



Anything but Conventional:

By Leveraging New Modeling Techniques and Better Data,
Tens of Millions More Consumers Get Even More
Predictive Credit Scores

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EXECUTIVE SUMMARY

Credit scores help assess the risk of a consumer defaulting on a debt obligation over a defined period of time and are widely used across consumer lending. Availability of accurate, reliable and fair credit scores is therefore critical to making credit more accessible to creditworthy consumers. VantageScore continues to pave the way for new and innovative approaches to provide accurate assessments of risk while increasing the population of consumers who can receive a credit score.

This analysis shows that:

- There are tens of millions of consumers including those with relatively low levels of credit risk who are not scoreable with conventional models.
- Given the same credit score, there is no statistically significant difference in default outcomes between conventionally scored consumers and newly scoreable consumers even though different elements of their credit report are being utilized.
- Newly scoreable consumers do not exhibit different default rates (measured as delinquency of 90 days or more over 24-months) compared to conventionally scored consumers with similar scores.
- Further, across all product categories, how quickly a consumer defaults on a new loan is comparable between newly scoreable consumers and conventionally scored consumers with similar scores.

INTRODUCTION

Approximately 40 million consumers are labeled “unscorable” (often referred to as “credit invisibles”)¹ and become credit marginalized due to their unconventional (or lack of repeated and/or regular) use of credit. Some are penalized by conventional scoring models because they prudently avoid constant use of credit. Traditional credit calculations are based on methods from more than 30 years ago when computing and data systems were slower and the math involved in scoring consumers required more simplistic calculations to measure credit risk.

Traditional credit measurement primarily focused on simple aggregated calculations (e.g., utilization, balances, age of credit and missed payments) driven by credit card data to develop the credit score model and did not examine deeper multi-dimensional characteristics.

There is a myth in the consumer credit world that only recent and repeated credit users can be reliably scored. This use of credit is restricted mainly to regular credit card or bankcard data. Yet many other forms of credit such as department store (i.e., private label) credit cards, installment loans (e.g., auto loans, personal loans, student loans and mortgages) are not necessarily evaluated around regular, repeated use. These trades are still on a credit report and hold valuable insights to a consumer’s credit history but cannot always be captured by traditional measures. These loans quickly fall out of credit score calculations once they are closed or go dormant, even with successfully completed payment histories intact.

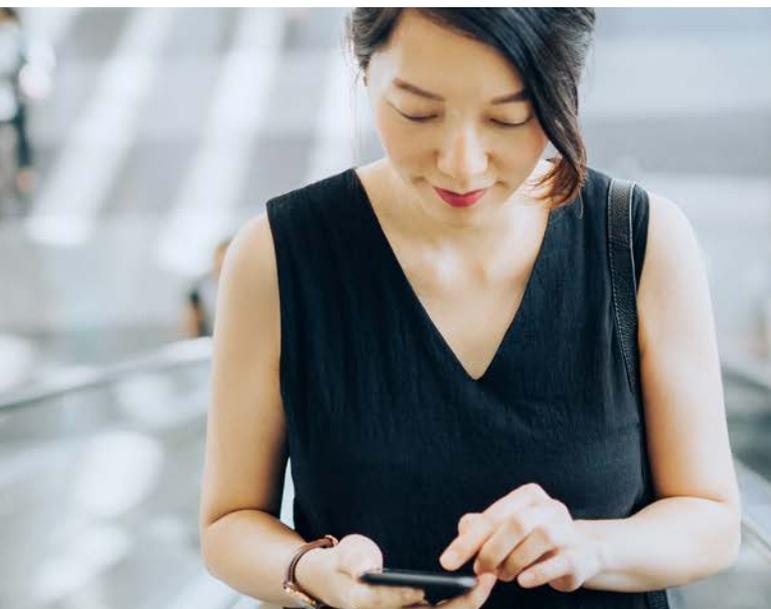
Today more modern methods are at the fingertips of data scientists. These include machine learning and distributed computing environments, which enable risk modelers the ability to analyze thousands of multi-dimensional attributes quickly and develop accurate assessments that traditional methods simply overlook, causing approximately 40 million consumers to become “invisible.”

So, are these 40 million consumers truly unscorable or are traditional methods (employed over 30 years ago) a marginalizing driver for this particular population?

The purpose of this paper is not to re-visit how to score all consumers but to demonstrate that by using modern data and methodologies, model developers can now accurately assess creditworthiness for the unscorable consumer. Critics and skeptics naively assert that is a “loosening of standards” or “race to the bottom” but their misguided assertions miss the point.

Newer modeling techniques do not try to squeeze a round peg into a square hole in order to score more people. Instead, these modern methods allow data scientists to consider thousands of multi-dimensional credit data relationships and identify the strongest attributes necessary to accurately assess a consumer’s creditworthiness.

1 The VantageScore 4.0 model allows lenders to accurately assess approximately 40 million more consumers than conventional models.



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OVERVIEW & METHODOLOGY

This white paper examines the effectiveness of new methods aimed at assessing the traditionally “unscorable” consumers and addresses the myth that only traditional measures of credit risk can effectively determine creditworthiness. VantageScore 4.0, the most recently introduced credit scoring model by VantageScore Solutions, utilizes machine learning techniques in order to develop attributes aimed at scoring those that fail to meet conventional scoring modeling criteria.² The results in this white paper show that newer methods achieve similar prediction accuracy compared with conventional models when measuring credit behavior over the standard 24-month period.

To assess how modern credit score modeling techniques compare with conventional scoring techniques, this analysis uses VantageScore’s most recent validation data from 15 million randomly selected and anonymized credit reports in the 2015-2017 timeframe from the three national credit reporting agencies and examines the payment behaviors.

The analysis compares the bad rates (or loan default), as defined as 90 days or more past due (90+ DPD) on accounts, over a 24-month period and shows that both conventional and unconventional credit scores are unbiased. In other words, consumers in a given score range show similar risk of default regardless of how their score was calculated.

TRADITIONAL METHODS FOR CREDIT SCORES: WHY THEY DON’T WORK FOR ALL CONSUMERS

You’ve likely heard of the old adage: You can’t fit a square peg into a round hole. Yet, for approximately 40 million consumers in the United States, this adage translates to “you can’t get a credit score because your credit use doesn’t fit our model architecture.” Many years ago, when credit scoring models were originally developed, there was a hard rule implemented to credit data that stated ‘only use trades that have been reported within the past six months’ for developing attributes (or characteristics) regarding balances and credit usage. The data below show that this rule only works well on general credit card data.

Figure 1 shows the extent to which tradelines are reported over a 24-month timeframe. While there is some decline in report activity going farther back than six months, there is still valuable data to leverage.

Figure 1: Latest Reported Activity on Tradelines Open 24-Months Earlier

Months reported	Overall	By Industry				
		Auto	Bankcard	Mortgage	Installment	Retail
<6 months	82.6%	70.8%	87.7%	82.0%	74.1%	77.0%
6-24 months	17.4%	29.2%	12.3%	18.0%	25.9%	23.0%

Any information from tradelines with the last reported activity older than six months are cut away and discarded from a conventional model, leaving many consumers unscorable, especially those who choose to use revolving credit sparingly.

For example, an auto tradeline that a consumer has successfully paid off five months ago is acknowledged by a traditional scoring model but it is removed after seven months. The information that the “worst status” was clean (i.e., the entire loan was paid off) still provides predictive value as it signals positive credit behavior.

THE BANK CARD BIAS FACTOR

A closer inspection by product type shows large discrepancies in terms of recently reported activities. Bankcards have the highest rates of recently reported activity. Roughly only one in eight of these tradelines are not reported within six months. As a result, most traditional credit scoring models have weighed heavily on bankcard specific activities when assessing credit risk. This is an inherent bias towards a specific product type that many consumers may choose to not regularly use.

All other product types have a higher percentage of the tradelines with the latest report longer than six months ago. Auto and installment loans have more than 25 percent of tradelines with activity more than six months ago, causing them to be removed from traditional credit score model calculations.

² VantageScore 4.0 applied specific machine learning techniques on credit data to determine how to evaluate the traditionally unscorable consumer. For more information, read a companion white paper “[Scoring Credit Invisibles – Using Machine Learning Techniques to Score Consumers with Sparse Credit Histories.](#)”

This begs the following question: should all tradelines be treated identically when evaluating credit? Installment loans, such as auto loans, have a fixed term and set payment amounts and, as a result, show different behaviors compared to credit cards. Given this, it does not make intuitive sense that all tradelines be treated by scoring models in the same way.

Indeed, successful management of an installment loan obligation presents insights into how a consumer has managed loans in the past. Bankcard data highlights other features such as flexibility of payment and credit line management, but these behaviors do not exist in other types of loans. Setting an arbitrary 6-month cut-off leading to removal of trades containing valuable information without any empirical justification other than “that’s how it was done originally” means there is no room for enhancement.

Modern data modelling techniques and computational resources have evolved dramatically since 30-plus years ago. Methods involving machine learning routines allow modelers to quickly consider highly complex data interactions that would have been previously unimaginable to analyze. Using modern data methods to unearth previously unconsidered relationships in credit data seems a natural choice to improve credit scoring to all consumers.

PERFORMANCE CHECK #1:

How Do Default Rates of Unconventionally Scored Consumers Compare with Conventionally Scored Consumers?

A credit score model should be able to measure and rank-order the default risk of loans in a lender’s portfolio. The expectation of a risk manager is that a credit score accurately evaluates the likelihood that a consumer will default over a given time frame. High- risk borrowers receive low scores and low-risk borrowers receive high scores.

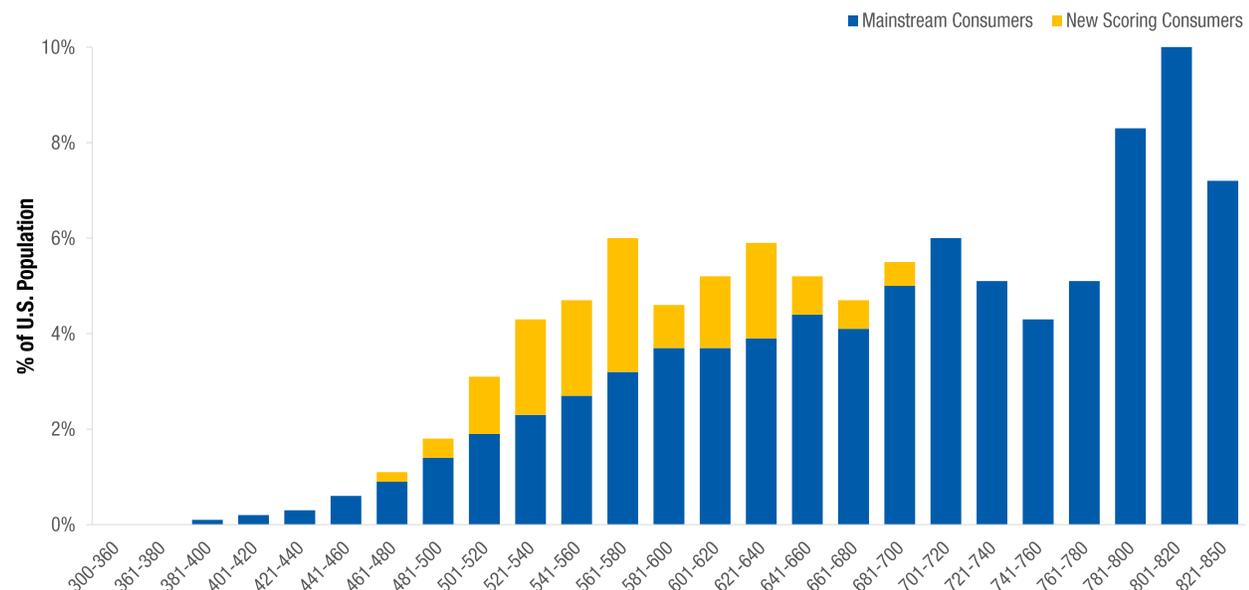
So how does one show that a credit score is doing an accurate job when assessing whether a set of consumers will default, on their debts?

When building a credit score model, data scientists typically create segments that combine to make a single scoring model. These segments must be aligned on their default “odds” to create a single score distribution. This means a score, say of 660, estimates the same “odds” of default for consumers regardless of which segment their scores come from. For example, taking the machine learning-driven segments and aligning the “odds” of default to the conventionally built segments ensures that the assessed default risk is consistent across both segments.

Default, in VantageScore 4.0’s case, is an account that is 90+ Days Past Due (DPD) in the next 24 months. Figure 2 shows the overall score distribution for VantageScore 4.0 and differentiates where the newly scored, or unconventionally scored, consumers fall in the overall score distribution.

Figure 2: VantageScore 4.0 Score Distribution by Consumer Type

VantageScore 4.0 Score Distribution



The fundamental consideration for a credit score model to work, regardless of how the score is calculated, is that it treats all consumers fairly. In other words, if two consumers have the same credit score, yet their scores are calculated using different elements of their credit report, the outcomes for both consumers should be unbiased when they get a loan. This means that given both consumers have the same score and open a new loan or continue to use an existing open loan, all else equal, the likelihood of default should be the same for both consumers.

How do you demonstrate that the credit scores are unbiased, or will achieve the same outcome? To further explore, read companion white paper [“Testing Credit Scoring Models for Statistical Bias: Ushering a New Era of Transparency”](#). As part of VantageScore’s annual validation process, a statistical bias test is used to determine if consumers from different ethnicities are impacted differently when scored by VantageScore. The test determines the default rate curve (a representation of the relationship between credit score and default rate) for each ethnic group and then compares it to that of the overall population to see if there is statistical bias. The results of this test demonstrate that VantageScore has no inherent bias when assessing credit risk for minorities; meaning, regardless of an individual consumer’s ethnic background, his/her credit score measures the same risk.

This same test can be used to assess whether unconventionally scored consumers are “treated the same” as conventionally scored consumers. If the two default rate curves for conventionally scored and unconventionally scored consumers, respectively, do not show a statistically significant difference, it can be concluded that there is no bias. The statistical bias test can be depicted graphically by building “confidence intervals” to determine if one curve is significantly different from the other. If the tested curve, in this case the unconventionally scored curve, stays within the confidence intervals, then the two curves are statistically unbiased and measure the risk similarly.

Figure 3: Statistical Test for Bias: Conventional versus Unconventional with confidence intervals

Statistical Bias: Default Profiles of Conventional vs. Unconventional with confidence intervals

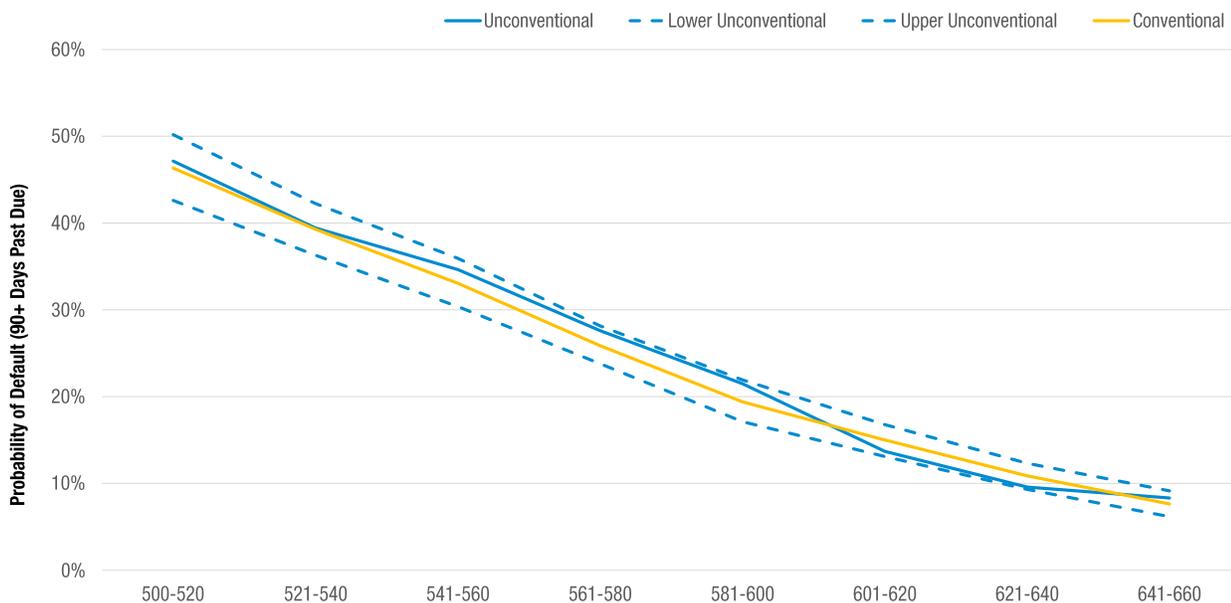


Figure 3 shows that the default curve for unconventionally scored consumers (solid blue line) never goes above or below the confidence intervals of the default curve for unconventionally scored consumers. This indicates that unconventional consumers do not have different default rates compared to conventionally scored consumers. Although there are minor differences, these are statistically not significant and are well within acceptable limits. In other words, there are no fundamental differences in default outcomes for either type of consumer given the same credit score, regardless of which model is used.

PERFORMANCE CHECK #2:

Do Newly Scoreable Consumers Default at a Quicker Rate than Conventionally Scored Consumers?

As demonstrated previously, over a standard period of time, 24 months, the rate at which unconventional consumers default on a loan is similar to the rate for conventional consumers with the same score.

Still, lenders may be concerned that these consumers may, on average, default at a much quicker rate after obtaining a new loan. To evaluate this concern, the following analysis tracks the first year of activity on a new account to see if unconventional consumers do exhibit faster missed payment activity versus their conventionally scored counterparts.

Figures 4a-4d show, by 20-point score bands ranging from 600 to 680 (illustrative of where new account origination activity occurs), the first 30 DPD for both conventionally (yellow line) and unconventionally (blue line) scored consumers.³

Figures 4a-4d

Figure 4a: 600-619 Score Range

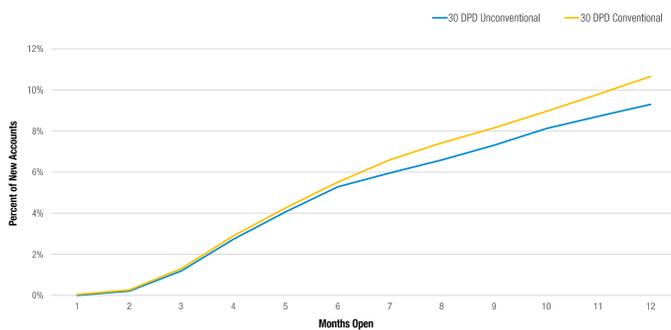


Figure 4b: 620-639 Score Range

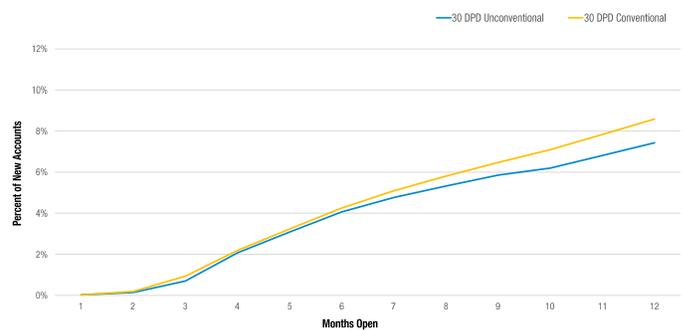


Figure 4c: 640-659 Score Range

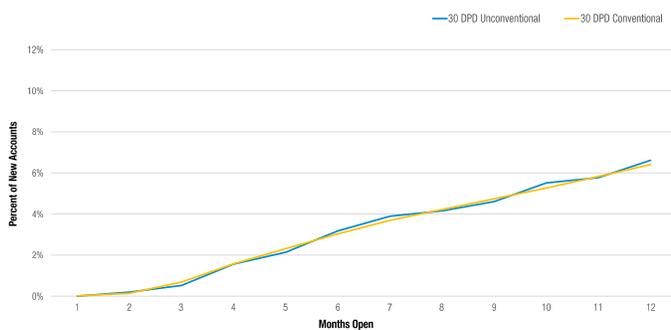
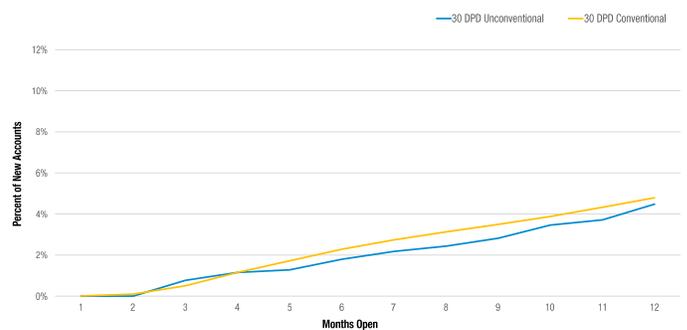
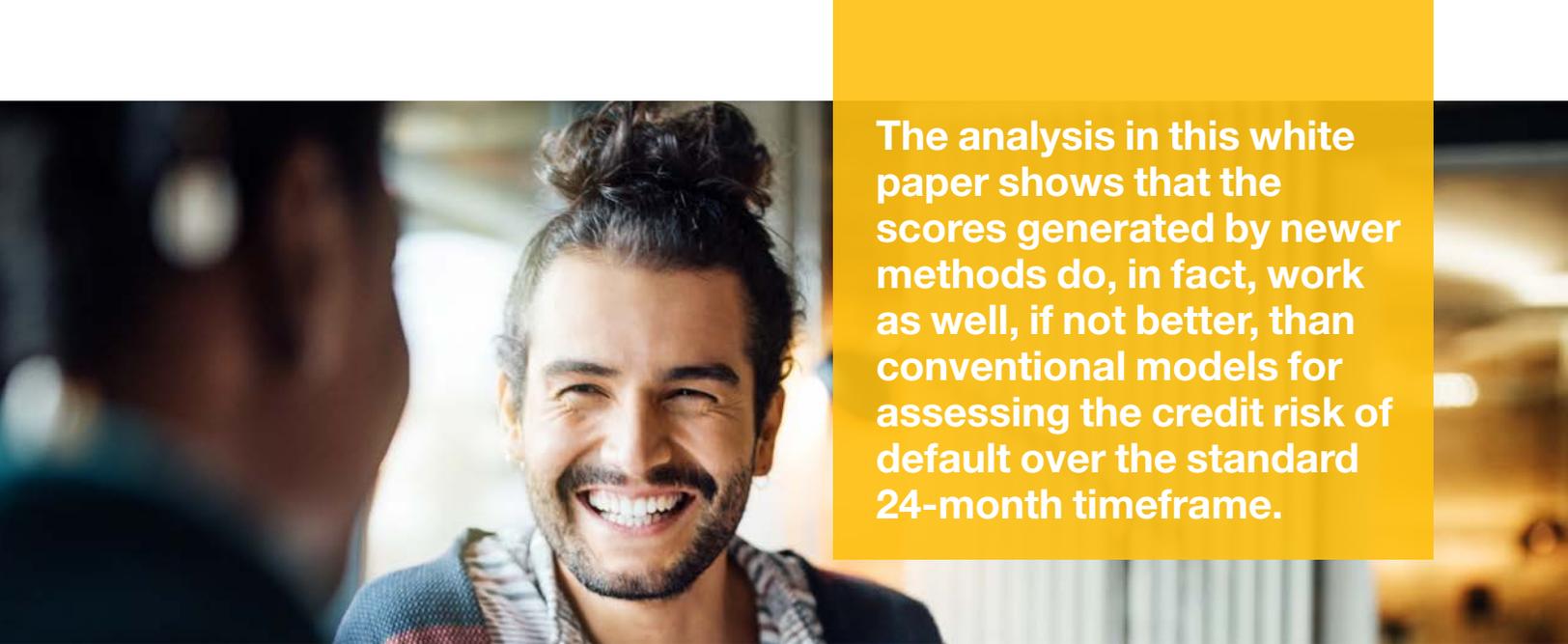


Figure 4d: 660-679 Score Range



In all instances, both conventionally scored consumers and unconventionally scored consumers exhibit similar payment behavior within the first year of acquiring a loan. In other words, unconventionally scored consumers do not default quicker or exhibit an increased risk when opening and paying new loans.

³ Data includes a cross section of different loan types including auto, credit card, mortgage, etc.



The analysis in this white paper shows that the scores generated by newer methods do, in fact, work as well, if not better, than conventional models for assessing the credit risk of default over the standard 24-month timeframe.

CONCLUSION

Currently there are about 40 million “unscorable” or unconventional consumers of credit who are invisible to a traditional credit scoring model due to their credit reports being incompatible with traditional credit risk model architectures. VantageScore 4.0 re-examined these credit reports using modern risk modeling techniques to identify data relationships to fairly and accurately assess credit risk for these underserved consumers.

While skeptics have claimed that these scores are merely a “race to the bottom” since the data in these consumers reports do not “fit” the traditional methods of scoring, the real bottoming out lies with older methods reliance on simple equations and outdated rules used to determine if a tradeline is scoreable. These “older school” calculations are driven by the historical reliance on bankcard type data and ignore other more complex relationships. Modern data and modeling methods have allowed for more complex relationships to be quickly assessed and for various credit behaviors to also be addressed.

The analysis in this white paper shows that the scores generated by newer methods do, in fact, work as well as conventional models in assessing the credit risk of default over the standard 24-month timeframe.

Critical for lenders, the data shows that new account payment behavior for unconventional consumers are similar to the conventionally scored consumers. These strong consistent results underpin the idea that credit scoring and credit risk models should constantly re-evaluate credit data to offer innovative solutions to previously unanswerable questions.

Credit scores aim to accurately, reliably and fairly determine the creditworthiness of a consumer. As long as the scores are effective in meeting these goals, they can be confidently utilized as part of a sound credit lending strategy. Bringing out previously unseen insights to consumer credit risk behaviors through modern and innovative approaches must become mainstream.

The VantageScore credit score models are sold and marketed only through individual licensing arrangements with the three major credit reporting companies (CRCs): Equifax, Experian and TransUnion. Lenders and other commercial entities interested in learning more about the VantageScore credit score models, including the VantageScore 4.0 credit score model, may contact one of the following CRCs listed for additional assistance:

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