but without the risk of making lending decisions based on extremely marginal or stale credit files. A better approach to evaluate these consumers is to augment the limited traditional credit information with alternative data that adds predictive value.

A growing number of alternative data providers has entered the market in recent years. What type of alternative data drives a stronger credit risk score? Based on our experience, data sources are most useful if they demonstrate:

- **Regulatory compliance.** The data source must comply with all regulations governing consumer credit evaluation. To comply with the Fair Credit Reporting Act, for example, a data provider must have a process in place for investigating and resolving consumer disputes in a timely manner.
- **Depth of information.** The deeper and broader the data, the greater the value. Consider a utility data repository. Does the data reflect both on-time and late payments? Is the account history captured from the beginning of service or just for a recent period? If the consumer has moved, are there records from multiple addresses?
- **Scope of coverage.** A database covering a broad percentage of consumers is optimal. If 40% of US adults live in rentals, then a random list of consumers matched against a rental payment database should yield a 40% hit rate.
- **Accuracy.** Clearly, inaccurate data compromises the value of the data. Alternative data repositories need to have a mature data management process in place to ensure data accuracy. It's important to ask questions such as: How reliable is the data? How is it reported? Is it self-reported? Are there verification processes in place?

- **Predictiveness.** The data should predict future consumer repayment behavior. For example, analysis of a telco database shows that consumers who make their telco payments on time are more likely to pay their credit obligations than those who have missed telco payments. Such a data source would add value for credit risk evaluation.
- **Orthogonality.** Useful data sources should be supplemental or complementary to what's captured in traditional credit reports. For example, if a repository collects foreclosure data from public record information, that data may provide little added value to foreclosure data already in consumer credit reports.

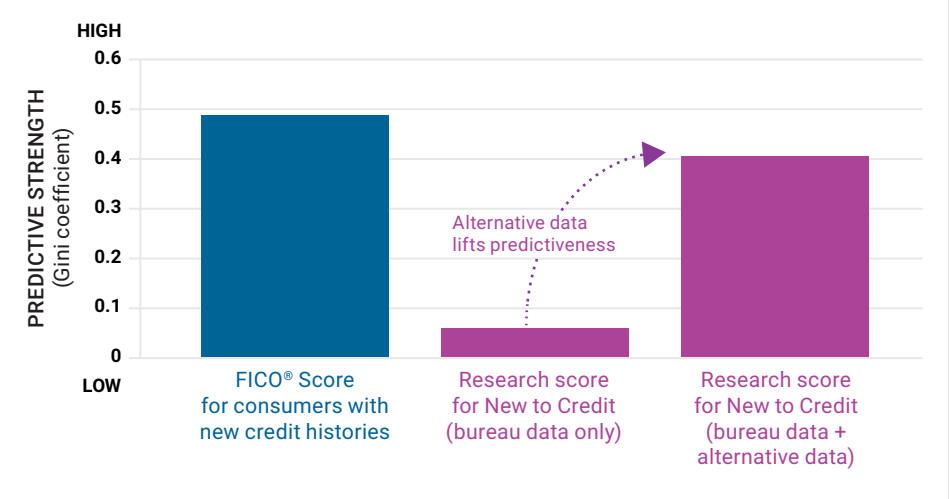
We have worked with alternative data for many years and developed credit scores that effectively assess risk for underserved consumers. Our research has found that deposit account information, supplemental public record information, telco payment history and property/asset data are especially predictive of future repayment behavior.

FICO has built scoring models using alternative data and validated them on client portfolios across numerous industries. The results have shown that over 70% of traditionally unscorable consumers can be assigned a statistically meaningful credit score by leveraging these types of alternative data.

While the use of alternative data can be effective in expanding the scorable universe, there are potentially significant operational and cost considerations. Any scoring solution in this space should be provided by a data modeler with experience in mining alternative data and knowledge of how to navigate the modeling, business and regulatory implications.

Figure 4

Increasing Predictive Power with Alternative Data



Conclusion

Expansion of the scorable universe should be undertaken with great care, discipline and analytic rigor. Generating credit scores solely using traditional data for consumers with either very thin or stale credit files can do more harm than good. A misleading score may be worse than no score at all.

For lenders interested in serving consumers with little traditional credit information, a better approach is to supplement traditional credit data with alternative data that meet regulatory compliance, have depth and scope, and are predictive of future repayment behavior. This is vital to developing credit scores that investors can trust and rely on, thus continuing to make credit more available and more affordable to consumers.

FICO will continue to conduct research on best practices in the use of scoring technology, as well as trends in the credit risk landscape. We'll publish findings in future Insights white papers and on our Risk and Compliance Blog.

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