SEGMENTATION FOR
CREDIT-BASED DELINQUENCY MODELS

June 2006

Overview

The objective of segmentation is to define a set of sub-populations that, when modeled individually and then combined, rank risk more effectively than a single model tested on the overall population. Typically, the performance improvement is measured across the entire population, but the litmus test is the improvement in performance as measured at the individual creditor portfolio level. The credit-based delinquency model development process offers perhaps the ultimate flexibility in segmentation options resulting from large sample sizes and variety of individuals across the entire risk spectrum. This paper outlines the role of segmentation in the improvement of credit-based delinquency models and presents innovative methodologies for the segmentation process.

The Role of Segmentation

How does segmentation improve scoring system performance? The premise of segmentation is that the credit characteristics (independent variables) have a different relationship with risk (dependent variable) for different sub-populations. By identifying the appropriate sub-populations, the characteristics that are most predictive in isolating risk are optimized for that group.

If we consider two perspectives—a sub-prime lender and prime lender—that target individuals with vastly different risk profiles, the value of segmentation becomes clear. Consider the characteristic "number of accounts with a worst repayment performance of 90 days past due or more (severely delinquent/derogatory)," which is an important characteristic in discriminating between high and low risk individuals.

From the perspective of a sub-prime lender, the number of severely delinquent/derogatory accounts is a pervasive and defining element of the target population, but not necessarily a good predictor of who will be lower risk. Further, this characteristic is not likely to have a significant impact on the accept/decline decision. For individuals with tarnished credit, there may be little difference in risk with increasing numbers of severely delinquent/derogatory accounts.
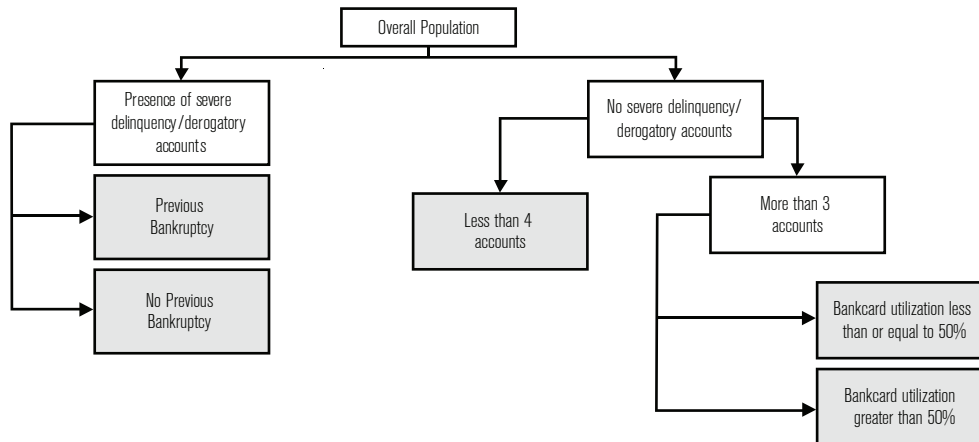
From the perspective of a prime lender, the difference in the number of severely delinquent/derogatory accounts will be a significant factor in ranking risk. For prime populations that may be fairly homogeneous, the difference between having zero and one severely delinquent/derogatory account may be the basis for the accept/decline decision or the difference between the lowest and the highest interest rate.

Suppose a single model solution is developed that uses the number of severely delinquent/derogatory accounts as one of the components to rank order risk. The resulting solution may be effective for determining whether an account is directed to a sub-prime lender or a prime lender, and effective for the prime lender in rank ordering risk. It may, however, have little or no value to the sub-prime lender in rank ordering risk. One potential solution would be to segment the population using the number of severely delinquent/derogatory accounts and build models on each population separately, optimizing the relationship of that characteristic to the risk prediction of the respective segment.

Traditional Segmentation Strategies

Many techniques exist for segmenting a population. The previous example relies on using a single characteristic to define a segment. The use of characteristics is common in segmentation schemes and typically involves multiple characteristics to define a sub-population, as demonstrated below.

Figure 1. Traditional Segmentation Scheme Example

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                        ┌─────────────────┐
                        │ Overall Population │
                        └─────────────────┘
         ┌─────────────────────────┴─────────────────────────┐
┌──────────────────┐                              ┌──────────────────┐
│ Presence of severe │                              │ No severe delinquency/ │
│ delinquency/derogatory │                          │ derogatory accounts │
│ accounts │                                        └──────────────────┘
└──────────────────┘                      ┌─────────────────┴─────────────┐
┌──────────────────┐              ┌──────────────┐              ┌──────────────┐
│ Previous │                      │ Less than 4 │              │ More than 3 │
│ Bankruptcy │                    │ accounts │                  │ accounts │
└──────────────────┘              └──────────────┘              └──────────────┘
┌──────────────────┐                                    ┌──────────────────────┐
│ No Previous │                                          │ Bankcard utilization less │
│ Bankruptcy │                                           │ than or equal to 50% │
└──────────────────┘                                     └──────────────────────┘
                                                         ┌──────────────────────┐
                                                         │ Bankcard utilization │
                                                         │ greater than 50% │
                                                         └──────────────────────┘
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Segmentation using individual characteristics has been the traditional methodology used for credit-based delinquency models. The segmentation scheme is typically derived using regression tree analysis, such as Classification and Regression Trees (CART) or Chi-squared Automatic Interaction Detector (CHAID); these techniques segment the population based on the relationship of independent and dependent variables.

Ultimately, using the characteristic-centric, tree-based approach creates a rank ordering system that results from a number of nodes (tree endpoints) with differing bad rates. However, scoring vendors have long promoted the value of using statistically derived scores instead of decision trees or manual processes to rank order individuals.

When viewed from the perspective of the sub-prime and prime lender, the characteristic-based approach is still sub-optimal because there is no one characteristic that when split one or more times approximates a lender's target population. Since there are many factors that influence whether an individual is sub-prime or prime, evaluating overall risk one characteristic at a time is inefficient because it requires numerous nodes to assess all of the relevant factors.

Why do traditional credit-based delinquency model vendors use characteristic-based methodologies to rank order risk for segmentation while they criticize their use for credit decisions? The answer lies in complacency and lack of innovation. With a historical lack of competition in the tri-CRC, credit-based delinquency model arena, the incumbent vendors have had no compelling reason to use advanced methodologies to extract additional predictive power from the rich databases of consumer credit behavior.

The New Era of Segmentation

Is characteristic-based segmentation dead? No. There is still value in using characteristic-based segmentation, but it must be used in conjunction with other approaches to produce a robust, powerful credit-based delinquency model. The new era of segmentation uses scores that group individuals with similar behaviors along a number of dimensions.

The use of scores to segment the population is consistent with consumer credit markets as higher risk individuals are directly or indirectly cascaded to non-prime or sub-prime lenders based on decisions derived from some type of credit score—not by individual credit characteristics. By using a risk-based segmentation score, individuals are compared to individuals with similar risk profiles; segmenting the credit population into risk tiers approximates creditors' target markets and enables effective risk assessment across the entire credit risk spectrum.

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Figure 2 shows the segmentation scheme used by VantageScore. The scheme leverages characteristic-based segmentation in conjunction with a general risk score and a profile model. The profile model identifies whether an individual has the profile of someone who will file for bankruptcy or someone who will default (90+ days past due/charge off).

Figure 2. VantageScore Segmentation Scheme
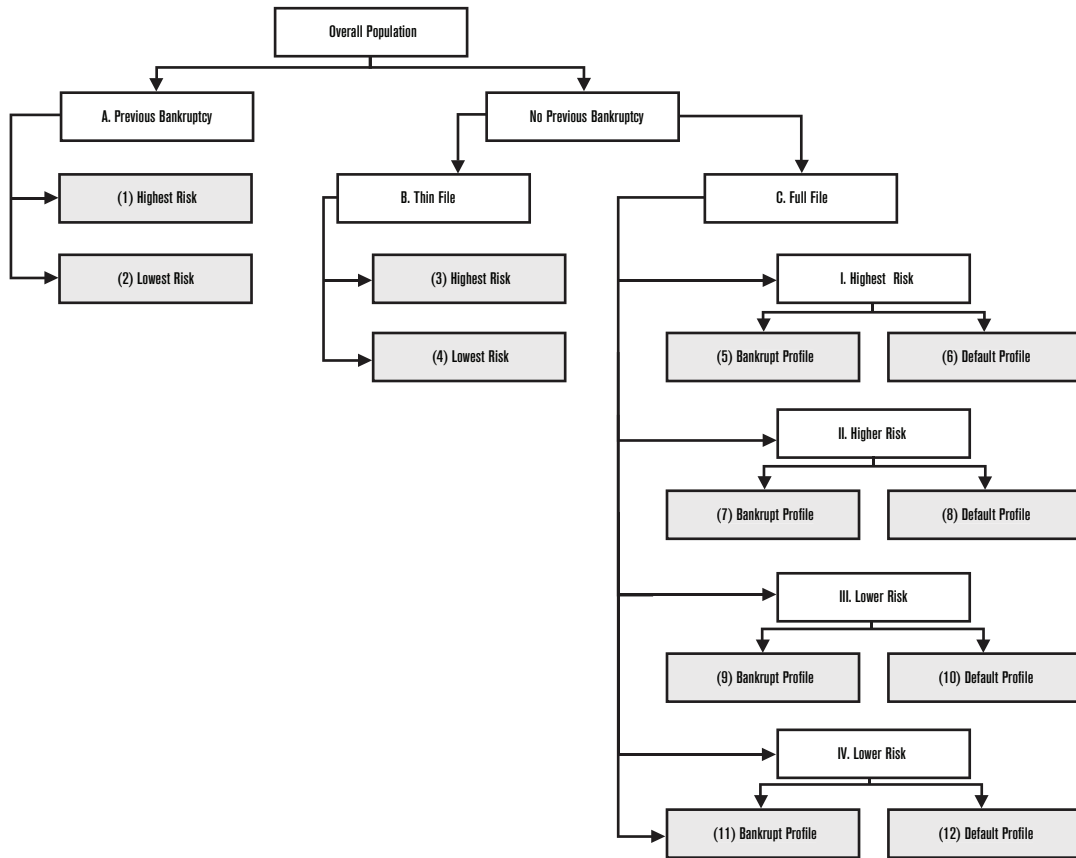
Previous bankruptcy was defined by a presence of a bankruptcy public record or a bankrupt status indication on an account. Thin file was defined by an individual having one or two accounts and no previous bankruptcy. Individuals with full files had no previous bankruptcy and three or more accounts.

Previous bankruptcy and thin file splits were defined heuristically. Previous bankruptcy, thin and full file sub-populations were then divided into risk tiers using a risk-based segmentation score; CART analysis was used to determine the segmentation score cuts for the different risk tiers. The bankrupt/default profile model was used to divide the risk tiers into bankrupt and default profile sub-populations, and were also defined using CART.

The following table shows the breakdown of the population percentages, overall bad rates, default rates (90+ days past due to charge-off) and bankruptcy rates for the different segmentation levels and end nodes upon which segment scorecards were developed, as observed in the VantageScore development sample.

Table I. Segment Percentages and Bad Rates

Segment	% Total	Bad Rate	Default Rate	Bankruptcy Rate
A. Previous Bankruptcy	5.2%	16.60%	11.30%	5.31%
(1) Highest Risk	1.3%	35.90%	26.50%	9.42%
(2) Lowest Risk	3.8%	9.89%	6.02%	3.88%
B. Thin File	6.1%	9.88%	9.37%	0.51%
(3) Highest Risk	0.9%	36.10%	34.30%	1.77%
(4) Lowest Risk	5.3%	5.64%	5.33%	0.31%
C. Full File	88.7%	6.42%	4.52%	1.89%
I. Highest Risk	10.5%	32.00%	24.40%	7.59%
(5) Bankrupt Profile	3.6%	31.20%	17.60%	13.60%
(6) Default Profile	6.9%	32.40%	27.90%	4.44%
II. Higher Risk	12.9%	11.00%	7.57%	3.47%
(7) Bankrupt Profile	4.1%	11.70%	4.94%	6.72%
(8) Default Profile	8.8%	10.80%	8.79%	1.96%
III. Lower Risk	13.0%	4.09%	2.29%	1.80%
(9) Bankrupt Profile	5.5%	5.11%	1.86%	3.25%
(10) Default Profile	7.5%	3.34%	2.61%	0.73%
IV. Lowest Risk	52.3%	0.73%	0.34%	0.38%
(11) Bankrupt Profile	22.2%	1.06%	0.34%	0.72%
(12) Default Profile	30.1%	0.48%	0.35%	0.13%
Overall	**100.0%**	**7.16%**	**5.17%**	**1.98%**

Individuals with a previous bankruptcy (A) constituted just over five percent of the development sample; however, to develop a score that is effective across a variety of creditor target markets, individuals with a previous bankruptcy were isolated and segmented into highest and lowest risk groups (1 and 2) using a risk segmentation score.

Individuals with a thin file (B) comprised six percent of the development sample and represent a vital target market for most lenders. While the thin file definition of up to two accounts is somewhat restrictive, the segment was defined to ensure that VantageScore was optimized for individuals with limited credit. Individuals with thin files were segmented into highest and lowest risk groups (3 and 4) using a risk segmentation score. More than five percent of the development population consisted of lowest risk thin files (4) with overall bad rates that are within most creditors' risk tolerance.

The full file segment (C) comprised eighty-nine percent of the development sample, with the lowest risk tier constituting over fifty percent of the development sample, and each of the other risk tiers contributed approximately twelve percent to the development population. The bad rate statistics show that there is very little difference in the overall bad rates of the bankrupt/default profile pairs by risk tiers, although the underlying contribution of bankruptcy and default risk is significantly different.

Score Distributions

The following graphs depict:
- Overall score distribution
- Score distribution by
  - Previous bankrupt and thin file
  - Full file highest and higher risk by segment
  - Full file lower and lowest risk by segment

Note, the scales for the three segment distribution graphs are different. This is because of the large size differences between each segment grouping relative to the total score development population.
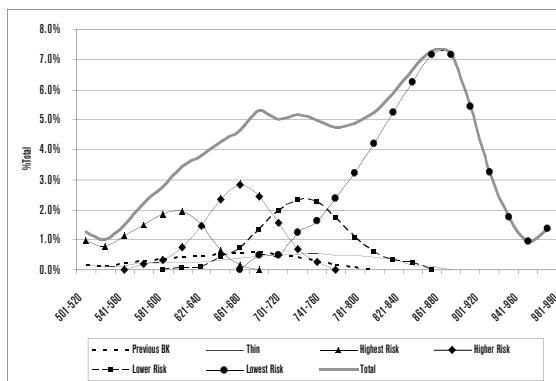
Figure 3. Score Distribution –
Overall and by Branch Figure

Figure 4. Score Distribution –
Previous Bankrupt and Thin File by Segment
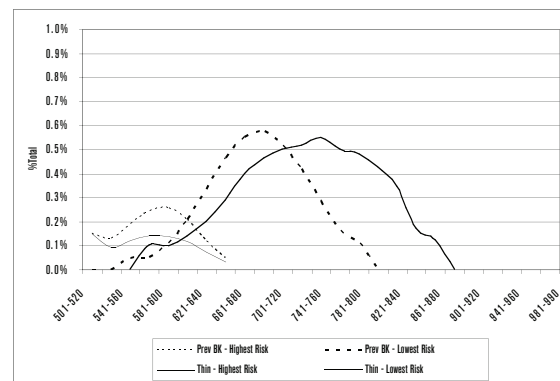
Figure 5. Score Distribution –
Full File Highest and Higher Risk by Segment
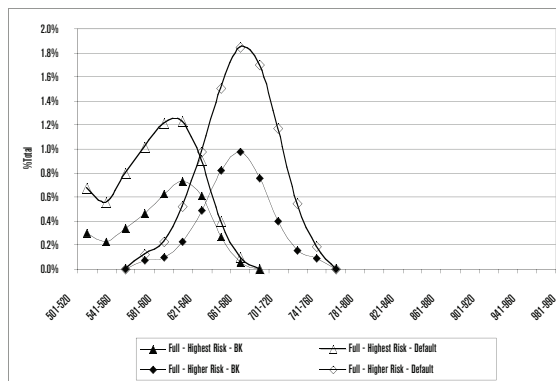
Figure 6. Score Distribution –
Full File Lower and Lowest Risk by Segment
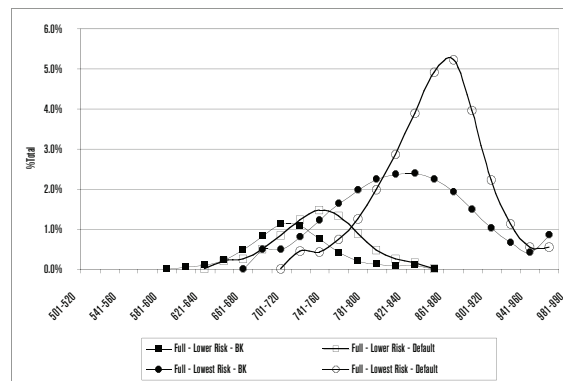
Figure 3 shows overlap across each of the segment branches. The order of the distribution peaks corresponds with the bad rate of each branch, which is apparent for the full file branches (highest, higher, lower and lowest risk), but less so for the previous bankrupt and thin file branches that have broad, flat distributions.

For full file branches, the overlap suggests additional discriminating power beyond the segmentation score, which divided the full file population into mutually exclusive sub-populations. By creating the homogenous risk tiers, individuals with similar characteristics, as defined by the risk segmentation score, are further stratified when modeled relative to their peer groups.

The lowest risk groups in the previous bankrupt and thin file branches (Figure 4) represent the bulk of the previous bankrupt and thin file branches and have broad score distributions that suggest good stratification of risk.

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For the full file segments (Figures 5 and 6), the bankrupt and default segment for each risk tier largely overlap, as a result of the similar bad rates associated with the bankrupt/default pairs by risk tier. It is important to note that the maximum scores for each bankrupt/default pair by risk tier is the same, which will have implications in later discussions regarding adverse action assignment. Despite the overlapping distribution of the bankrupt/default pairs, the underlying profiles and predictive characteristics associated with bankrupt and default profiles are vastly different, as highlighted in the following discussion.

Segment Profiles

The following graphs show the relationship of the bad rate (90+ days past due, charge off or bankrupt) to several credit characteristics for selected branches of the segmentation tree and for each segment. The branches of tree plotted on the graphs are the **previous bankrupt** branch (segments 1 and 2, highest and lowest risk, respectively) the **thin file** branch (segments 3 and 4, highest and lowest risk, respectively) and the **full file** branches: **highest risk** (segments 5 and 6, bankrupt and default profile, respectively), **higher risk** (segments 5 and 6, bankrupt and default profile, respectively), **lower risk** (segments 9 and 10, bankrupt and default profile, respectively), and **lowest risk** (segments 11 and 12, bankrupt and default profile, respectively). The graphs illustrate the similarities and differences between the segments and help establish the need for segmentation.

The first two graphs, Figures 7 and 8, show the bad rates of the branches/segments by the average number of 90+ day past due ratings (including charge-off and bankruptcy) for that branch/segment. Higher numbers of delinquent/derogatory accounts correlate with higher bad rates.

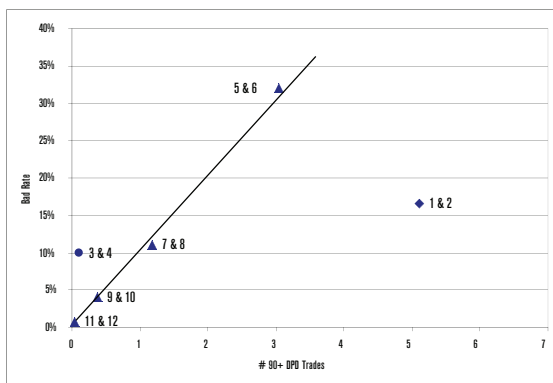Figure 7. The Number of 90+ Day Past Due Ratings by Branch   Figure 8. The Number of 90+ Day Past Due Ratings by Segment
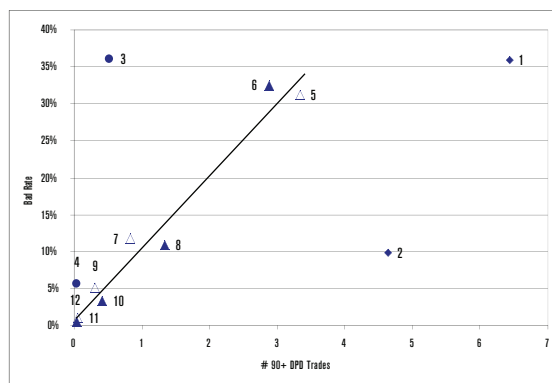

Figure 7 shows an increasing linear relationship between the average number of 90+ day past due trades and the branch bad rates for the full file branches (5 and 6, 7 and 8, 9 and 10, and 11 and 12); however, the previous bankruptcy branch (1 and 2) lies far to the right of the trend line and the thin file branch (3 and 4) lies to the to the left of the trend line. Looking at the same characteristic for each segment (Figure 8), the trend for full file segments remains unchanged and the bankrupt and default profile segments demonstrate the same relationship to the dependent variable; the previous bankrupt segments still lie to the right of trend line and the thin file segment remain to the left of the trend line.

The relationships shown above suggest that if a single model were developed on the population and "Number of 90+ Ratings" was a significant variable, individuals with a previous bankruptcy would receive a score indicating riskier performance than actually observed since they would be penalized more than individuals in segments 5 and 6 even though they have a lower bad rate. The opposite is true of the thin file group such that individuals in the thin file group would be penalized similar to individuals in segments 9 through 12 even though the risk of the individuals in the thin file group are far riskier. While it cannot be implied that a single model solution would not work when applied to individuals with previous bankruptcies or thin files, it does suggest that the solution may be sub-optimal. Additionally, the interpretation of the score for those two populations would be different than the interpretation of the score on the full files, such that the risk of individuals with a previous bankruptcy would be overestimated and the risk of individuals with a thin file would be underestimated.

The next two graphs display the variable "Number of Bankcards with Utilization Greater Than or Equal to 90%". As the number of bankcards with utilization greater than or equal to 90% increases, the bad rate also increases.

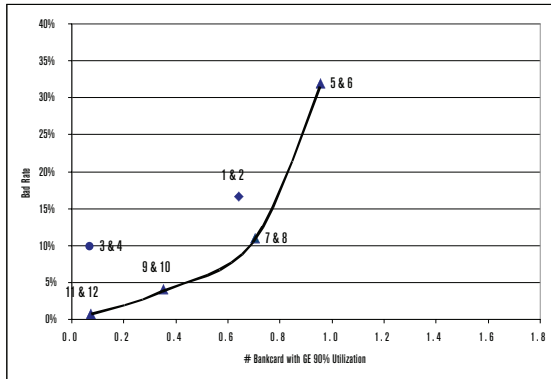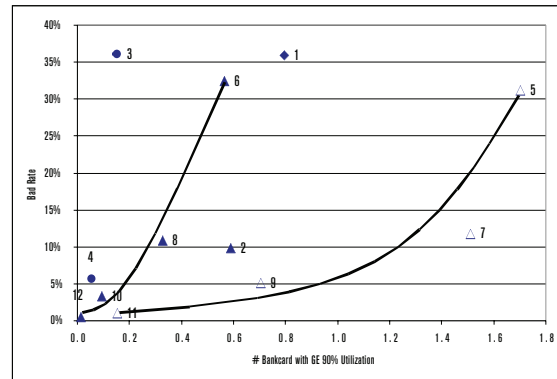**Figure 9. Number of Bankcards with Utilization Greater Than or Equal to 90% by Branch**

Figure 10. Number of Bankcards with Utilization Greater Than or Equal to 90% by Segment

In Figure 9, an increasing non-linear trend between the number of bankcards with high utilization and bad rate is observed for the previous bankrupt and full file branches, while the thin file branch lies to the left of the trend line. When the individual segments are broken out, the previous bankrupt segments and default profile segments lie along a similar trend line, while the bankrupt profile segments lie far to the right and the thin file segments still fall to the left of the curve. A single model solution with the number of bankcards with high utilization as a predictive characteristic would overestimate the risk associated with bankrupt profiles (5, 7, 9, and11) and underestimate the risk of thin file segments (3 and 4).

While only two characteristics are detailed in the paper, there are numerous other predictive characteristics that follow similar trends. In general, one would expect that for individuals with thin files, small incremental changes in characteristic values would result in significant changes in bad rates, simply because the range of values varies only slightly for individuals with one or two accounts, as compared to individuals with full files that may have more than 50 accounts.

For individuals with previous bankruptcies, one would expect varying relationships. In some respects, individuals with previous bankruptcy should mirror thin files, where individuals are trying to reestablish credit with only a few trades, in a manner similar to thin files' initial establishment of credit. In other scenarios, previous bankrupts have had the majority of their accounts classified as derogatory resulting from the bankruptcy filing and, as a result, historical delinquency variables may have weak correlations with the future propensity to go bad.

Of particular interest is the difference between bankrupt and default profiles. At the risk tier level (full file branch), the relationship between the number of bankcards with high utilization and bad rate looks very reasonable and logical; however, upon separating the bankrupt and default profiles, the underlying relationships are immensely different. The bankrupt and default profiles represent two entirely different approaches to credit that must be interpreted independently, which is emphasized by the historic approach of separate models to predict general risk and bankruptcy.

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Advanced Segmentation Methodology Benefits

The relative contribution of the segmentation to performance improvement is demonstrated below where the performance of VantageScore is compared to a single benchmark model (Master Score) developed on the VantageScore development population.

Table II. Segment Performance Improvements

Segment	KS Test VantageScore	KS Test Master Score	Difference	% Improvement
A. Previous Bankruptcy	44.00	41.37	2.63	6.36%
(1) Highest Risk	25.66	22.99	2.67	11.61%
(2) Lowest Risk	35.22	30.72	4.50	14.65%
B. Thin File	55.01	52.77	2.24	4.24%
(3) Highest Risk	27.56	23.13	4.43	19.15%
(4) Lowest Risk	45.63	43.09	2.54	5.89%
C. Full File	65.45	64.10	1.35	2.11%
I. Highest Risk	28.69	25.03	3.66	14.62%
(5) Bankrupt Profile	29.63	24.16	5.47	22.64%
(6) Default Profile	28.17	25.39	2.78	10.95%
II. Higher Risk	26.07	21.71	4.36	20.08%
(7) Bankrupt Profile	24.86	18.66	6.20	33.23%
(8) Default Profile	26.65	23.37	3.28	14.04%
III. Lower Risk	31.63	26.37	5.26	19.95%
(9) Bankrupt Profile	30.23	23.68	6.55	27.66%
(10) Default Profile	30.80	26.67	4.13	15.49%
IV. Lowest Risk	47.62	42.77	4.85	11.34%
(11) Bankrupt Profile	47.90	43.60	4.30	9.86%
(12) Default Profile	41.39	36.59	4.80	13.12%
Overall	**63.79**	**62.32**	**1.47**	**2.36%**

VantageScore showed significant improvement in predictive power over the single model solution as measured using the Kolmogov-Smirnov (KS) test. Significant improvement was observed on individuals with previous bankruptcy and thin files, as well as on each of the different risk tiers.

On the full file risk tiers both bankrupt and default profiles' performance benefited significantly. Improvement on bankrupt profiles showed lift in KS of 9.86% (lowest risk) to 33.23% (higher risk), while improvement on default profiles showed lift in KS of 10.95% (highest risk) to 15.49% (lower risk). Overall, the higher and lower risk groups, which are likely to be around the cuts for many lenders, demonstrated the most improvement, 20.08% and 19.95%, respectively.

The improvement in performance can be attributed to two factors:
  1) Optimal parameter estimation of characteristics at the segment level rather than compromised parameter estimation at the population level, as articulated in the segment profile discussion.
  2) The introduction of additional characteristics that may not be predictive on the entire population, but help discriminate individuals within the homogenous segments, as demonstrated by the use of more than 100 variables in the overall solution, compared to the 20 characteristics in the single model benchmark solution.

Performance of VantageScore

The previous section showed two examples of why, conceptually, segmentation can improve a scoring system's performance. The proof, however, is how the segmented solution performs at the creditor level.

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The performance of VantageScore for each CRC was compared to proprietary risk scores offered independently by each of the CRCs and included Equifax's Equifax Risk Score 3.0℠, Experian-Scorex's Scorex PLUS for existing accounts and TransUnion's TransRisk Account Management 2.0. The performance was measured on existing accounts for several creditors across five industries: bankcard, retail, finance, automotive and mortgage. Existing accounts were defined as those open on the observation point.

The performance, as measured by the KS test, was evaluated for each credit reporting company on the identical set of consumers and performance flags. The scores were tested using two performance definitions:
  1) An overall bad definition, including accounts 90+ days past due, charge off or bankruptcy.
  2) A bankruptcy definition; each bad definition was contrasted to good accounts that were no worse than 30 days past due during the outcome period.

To emphasize the power of VantageScore relative to the credit-based delinquency model offerings and not inter-company comparisons, the KS statistics were ordered by performance; hence there is no interpretation to the order of the bar and the contributing credit reporting company.

Figures 11 through 16 demonstrate the power of VantageScore on overall bad and bankrupt performance definitions. While results are displayed for only a limited set of creditors, the results shown are representative of the performance across a broad range of lenders.

Figure 11. Comparison of VantageScore and Credit-Based Delinquency Models for Bankcard Portfolios on an Overall Bad Definition
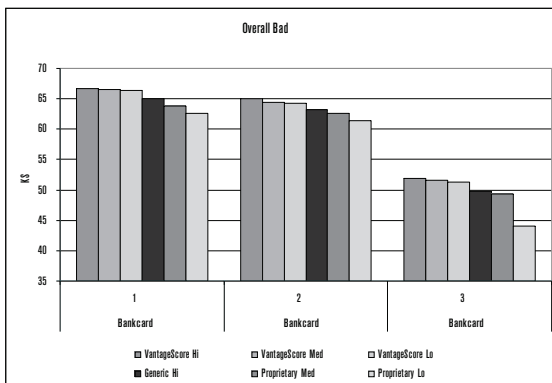

Figure 12. Comparison of VantageScore and Credit-Based Delinquency Models for Bankcard Portfolios on a Bankruptcy Definition
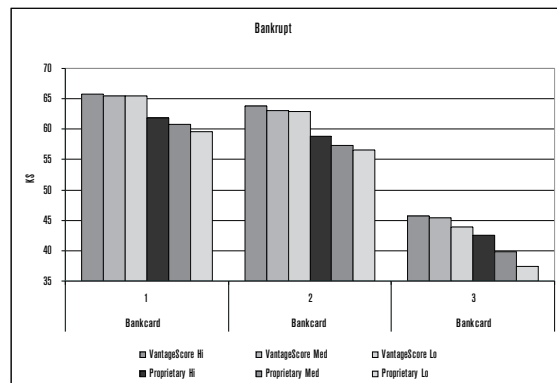

Figure 13. Comparison of VantageScore and Credit-Based Delinquency Models for Finance and Retail Portfolios on an Overall Bad Definition
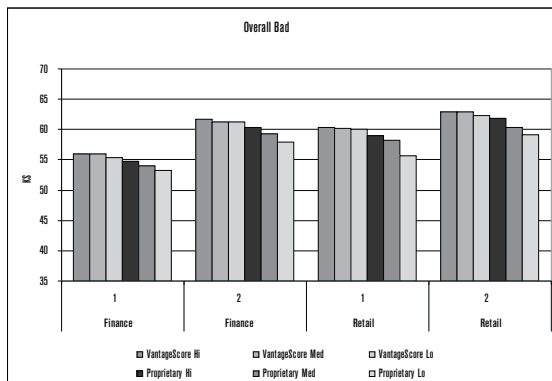

Figure 14. Comparison of VantageScore and Credit-Based Delinquency Models for Finance and Retail Portfolios on a Bankruptcy Definition
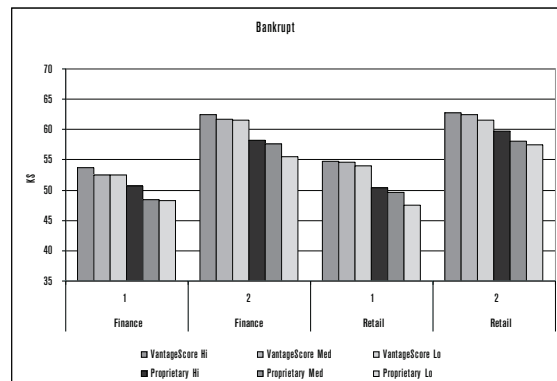
Figure 15. Comparison of VantageScore and Credit-Based Delinquency Models for Automotive and Mortgage Portfolios on an Overall Bad Definition
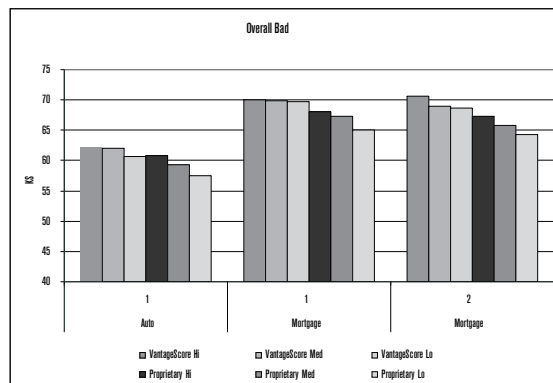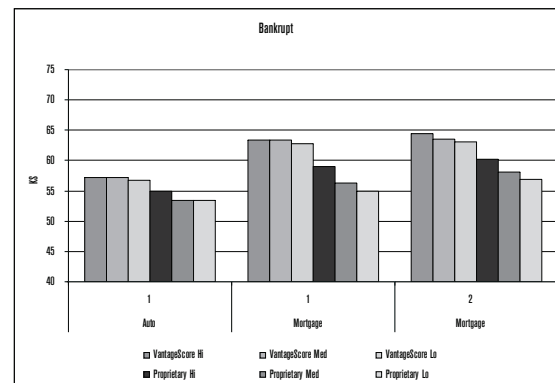
Figure 16. Comparison of VantageScore and Credit-Based Delinquency Models for Automotive and Mortgage Portfolios on a Bankruptcy Definition

The results show that VantageScore performs significantly better than competing risk scores across major industries when evaluated on a 90+ day past due definition and better on a bankruptcy definition. On an overall bad definition, KS improvement ranges from one to two points across each of the industries. On the bankruptcy performance definition, KS improvement ranged from a substantial three to five points.

The sizeable improvement on the bankruptcy definition can be attributed to the innovative approach to segmentation through the identification of individuals with bankrupt profiles, where the underlying data predicts differently. In the past, bankruptcy and default prediction were viewed as competing outcomes, where individuals with a propensity to file bankruptcy appeared to have more in common with individuals who looked 'good' than those who looked 'bad'; in the end it plays out to be the classic segmentation scenario, where the data predicts differently.

While the score predicts bankruptcy significantly better than competing risk scores, use of a bankruptcy score in tandem with VantageScore should be tested to assess further improvement of bankruptcy risk prediction.

Adverse Action

At first glance, a credit-based delinquency model that combines characteristics, a risk segmentation score and profile score would represent a very complicated adverse action methodology. In reality, however, the assignment of adverse action reason codes, while not simple, is quite logical with an underlying difference from maximum points methodology.

Adverse action reason codes need to be assigned based on the components that had a negative impact on an individual's score, including characteristic-based segment assignment, score-based segment assignment and the segment score itself. For example, with VantageScore, individuals with a previous bankruptcy represent a sub-population with a 16.6% bad rate (90+ days past due, charge off or bankruptcy). Once assigned to the previous bankrupt branch, an individual with a previous bankruptcy can only achieve a score of approximately 800 out of the maximum 990, meaning there is a 190 point penalty (990-800) for having a previous bankruptcy. If placed in the highest risk tier of previous bankrupt branch, the highest possible score is approximately 660, indicating an additional penalty of 140 points (800-660). Hence, an individual in the previous bankrupt, highest risk segment should receive adverse action reasons associated with the characteristic-based segment assignment, segmentation score-based risk tier assignment and the segment model.

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An individual's final score can be summarized by the following equation:

$$\begin{array}{r} \text{Maximum Score} \\ \text{- Impact of Attribute-Based Segment Assignment} \\ \text{- Impact of Risk Tier-Based Segment Assignment} \\ \underline{\text{- Impact of Segment Score}} \\ = \text{Final Score} \end{array}$$

Omitted from the equation is reference to the bankrupt/default score because there is no impact on an individual's maximum score by being assigned into either the bankrupt or default profile segment. Referring to Figures 5 and 6, it is observed that the maximum score for bankrupt and default tiers is the same for each risk band, hence there is no penalty for a bankrupt or default profile segment assignment.
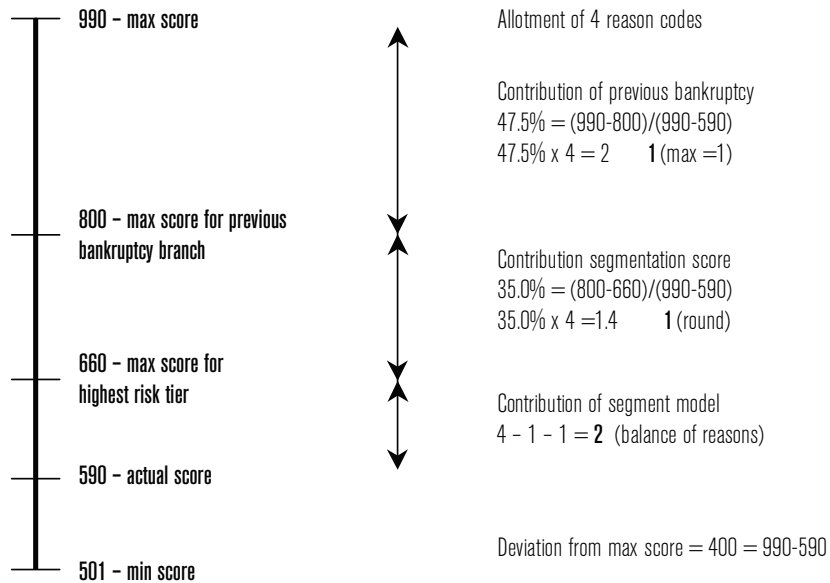
Not all of the segments are subject to the same impacts. For example there is no characteristic-based adverse action assignment for full file because someone assigned to the full file branch can still achieve the maximum score. Individuals in the lowest risk tiers are not penalized by the risk tier assignment and receive no reasons based on the segmentation score.

Table III. shows the possible sources for adverse action reasons for each of the segments.

Table III. Adverse Action Reason Sources

Segment	Characteristic Based	Segmentation Score Based	Segment Model
1 – Previous BK: Highest Risk	X	X	X
2 – Previous BK: Lowest Risk	X		X
3 – Thin File: Highest Risk	X	X	X
4 – Thin File: Lowest Risk	X		X
5 – Full File: Highest Risk, Bankruptcy Profile		X	X
6 – Full File: Highest Risk, Default Profile		X	X
7 – Full File: Higher Risk, Bankruptcy Profile		X	X
8 – Full File: Higher Risk, Default Profile		X	X
9 – Full File: Lower Risk, Bankruptcy Profile		X	X
10 – Full File: Lower Risk, Default Profile		X	X
11 – Full File: Lowest Risk, Bankruptcy Profile			X
12 – Full File: Lowest Risk, Default Profile			X

The number of reasons from each impact source is calculated based on the percent contribution of each component to the drop in the final score. The segment model receives the balance of the reason codes. Consider the following example: an individual is assigned to segment one, previous bankruptcy highest risk, and receives a final score of 590 points.

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990 – max score	Allotment of 4 reason codes
	Contribution of previous bankruptcy 47.5% = (990-800)/(990-590) 47.5% x 4 = 2 **1** (max =1)
800 – max score for previous bankruptcy branch	
	Contribution segmentation score 35.0% = (800-660)/(990-590) 35.0% x 4 =1.4 **1** (round)
660 – max score for highest risk tier	
	Contribution of segment model 4 – 1 – 1 = **2** (balance of reasons)
590 – actual score	
	Deviation from max score = 400 = 990-590
501 – min score	

The individual would receive one reason due to previous bankruptcy (previous bankruptcy is either yes or no, so only one reason is returned), one reason from the segmentation risk score and two reasons from the segment model (the balance of the four reasons). The order of the characteristics would be based on a difference from maximum point methodology; the reasons from each source can be pooled and ranked because the final model and segmentation score are odds equalized, enabling direct comparison of the deviations.

Conclusion

Segmentation plays a critical role in the development of powerful, robust risk scores. New innovations in segmentation that leverage risk and profiles scores can provide significant lift in credit-based delinquency model performance. Characteristic-based segmentation still plays a role in segmentation, but should be combined with score-based methodologies to maximize scoring system performance.

Improvement in bankruptcy prediction can be achieved via segmentation, but it is still prudent to access the benefits associated with a stand-alone bankruptcy score to achieve maximum risk prediction.

Adverse action reasons should be attributed to the different components of the segmentation schemes. A contribution-based approach using a maximum value methodology provides an accurate, quantitative system to assign adverse action reasons.

VantageScore leverages the most advanced segmentation methodology of any score in the marketplace, credit reporting company-based or custom. The benefits of the advanced segmentation are reflected in the superior performance of VantageScore relative to other commercially available credit-based delinquency models. This superior performance is observed across multiple industries, products and lenders.

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