Credit Score Basics, Part 3: Achieving the Same Risk Interpretation from Different Models with Different Ranges

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OVERVIEW

Most generic credit scores essentially provide the same capability to lenders: Rank order consumers based on their propensity to default, where default is defined as becoming 90 or more days late on a debt within a two-year timeframe. The score places higher credit quality consumers at the higher end of the score range and lower quality consumers at the lower end of the range. If a score of 700 was identified on a score with a range of 500 to 1000, then a 700 might represent "C" quality credit. But a 700 score on a range of 300 to 900 is more likely to represent "B" quality credit. Knowing the scale range that a particular score falls within is necessary for proper interpretation of the score. The mathematics of credit scoring always defines the score in the context of its range – the minimum and maximum possible values that can be achieved. When scores are quoted, it's critical to also quote the range in order to convey an accurate understanding.

VantageScore Solutions, LLC has published a three-part series of white papers describing important, but less known attributes and applications of credit scores, aimed at closing knowledge gaps that exist among general users of credit scores. The first paper, *What's Behind Credit Scores*, covers the relationship between consumer risk and credit scores. The second installment, *An Overview of Ways Lenders Use Credit Scores for Credit Approval*, describes three possible scenarios for ways that lenders may utilize credit scores in their business strategies. This paper tackles methodologies for interpreting risk from different models utilizing different ranges.

In fact, it's unclear to many that different score models use different score ranges. Once discovered, score users frequently ask how to translate a score value based on a particular range from one score model to a score value from another model that uses a different range in order to provide the same risk interpretation. Described below are three methodologies for converting disparate score values from different ranges into the same risk assessment.

SUMMARY HIGHLIGHTS

- Many credit score models exist, with unique ranges and proprietary approaches to model development. Understanding the context of each model, such as score range, is necessary to understanding the level of risk that a particular score value represents.
  - » The same score value from different models almost always represents a different level of risk. In other words, a 700 from the VantageScore® model will have a different risk level than a 700 from other score developers.
- Conversion of the risk level from one score to another is useful and necessary for lenders attempting to evaluate or use multiple models. Conversion methods can be designed to approximate risk between multiple models or provide highly accurate custom conversions for a specific portfolio.

CONVERTING FROM ONE SCORE MODEL TO ANOTHER

Most credit score models use a similar mathematical approach, called regression, to develop the scoring algorithm. The output of regression models is an unfriendly and not very useful expression, for example -2.3456 to +4.1234. Model developers have overcome this awkwardness by translating the regression output to a more suitable scale, for example, 501 to 990. One can think of the score transformation similar to the conversion of kilometers-per-hour to miles-per-hour: the conversion does not affect the speed, but converts it to a more familiar frame-of-reference. Further, it facilitates easy score comprehension, as well as application within business strategy design.

Model developers design the score range (minimum to maximum value) to be broad enough such that the population is sufficiently distributed across the range. Lenders can then manage their population by selecting score cut-offs that represent meaningfully different risk levels at each cut-off. Note, the range is defined by the score designers and can vary based on the intended applications for the score. Commercially available credit scores are available with many different score ranges; examples include a range of 100 to 900, an 800 point spread, and a range of 300 to 850, a 550 point spread.

As noted earlier, an important consequence of using different ranges is the fact that a score of 700 on one range (for example, the VantageScore range with a minimum and maximum of 501 to 990) may not indicate the same level of risk as a score of 700 where the score range is 100 to 900. As a result, lenders who desire to switch from using one score to another need a methodology to convert score values into the same risk indications.

Three methods for converting score values from one score to another are presented below: "Simple Logistic Alignment," "Risk-Based Pricing Table Alignment" and "Portfolio Multi-Score."

METHOD 1: SIMPLE LOGISTIC ALIGNMENT

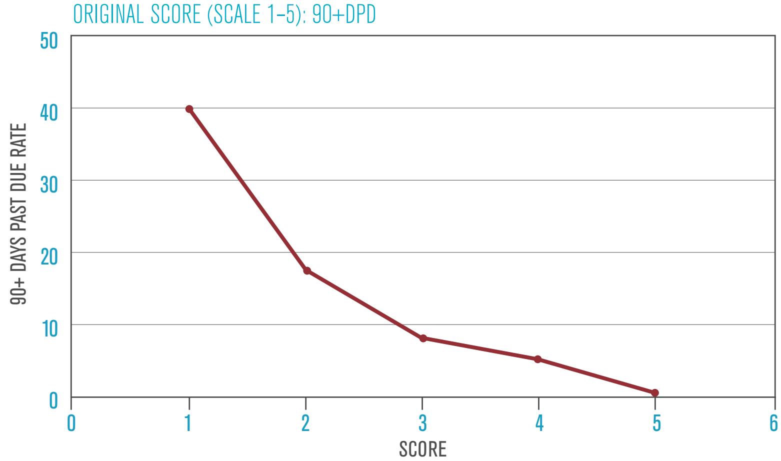
In order to illustrate how the *Simple Logistic Alignment* conversion method works, it was first necessary to create two hypothetical credit scores. In our example, one credit score has been named **"Original Score"** and the second bears the name **"Other Score."** The score designs are as follows:

- "Original Score" has a range of 1 to 5
- "Other Score" has a range of 630 to 900
- Both scores have been designed to rank order based on the propensity for consumers within the population to become 90 days or more delinquent (90+dpd)

Performance charts reflecting the alignment between the score values and propensity to default have also been generated for this example, as seen in Figure 1 below. (Refer to the first white paper in VantageScore Solutions' series on credit scores, *What's Behind Credit Scores*, for an explanation of performance charts.)

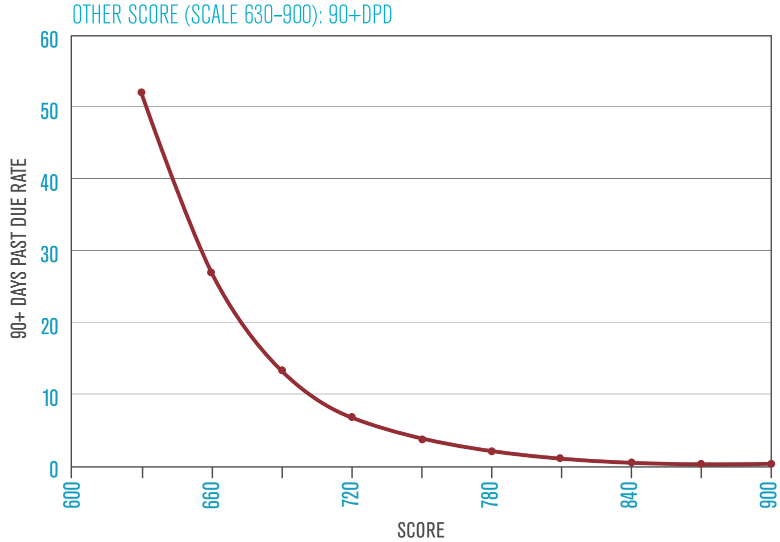
FIGURE 1
PERFORMANCE CHARTS

ORIGINAL SCORE (SCALE 1–5): 90+DPD



ORIGINAL SCORE	90+DPD
1	40
2	16
3	8
4	4.5
5	0.4

OTHER SCORE (SCALE 630–900): 90+DPD

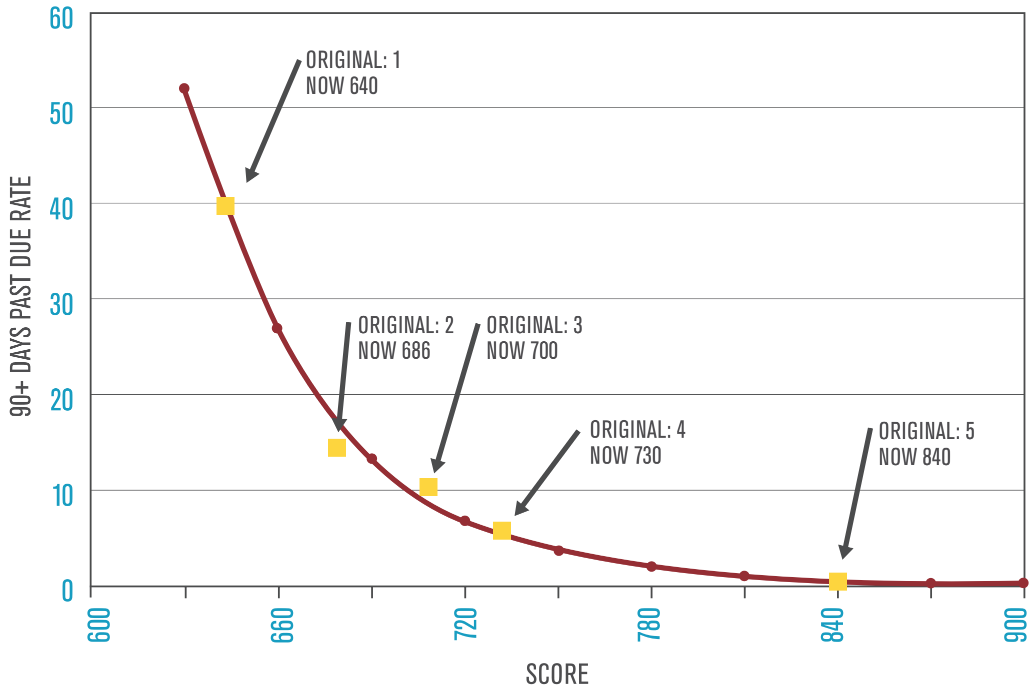


OTHER SCORE	90+DPD
630	51.2
660	25.6
690	12.8
720	6.4
750	3.2
780	1.6
810	0.8
840	0.4
870	0.2
900	0.1

METHOD 1: SIMPLE LOGISTIC ALIGNMENT
(Cont.)

FIGURE 2

90+DPD VERSUS SCALE 630 TO 900: LOG MODELLED INTERPOLATING 1 TO 5 SCALE



In this example, we calculate a simple logistic regression relationship pivoting on 90+dpd values:

- “Other” score value= -43.2809*LN(90+dpd value for Original Score) +800.3422

Applying this method to the two example scores, the conversion of score values can be seen on the graph in Figure 2 above. For example, using a score value of “2” from the Original Score and applying the logistic regression calculation (-43.2809*LN(14)+800.3422), the equivalent value for the “Other Score” is determined to be “686.” The conversions for the remaining score values are similarly plotted.

This method can provide a *reasonable approximation* for converting one score to another by pivoting on propensity for default values. To provide a reasonably accurate result with this method, a key assumption is made that the propensity for default values are determined on similar populations, products and timeframes.

METHOD 2: RISK-BASED PRICING TABLE ALIGNMENT

The new "risk-based pricing (RBP) notice" rule adopted into the Fair and Accurate Credit Transactions Act (FACT ACT) requires the generation of tables showing the distribution of credit score ranges across the U.S. population for every credit score model on the market used by lenders in evaluating consumer credit applications.

RBP tables classify the U.S. population from the credit reporting company providing the score into percentiles based on consumer scores using a specific algorithm. In the table below, a representative sample of the U.S. population is scored using the VantageScore model. The population is then grouped into percentiles and the minimum and maximum score values are aligned by percentile. For example, consumers with scores between 724 and 728 rank higher than 45.00% of the population but less than 46.00% of the population. (See Figure 3)

FIGURE 3

VANTAGESCORE (501-990)		
MINIMUM	MAXIMUM	"Ranks Higher Than X%" CUMULATIVE
501	520	1%
...	...	...
724	728	45%
729	733	46%
734	737	47%
738	741	48%
742	747	49%
748	751	50%
752	757	51%
758	762	52%
763	768	53%
769	774	54%
775	780	55%
...	...	...
980	990	100%

METHOD 2: RISK-BASED PRICING TABLE ALIGNMENT

(Cont.)

The availability of these RBP distributions offers an alternative approach for mapping one score range to another. Converting between two scores using Method 2 is demonstrated with VantageScore, and its range of 501-990, and a proprietary score from one of the three national credit reporting companies (CRC) having a range of 300-900. Subsets of the RBP distributions for VantageScore and for the CRC Credit Score are shown in Figure 4 below.

FIGURE 4

VANTAGESCORE (501-990)				CRC CREDIT SCORE (300–900)		
MINIMUM	MAXIMUM	"Ranks Higher Than X%" CUMULATIVE		"Ranks Higher Than X%" CUMULATIVE	MINIMUM	MAXIMUM
...	...	...		...	...	...
724	728	45%	↔	45%	716	721
729	733	46%		46%	722	727
734	737	47%		47%	728	733
738	741	48%		48%	734	738
742	747	49%		49%	739	744
748	751	50%	↔	50%	745	749
752	757	51%		51%	750	754
758	762	52%		52%	755	758
763	768	53%		53%	759	763
769	774	54%		54%	764	767
775	780	55%	↔	55%	768	771
...	...	...		...	...	...

Using the two tables in Figure 4, scores can be translated from one range to the other by cross-referencing the same percentile value on both ranges to find the equivalent scores. Some examples:

- A consumer who has a VantageScore credit score of 724 falls in the 45th percentile. The 45th percentile of the same population has a CRC credit score between 716 and 721.
- A consumer CRC credit score of 745 falls in the 50th percentile. The 50th percentile on the VantageScore scale has a score between 748 and 751.
- A consumer who has a VantageScore credit score of 778 falls in the 55th percentile. The 55th percentile of a CRC credit score between 768 and 771.

The approach is an approximation for translating scores. However, in many situations where only a general translation is required, the approximation is sufficiently accurate.

METHOD 3: POPULATION MULTI-SCORE

While applicable for the majority of applications, the two approaches above may not provide sufficient accuracy for underwriting and credit management strategy design. For strategy design scenarios, the most accurate approach is to produce custom performance charts for the population using multiple score models.

When two scores are to be converted, every consumer in the candidate population is scored using both of the credit score models. Two performance charts, one for each credit score model, are produced that identify the propensity for default values for each score tier. The example below in Figure 5 shows a performance chart for a CRC Credit Score with its range of 300-900 and the VantageScore model, with the range of 501-990.

FIGURE 5

CRC CREDIT SCORE	
SCORE RANGE	90+DPD
912-937	0.38%
898-911	0.58%
885-897	0.56%
874-884	0.71%
860-873	0.96%
845-859	**1.07%**
827-844	1.45%
807-826	1.88%
785-806	2.50%
761-784	3.54%
735-760	4.86%
710-734	7.04%
684-709	9.23%
654-683	13.72%
622-653	20.22%
586-621	29.41%
554-585	46.99%
495-553	48.14%
450-494	65.03%
425-449	84.91%

VANTAGESCORE	
SCORE RANGE	90+DPD
971-990	0.11%
951-970	0.10%
931-950	0.12%
911-930	0.15%
891-910	0.19%
871-890	0.24%
851-870	0.36%
831-850	0.52%
811-830	0.75%
791-810	**1.07%**
771-790	1.56%
751-770	2.21%
731-750	3.09%
711-730	4.38%
691-710	6.27%
671-690	8.96%
651-670	12.16%
631-650	16.04%
611-630	21.23%
591-610	27.40%
571-590	34.30%
551-570	41.52%
531-550	48.28%
501-530	60.40%

METHOD 3: POPULATION MULTI-SCORE (Cont.)

With this method, the same consumers are scored in the same timeframe and custom performance charts are then created. In the example, a lender employing a strategy to maintain risk levels of 1.07% or less would establish the cut-off for the CRC Credit Score at 845. The same risk level, 1.07%, is achieved using a VantageScore cut-off of 791.

Method 3 provides a highly accurate and simple translation vehicle for converting between credit scores. Credit score users should discuss this approach with their CRC representatives to develop performance charts on their portfolios for multiple scores.

CONCLUSION

Credit score design has remained a black box for many years. This has often created confusion for score users who need to convert from a score that has deteriorated in predictive quality to a more predictive score. In this paper, VantageScore Solutions LLC offers three simple methods for translating from one model to another, thereby allowing users to maximize the benefit of using credit scores in their risk management processes.

GLOSSARY OF TERMS

Credit Score: A numerical expression representing credit risk generated from a statistical analysis of a person's credit report information, typically sourced from credit reporting companies.

Propensity of default (also likelihood of default and odds of default): The predicted probability that a consumer will default on a debt obligation, expressed as a percentage. All credit score values are aligned with corresponding "propensity of default" values.
90+ dpd: Shorthand expression for "90+ days past due." Once a consumer becomes 90+ days past due, he/she is said to be in default of the obligation.

Score range: The minimum-to-maximum values on the scale generated by a credit score model, for example: 501-990. Typically, consumers who pose less risk receive higher scores and those who represent more risk receive lower scores on the range. Hundreds of credit score models are available to lenders and consumers. Some models have the same or similar ranges, others have different ranges.

Performance chart (also odds chart): A table produced by credit score developers aligning credit scores within the score range with the propensity of default. A unique table is generated for each unique population.

Population: A specific set of consumers. Credit score models rank order consumers relative to other consumers within the same population. In other words, a credit score value is not an absolute value assigned to the individual at-large. The same consumer, appearing in two different populations, could theoretically receive two different scores because the score is relative to the performance of the other consumers in the distinct populations.