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Predictive Value of Credit Score Consistency



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INTRODUCTION

“Get a second opinion” is an age-old adage often heard when one is making life’s most important decisions. When decisions are confirmed (or verified) by a second assessment, the initial result is considered to be on solid ground. Comfort is gained by knowing there is consensus from independent sources. Alternatively, getting conflicting (or unverified) evaluations suggest that there is more uncertainty involved with the decision than what was initially thought. Thus, there may be unforeseen exposure to pursuing the original action. These situations require additional scrutiny, as there may be alternative considerations to review.

Yet, when using a credit score to determine whether to accept a loan application, many lenders rely on just one credit score to determine credit worthiness. Additional scores and data sources can provide further insight to confirm or even counter an initial assessment. The question arises: can lenders use a second credit score to provide an additional opinion that will enhance their confidence in their predictions regarding how a consumer will behave (i.e., pay or default)? Analytically speaking, is there additional predictive power that arises from the use of two credit scores versus a single credit score?

This white paper examines the use of two generic risk credit scores and demonstrates that there is superior predictive performance when the second credit score is used to verify the risk assessment provided by the original credit score. We call this increase in performance: *the predictive value of score consistency*.

The analysis considers the value of verification using VantageScore 3.0 at two nationwide Credit Reporting Companies¹ (“CRCs”). However, any two credit risk models may be used for verification to enhance predictive insight, provided the models used are designed to predict probability of default on the same types of accounts and are installed at separate CRCs.

The analysis builds on three elements:

1. Higher **predictive insight** means greater certainty regarding population risk which consequently will lower defaults.
2. A second score pulled from another CRC can verify the risk assessment of the first score and consequently enhance the **predictive insight** of the population.
3. Using scores with a consistent algorithm at independent data sources *verifies a greater percentage of the population risk assessment*.

¹ The three nationwide CRCs are Equifax, Experian and TransUnion

ANALYSIS SUMMARY

- Step 1: Credit score models are typically evaluated using measurements like a Gini coefficient to measure predictive effectiveness. What do Gini improvements mean in terms of a reduction in defaults regarding lending decisions?
 - A one-point Gini improvement in credit score model performance provides default reductions (improvements) of approximately nine percent for Prime lending decisions (a score cut-off of 720) and six percent for Near Prime lending decisions (a score cut-off of 660). A 2.5 point Gini improvement will decrease defaults by 23 percent for Prime lending decisions and 13.3 percent for Near Prime cases.
- Step 2: One way to increase the predictive performance of any credit score model is to verify an initial credit score with another, different brand of credit score obtained from a separate CRC.
 - Verified credit scores, regardless of the brand or version, deliver Gini improvements at least two points higher on the verified population than if only one credit score is used on that same population. Conversely, the population with unverified credit scores shows a drop in Gini performance of four to five points, meaning risk assessment for these consumers is less reliable. Consumers with unverified credit scores should be managed with greater scrutiny than verified consumers.
- Step 3: How often do credit scores “verify” the risk assessment? For this study, the process consisted of verifying the same population; first, using two proprietary credit scores obtained from two separate CRCs, and then comparing that initial verification result to a second verification using two separate VantageScore 3.0² scores pulled from two separate CRCs.
 - 75 percent of the consumers in the population were verified when two VantageScore 3.0 scores (from two independent CRCs) were used. The verification rate was consistent throughout the credit spectrum. Just 30 percent of the consumers were verified when using two proprietary CRC scores from two independent CRCs. The verification rate was similarly consistent across the credit spectrum.

Given the higher verification volume using VantageScore 3.0, predictive insight on this population was meaningfully higher which would consequently lead to lower defaults.

² While VantageScore 3.0 was used for this study, results would be similar if other versions of VantageScore were used including VantageScore 4.0.

Step 1: Higher predictive power equates to greater certainty regarding population risk

Predictive effectiveness for credit score models is measured by statistics such as a Gini coefficient. The Gini coefficient of a credit score model compares the distribution of defaulting consumers with the distribution of non-defaulting consumers across the credit score model’s range. The coefficient has a value of 0 to 100. A value of 0 indicates that defaulting consumers are equally distributed across the entire model’s range. In other words, the credit scoring model fails to assign more defaulting consumers to lower credit scores. A coefficient value of 100 indicates that the model has successfully assigned all defaulting consumers to the lowest score possible and all non-defaulting consumers to the highest score possible. A Gini coefficient of 45 or greater is considered a good result by industry standards.

How do Gini coefficient results affect lending decisions? In this example, we used three credit scoring models with decreasing predictive power on a sample of 500,000 new originations (Figure 1). The credit scoring models use the same standard scale (300 to 850) to make lending approval decisions.

Figure 1: Gini performance using three credit score models on the same portfolio

		Gini 90+ Days Past Due (DPD)	Gini Coefficient	Gini 90+ Days Past Due (DPD)	Gini Coefficient
Originations	Model 1	70.64	71.86		
	Model 2	69.65	70.89	0.99	0.97
	Model 3	68.07	69.27	2.57	2.59

How does the loss in predictive power impact defaults in lending decisions? Applying these three models on the same set of consumers to make loan approval decisions is highlighted in the table below (Figure 2). The impact of using less predictive models can increase defaults by up to 23 percent in Prime lending cases and 13 percent in Near Prime cases.

Figure 2: Default rate impact given credit score model predictive performance and credit score cut-off

		Default rate	Number of defaulting accounts	Additional lost accounts	Percent of additional losses
720 Score Cut-off	Model 1	0.53%	2,638		
	Model 2	0.57%	2,866	288	8.6%
	Model 3	0.65%	3,233	595	22.5%
660 Score Cut-off	Model 1	1.41%	7,035		
	Model 2	1.49%	7,463	428	6.1%
	Model 3	1.59%	7,970	935	13.3%
600 Score Cut-off	Model 1	2.94%	14,710		
	Model 2	2.98%	14,922	212	1.4%
	Model 3	3.05%	15,238	527	3.6%

Step 2: A second credit score pulled from a different CRC can verify the risk assessment of the first credit score and, consequently, enhance the predictive insight of the population

How do credit scores provide the ‘second opinion’?

Credit score models use a three-digit score to determine a consumer’s probability of default on a debt obligation. Models can use a variety of ranges, like 300 to 850, 200 to 900, 501 to 990, etc. which is challenging when trying to make a direct comparison between credit scoring models for second opinion purposes. Yet, the message is the same regardless of the model’s range: the higher the credit score, the more likely the consumer will pay on time.

All credit scoring models have an underlying principle of rank ordering consumers from best to worst in terms of probability of default. Given this principle, the rank-ordered population can be assigned to a specific population percentile to indicate their *risk tier* (relative to the rest of the consumers). This scaling approach is no different than the SAT/ACT score percentile or childhood development (e.g., height and weight profiles) population percentiles. For example, a consumer in the fifth percentile based on their credit score rank is in the top five percent of the population. A consumer in the 80th percentile is in bottom 20 percent of the population.

Using this percentile assignment approach, the consumer’s risk assessment from any credit score model can be compared with their risk assessment from another credit score model, given their ability to assign

the consumer to the same percentile or to very different percentiles. When the percentile from both credit score models is the same or very similar, the risk assessment is verified.

For the purposes of analysis, if the two percentile rankings are within four percentile ranks of each other, the scores are verified. When the percentile rankings are very different, the risk assessment is not verified. In this instance, a difference of five percentile ranks or greater indicates a greater risk exposure if the original credit score is used for credit evaluation.

VantageScore 3.0 credit scores were pulled from two separate CRCs on the same population of six million consumers. The percentile ranks were calculated using VantageScore 3.0 at CRC A and B, and the difference between percentile ranks were calculated. The risk assessment from the credit score at CRC A was considered verified if the difference in percentile ranks between the VantageScore from CRC A and CRC B was less than or equal to four percentile ranks. If the percentile rank difference was greater than five, the risk assessment from the credit score at CRC A was not verified.

If the percentile rank from CRC B was five percentile ranks higher, then the second credit score indicated a lower risk assessment than the original credit score. Conversely, if the percentile ranking from the second CRC was five percentile ranks lower than the second credit score, this indicated a higher risk assessment than the first credit score.

Figure 3 shows the OVERALL strength of a single VantageScore 3.0 as a predictor for originations with a

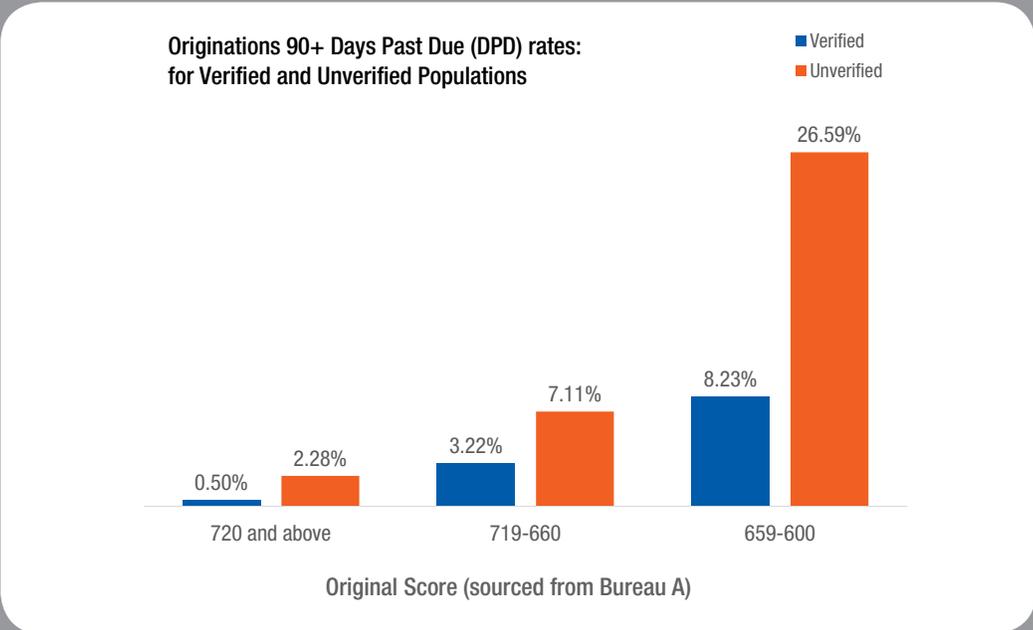
Figure 3: Predictive performance for verified vs. unverified populations

Verification status	New Account Originations		Existing Account Management	
	Gini 90+ Days Past Due (DPD)	Gini Coefficient	Gini 90+ Days Past Due (DPD)	Gini Coefficient
Significantly higher risks (5 ranks or more lower)	65.10	66.61	73.35	73.74
Verified (within +4 or -4 ranks)	72.76	73.88	82.34	82.90
Significantly lower risk (5 ranks or more higher)	65.45	66.81	73.59	74.45
Overall model	70.64	71.86	80.44	81.00

Gini 70.64 and for account management with a Gini of 80.44. Using the percentile rank verification approach, the population with verified credit scores, i.e., within four percentile ranks, has a Gini value of 72.76, two points higher than when only one credit score was used. Consumers with credit scores that could not be verified had a five Gini point loss in predictive performance, reflecting greater uncertainty in their risk assessment.

Those unverified credit scores suggest a lender should conduct further evaluations to ensure that it is not exposed to unnecessary defaults or lost revenue opportunities. The increase in predictive performance translates directly to improved default rates. Figure 4 shows the default rates by credit score bands, above 720 (Prime), 719-660 (Near Prime), 659-600 (Sub-Prime), for the verified and unverified populations.

Figure 4:
Default rates for
verified and unverified
populations by
score band

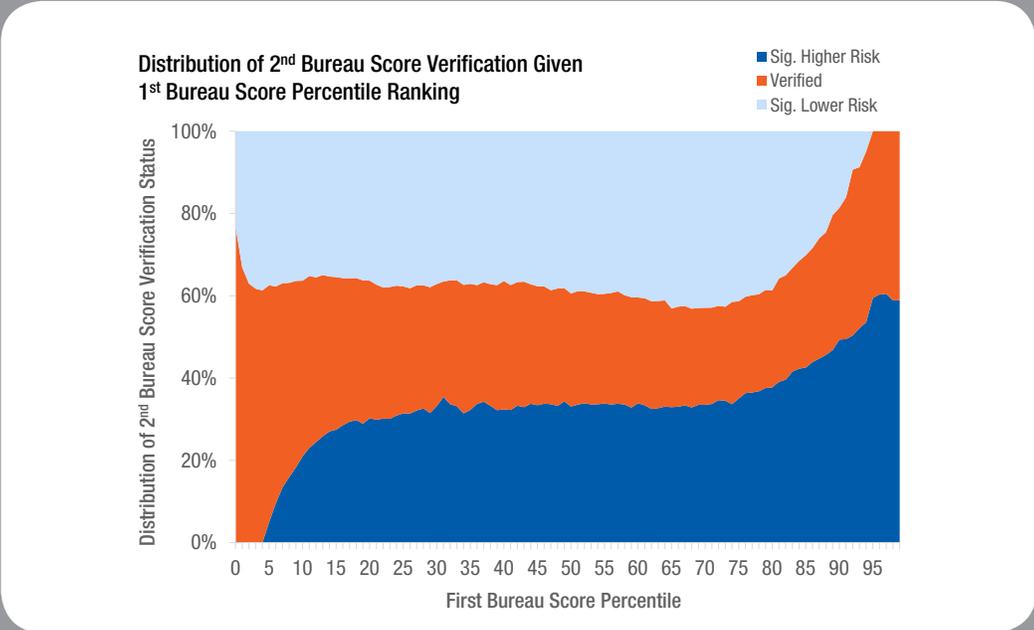
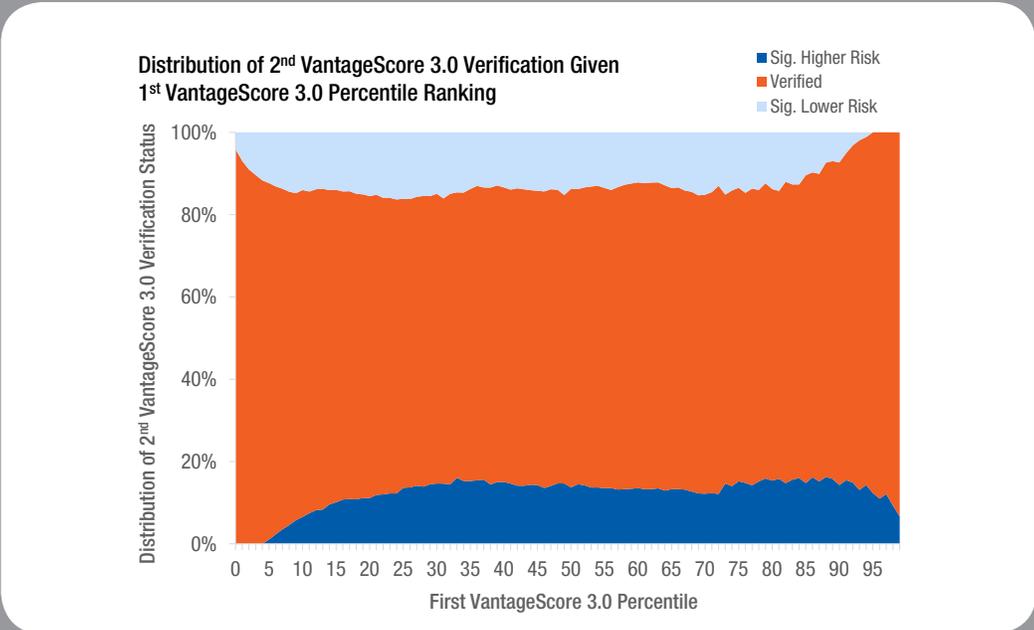


Note that the increase in predictive performance due to verification and resultant capacity to reduce defaults was not specific to VantageScore 3.0. Using the same customer data, two independent, proprietary CRC credit scores from two separate CRCs yielded similar results when verified by percentiles.

Step 3: Using credit scores from a consistent algorithm at independent data sources verifies a greater percentage of the population risk assessment

The following graphs show the verification volumes across the credit spectrum for verification using two VantageScore 3.0 credit scores versus verification using two proprietary CRC credit scores (Figure 5).

Figure 5:
Population verification percentage when using two VantageScore credit scores or two proprietary CRC credit scores



For a bulk of the range, the second VantageScore 3.0 verifies the original credit score approximately 75 percent of the time. In other words approximately three out of four consumers have their original VantageScore 3.0 credit score verified with a VantageScore 3.0 score from a second CRC. With the exception of the extremely high risk (bottom 10 percent) and low risk (top 10 percent), the verification of the VantageScore 3.0 credit score remains stable throughout the range.

Alternatively, the ability to verify a CRC proprietary credit score using a second proprietary CRC credit score occurs just 30 percent of the time. A lender is much less likely to get an increase in predictive accuracy when verifying two VantageScore credit scores versus two proprietary CRC credit scores.

The reason for this increased verification is due to VantageScore's unique approach in attribute and algorithm consistency. Attributes are designed and leveled across the three CRCs, which allows an identical algorithm to be implemented at each CRC. Consequently, the only differences occurring in a consumer's credit scores are due to differences in the data being reported and recorded at each CRC. Conversely, credit scoring models that have been independently developed and optimized for the data and structure at a single CRC reflect credit score differences due to data and the algorithm. See the characteristic leveling process white paper (<https://www.vantagescore.com/resource/25/characteristic-leveling-process>).

The net impact of this enhanced predictive insight for verified consumers within the overall population is: using VantageScore 3.0 with verification can minimize defaults on a larger percentage of consumers versus using verification with two proprietary credit scores, which have algorithms that are different and independently designed for the specific CRC.

CONCLUSION

The ability to make sound lending decisions is based on using credit scores that optimally identify consumer outcomes. The focus of this paper was to demonstrate that there is additional effectiveness in using two credit scores rather than a single score for lending decisions. Using a second credit score to verify the original credit score affords an additional opportunity to increase the accuracy of risk prediction and, therefore, manage default rates.

Using unverified credit scores, in contrast, results in an increase in the potential exposure in lending decisions that may require further scrutiny. "Getting a second opinion" on consumers' credit risk profiles can lower default rates about 10-20 percent in Prime and Near Prime lending decisions versus the use of a single credit score alone.

The use of two VantageScore 3.0 credit scores provides lenders with an even stronger verification process because this method verifies approximately 2.5 times more consumers than a verification based on two proprietary credit score models that had been developed independently. The improved verification performance is a function of the consistent algorithm used across the three CRCs that is one of the main benefits of all VantageScore models.

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:



Call 1-888-202-4025

<http://VantageScore.com/Equifax>



Call 1-888-414-4025

<http://VantageScore.com/Experian>



Call 1-866-922-2100

<http://VantageScore.com/TransUnion>

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