Existing Account Management: Building Effective Portfolio Management Tools

May 2011

OVERVIEW

In some ways, portfolio risk management is as much an art as it is a science. Taking place in a dynamic economic environment, the process continually seeks to evaluate the financial health of consumers and thereby judge the quality of the relationship for the lender. Through every phase of payment status (current, early and late stage delinquency) the core risk management processes weigh the likelihood that the consumer will become extremely delinquent against the likelihood that the consumer will remain in good standing. In the case of extreme delinquency, lenders are forced to incur delinquency management expenses or even charge-off the account. On the other hand, if a consumer remains in good standing, additional products and services may be offered, leading to greater profitability. While the purpose of this paper is to focus on minimizing losses, scores sourced from credit bureaus can also be used to identify profitable consumers.

In a perfect world with perfect information, risk managers would know with 100 percent certainty which consumer accounts will need to be charged-off and which accounts will remain current. Strategies would then be applied to exactly the right consumers: loss mitigation activities to those consumers whose account will need to be charged-off, no action to those who will remain current and marketing opportunities for those who improve. The result is an optimal outcome for the lender.

In reality, a host of known and unknown variables impact the likelihood that a consumer will remain current or which accounts will need to be charged-off. At best, that likelihood is reflected through probabilities, however, a degree of error within the process of arriving at those probabilities must always be acknowledged.

As long as a consumer remains current, for example, the statistical probability of charge-off is low. However, when a consumer enters early delinquency, charge-off probability significantly increases and continues to grow as the consumer becomes increasingly delinquent. As the probability of charge-off increases, risk management activity also increases with the goal of rehabilitating the consumer, returning him/her to current status, and/or minimizing the loss exposure to the lender. Further, a percentage of consumers in this process will inevitably be misclassified. Some consumers will be identified as high risk and likely to have an account that requires charging-off, but ultimately manage their account in a manner that avoids a charge-off. Other consumers, identified as low risk and likely to remain in good standing, enter a charge-off status.

The profit and loss implication of these outcomes to lenders can be dramatic. Consumers that remain in good standing with multiple products from the same lender can be highly profitable. Conversely, consumers whose accounts are charged-off result in significant losses for the lender. Between these extremes is a spectrum of financial outcomes driven by several factors. Among these factors is the magnitude of risk management intervention, the consumer's response to that intervention, and the degree to which consumers are misclassified. The totality of these factors impact lender profitability.

OVERVIEW (Cont.)

In the case of a consumer who is misclassified as good, but ultimately whose account is charged-off, the result—in the absence of intervention to limit lender exposure—can be maximum losses. In the case of a consumer who is misclassified as bad, but who remains in good standing, the result can be reduced profitability stemming from the lender implementing unnecessary risk exposure reduction strategies.

Risk analytics provide the analysis and tools to minimize misclassifications of prospective consumer outcomes so that the correct portfolio management strategies can be applied to ensure maximum profitability.

This paper will review the core issues associated with portfolio risk management and identify specific strategies and methods for maximizing profitability, including:

- 1. Credit score predictive performance for Portfolio Management. VantageScore® and a benchmark credit bureau-based score are used to assess risk on consumers at various stages of delinquency and timeframes reflecting stressed economic shifts.
- 2. Designing a portfolio risk management process. A portfolio risk management process using credit scores, segmentation and lender P&L scenarios that optimizes the portfolio profitability from a risk perspective is presented.
- 3. Risk Management Optimization Process Over Time. A champion-challenger approach for evaluating competing credit scores within this risk management process and for determining strategy update frequency is discussed.

STUDY HIGHLIGHTS

- VantageScore provides superior rank ordering capabilities in portfolio account management, enabling lenders to improve portfolio profitability.
 - » As delinquency severity increases, VantageScore demonstrates increasingly reliable predictive performance.
- As overall economic conditions have deteriorated over recent years, VantageScore
 retained its predictive strength more effectively than the benchmark score, providing
 greater risk management capabilities for lenders.
- A robust process for portfolio risk minimization is presented that allows lenders to achieve significant improvements in profitability.

1. CREDIT SCORE PREDICTIVE PERFORMANCE

KS ANALYSIS: DIFFERENTIATING GOOD AND BAD ACCOUNTS

Credit score effectiveness in differentiating high and low risk accounts is measured using a KS statistic. The KS statistic is a standard model performance metric that demonstrates the predictive power of credit scores to distinguish between good and bad accounts.

For this study, KS statistics were developed for both VantageScore and the benchmark bureau credit score on a bank card portfolio. The KS results demonstrate the predictive performance for each credit score. Early stage delinquency segment results are provided below (Figure 1).

In addition, VantageScore and the benchmark score's predictive performance were calculated across three specific 12-month periods from 2007 to 2009 to demonstrate the strength of VantageScore's predictive performance when compared with the benchmark score during different phases of broad economic volatility. Consumers were assigned to a specific segment by reviewing their entire file housed as the credit bureau and identifying their maximum delinquency status.

FIGURE 1
EARLY STAGE DELINQUENCY KS SUMMARY

SEGMENT	TIME PERIOD	VANTAGE SCORE KS PERFORMANCE		BENCHMARK KS PERFORMANCE		KS % Improvement	
		90 DPD*	C/0	90 DPD	C/O	90 DPD	C/0
	Dec 06	63.96	66.06	62.78	63.73	2%	4%
ALL CURRENT	Dec 07	64.81	66.67	63.78	65.12	2%	2%
	Dec 08	61.52	63.55	59.98	61.41	3%	3%
	Dec 06	50.63	56.1	45.44	49.33	11%	14%
30 DPD MAX	Dec 07	51.2	56.59	45.74	49.04	12%	15%
	Dec 08	48.51	53.72	42.38	45.51	14%	18%
	Dec 06	45.54	53.65	36.17	42.79	26%	25%
60 DPD MAX	Dec 07	45.97	52.35	36.75	41.15	25%	27%
	Dec 08	44.34	49.97	33.26	36.92	33%	35%

^{*}DPD = Days Past Due

For early stage delinquency segments, VantageScore shows increasing effectiveness in identifying future default activity as a consumer's credit profile reflects more severe delinquency. In addition, when comparing year-over-year changes in VantageScore's KS performance with the benchmark score's performance, relatively minor changes are noted in VantageScore (1 to 2 point changes in KS score), while the benchmark KS score clearly degrades over time (3 points or more).

To take the most extreme example, in the 60+ DPD Max segment, the benchmark KS in December 2008 was 33.3 for accounts likely to become 90+ DPD (last row, Figure 1 above). VantageScore, by contrast, had a KS of 44.3 for accounts likely to go 90+ DPD, an improvement over the benchmark of more than 33 percent.

¹ KS: Kolmogorov-Smirnov test

1. CREDIT SCORE PREDICTIVE PERFORMANCE (Cont.)

Differences in KS values between the benchmark and VantageScore become more dramatic as the study population enters deeper levels of credit distress (Figure 2).

FIGURE 2
LATE STAGE DELINQUENCY KS SUMMARY

SEGMENT	TIME PERIOD	VANTAGESCORE KS PERFORMANCE			HMARK DRMANCE	KS % Improvement	
		90 DPD	C/0	90 DPD	C/O	90 DPD	C/O
	Dec 06	44.35	48.53	33.44	36.04	33%	35%
90 DPD MAX	Dec 07	45.42	51.10	34.81	38.23	30%	34%
	Dec 08	43.03	47.73	34.23	36.92	26%	29%
	Dec 06	41.50	45.64	28.14	29.34	47%	56%
120+ DPD MAX	Dec 07	44.69	48.65	28.39	28.84	57%	69%
	Dec 08	39.60	43.58	39.60	43.58	41%	50%

The study demonstrates that VantageScore offers results that lead to superior decision making in circumstances where consumers are highly delinquent on other trades. In one case (likelihood of charge-off for 120+DPD Max segment—last row, Figure 2), the overall score improvement compared with the benchmark score rises to nearly 50 percent.

In addition, absolute KS scores for VantageScore remain consistently strong — ranging from 45 to 51—over the study time-horizon. By contrast, the benchmark score progressively loses its predictive ability as the segments degrade into deeper states of delinquency.

These results demonstrate the predictive and robust strength of VantageScore for use in portfolio management strategies.

Four steps are offered in the following section for designing a portfolio risk management strategy that can be used in any portfolio. First, a simple Profit & Loss matrix is defined that establishes the benchmark consequences of potential account charge-off in the event of extreme delinquency. Next, the example portfolio is scored and rank ordered, after which the P&L impact of applying a risk management strategy at each tier of the resulting borrower population is estimated. Finally, the benefits of driving greater portfolio profitability through segmentation are analyzed.

2. DESIGNING A PORTFOLIO RISK MANAGEMENT PROCESS The process design consists of four steps:

- 1. Defining the Profit & Loss matrix
- 2. Scoring & rank ordering the portfolio
- 3. Estimate the P&L impact of applying a risk management strategy at each tier
- 4. Portfolio segmentation for increased profitability

DEFINING THE PROFIT & LOSS MATRIX

The following profit and loss example summarizes the income and loss dynamics of a typical revolving account, such as a credit card with a \$2,000 balance. The profitability estimates represent order-of-magnitude and are directionally aligned. A 12-month time period is assumed for the example (Figure 3). Actual consumer behavior may or may not match expectations. If the consumer is expected to remain current, and does, the profitability is \$200. Instead, if that account is charged-off, the loss is \$2,000. If the account is expected to become a charge-off, and the lender preemptively acts on the account, the lender loses nothing if the consumer instead remains current. On the other hand, if the account is expected to become a charge-off, and it does become a charge-off, the lender who preemptively acts on the account can reduce losses by a wide margin—in this example to only \$100.

FIGURE 3 **P&L MATRIX**, **SAMPLE CONSUMER POPULATION**

	EXAMPLE	ACTUAL E	BEHAVIOR
OF	P&L METRICS	CURRENT OFF	CHARGE OFF
CTED	REMAINS CURRENT	\$200	(\$2,000)
EXPECTED BEHAVIOR	CHARGE OFF	\$0	(\$100)

SCORING AND RANK ORDERING THE PORTFOLIO

Here we apply credit scores to the consumers in the portfolio, and then rank order the consumers from lowest credit quality to highest credit quality (Figure 4). For this example, consumers are grouped into five-percent risk tiers. Using the general credit score performance charts (or customized lender performance charts), each tier is assigned a risk level that reflects the probability of charge-off for a consumer in that tier. In this case, for example, 52.8 percent of consumers in the highest risk tier (0 - 5 percent) are expected to have their account charged-off.

FIGURE 4
RANK-ORDERED EXAMPLE
PORTFOLIO BY EACH 5 PERCENT TIER

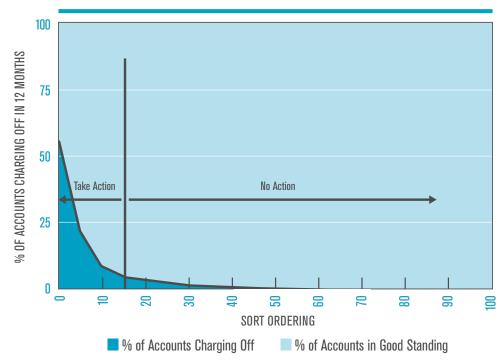
PERCENT OF PORTFOLIO	% G00D	% CHARGE-OFF
0% - 5%	47.20%	52.8%
5% – 10%	75.90%	24.1%
10% – 15%	83.70%	16.3%
15% – 20%	88.63%	11.4%
20% – 25%	92.16%	7.8%
25% – 30%	94.30%	5.7%
30% – 35%	95.10%	4.9%
35% – 40%	95.70%	4.3%
40% – 45%	96.75%	3.2%
45% – 50%	97.70%	2.3%
50% – 55%	98.39%	1.6%
55% - 60%	98.84%	1.2%
60% - 65%	99.15%	0.8%
65% – 70%	99.43%	0.6%
70% – 75%	99.66%	0.3%
75% – 80%	99.78%	0.2%
80% - 85%	99.85%	0.2%
85% – 90%	99.89%	0.1%
90% – 95%	99.82%	0.1%
95% – 100%	99.93%	0.1%

ESTIMATE THE P&L IMPACT OF APPLYING A RISK MANAGEMENT STRATEGY AT EACH TIER

In this example, the financial impact is calculated when risk mitigation actions are applied to the riskiest 15 percent of the population. A portfolio of 941,180 accounts that has an overall default rate of 2 percent is assumed. The table shown in Figure 4 can be graphically represented as illustrated in Figure 5.

FIGURE 5

DISTRIBUTION OF GOOD AND BAD ACCOUNTS
WITH 15 PERCENT SCORE CUT



When expected behavior is compared with actual behavior, the portfolio divides into four segments, with consumers distributed as illustrated in Figure 6.

FIGURE 6

DISTRIBUTION OF CONSUMER BEHAVIOR
IN EXAMPLE PORTFOLIO

	EXAMPLE	ACTUAL E	BEHAVIOR
OF	P&L METRICS	ACTUAL BEHAVIOR REMAINS CHARGE CURRENT OFF 781,773 5,199	
CTED	REMAINS CURRENT	781,773	5,199
EXPECTED BEHAVIOR	CHARGE OFF	137,761	16,747

2. DESIGNING A PORTFOLIO RISK MANAGEMENT PROCESS (Cont.) Using the consumer behavior matrix in Figure 6, profitability is calculated as follows:

When all accounts that were assumed to remain current actually do remain current, the portfolio will generate profits of \$156 million (781,773 x \$200).

The 15 percent score cut identifies 16,747 consumers whose accounts are charged-off (as expected), losing \$1.67 million ($16,747 \times 100). (If those accounts had not been flagged, losses from charge-off would have been 20 times worse ($16,747 \times $2,000 = 32 million).)

The 15 percent score cut, however, does not identify 5,199 consumers whose accounts are, in fact, charged-off, resulting in an additional loss of \$10.4 million ($5,199 \times $2,000$).

FIGURE 7
SUMMARY PROFITABILITY BY 15 PERCENT CUT-SCORE

AT 15% CUT-OFF EXPECTED	ACTUAL	STRATEGY	NO. OF ACCOUNTS	\$ IMPACT
CURRENT	CURRENT	DO NOTHING	781,773	\$156,354,600
GURKENI	CHARGE OFF	DO NOTHING	5,199	(\$10,398,000)
CHARGE OFF	CURRENT	LINE ACTION	137,761	\$0
GRANGE OFF	CHARGE OFF	LINE ACTION	16,747	(\$1,674,700)
		TOTAL PROFIT		\$144,281,900
		PROFIT/ACCOUNT		\$153

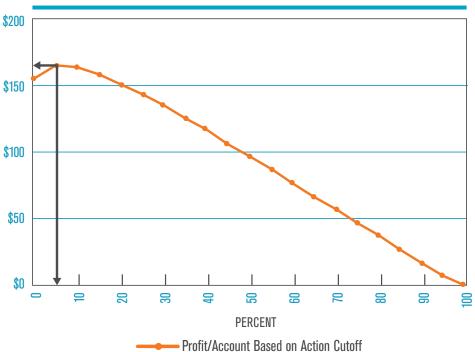
By enacting the 15 percent score cut as a policy, the lender mitigates losses in the "at risk" population when compared with not enacting the policy. The lender loses only \$1.67 million (16,747 x \$100) rather than \$33.5 million if the policy toward the "at risk population" had not been enacted (16,747 x \$2,000).

At the same time, this policy causes the lender to incorrectly apply risk mitigation actions against 137,761 consumers. As a result, those customers did not deliver the expected profit of \$200/each, causing the lender to forego profit of \$28 million (137,761 * 200). Net savings using this decision process is \$5.5 million (\$28 million - \$33.5 million).

When the portfolio is managed by using a 15 percent score cut, taking all four groups together as illustrated above, the overall profitability of the portfolio is \$144 million, or \$153 per account.

Figure 8 shows the per-account profitability for each five percent change in score cut in the example portfolio.

FIGURE 8 PROFIT PER ACCOUNT DEPENDING ON SCORE CUT



In this case, the 15 percent score cut policy is not optimal. All other things being equal, the optimal policy would be to set a five percent score cut. In other words, risk strategies are applied to the riskiest five percent of the portfolio and no actions are taken on the remaining 95 percent of the portfolio. This strategy leads to increased profitability per account of \$11, for a total of \$164 per account (\$155 million total profit for the example portfolio).

After generating a Profit & Loss matrix that established the benchmark consequences of potential account behavior, scoring and rank ordering the example portfolio was the next step. The P&L impact of applying a risk management strategy through the various tiers of the borrower population was then estimated. The final step is examining a method for driving greater portfolio profitability through segmentation.

PORTFOLIO SEGMENTATION FOR INCREASED PROFITABILITY

Robust risk management processes consider a variety of lender-specific and external data to develop a specific risk strategy. Data, including the consumers' credit files, may be used to generate a segmentation strategy that assigns consumers to specific segments for which specific risk mitigation activities are prescribed.

For example, consumers can be categorized according to the greatest level of delinquency observed across their entire credit file. Leveraging this external, holistic view of consumers allows a lender to proactively identify "at risk" consumers, even though the consumer may

not exhibit risky behavior on the lender's specific portfolio. Segmenting the portfolio based on consumers' current credit profiles, and managing risk within each segment, increases the effectiveness of an overall segmentation strategy.

Naturally, score cuts, P&L matrices and risk strategies vary depending on consumers' level of delinquency. Score cuts are therefore set for each segment, depending on consumer default profiles. The process of determining risk mitigation activities is repeated for each segment, resulting in profit-maximized score cuts by segment.

For the sake of simplicity and illustration, only two profit and loss matrices are provided as the example for managing a portfolio of multiple segments. With actual portfolios, a more comprehensive policy may be used to manage each segment.

Consumers are first categorized into six segments according to the maximum delinquency on their credit file (Figure 9).

FIGURE 9
CONSUMER PROFILE SEGMENTS

SEGMENT	STATUS
1	All accounts current over past 12 months
2	Worst account status is 30 DPD over past 12 months
3	Worst account status is 60 DPD over past 12 months
4	Worst account status is 90 DPD over past 12 months
5	Worst account status is 120+ DPD over past 12 months
6	Worst account status is charged-off

A consumer portfolio of bank card accounts – all of which were current as of December 2006 at the specific lender—are segmented according to maximum delinquency on their credit profile as of that date (Figure 10).

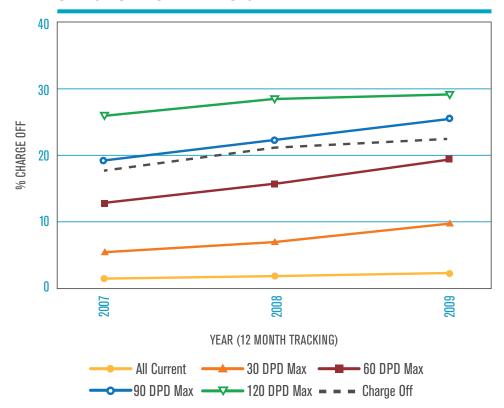
FIGURE 10 **PORTFOLIO SEGMENTATION**

				PAST 12	2 MONTHS			% 0F	AVERAGE
	SEGMENT	CURRENT	30 DPD	60 DPD	90 DPD	120+ DPD	C/0	POPULATION	VANTAGESCORE
	1	ALL TRADES						86.44	815
PRE-CHARGE	2		MAX					5.28	679
OFF STATUS	3			MAX				1.86	628
	4				MAX			1.19	603
	5					MAX		1.29	587
POST-CHARGE OFF STATUS	6						MAX	3.96	589

2. DESIGNING A PORTFOLIO RISK MANAGEMENT PROCESS (Cont.)

As might be expected, the credit quality of these consumers worsens in each successive segment, with late stage segments averaging VantageScore credit scores in the 580s. (The full VantageScore range is 501-990.) In addition, future default rates for the individual segments stratify in an upward trend when measured as 12-month charge-off activity (Figure 11).

FIGURE 11 CHARGE-OFF ACTIVITY BY SEGMENT



3. RISK
MANAGEMENT
OPTIMIZATION
PROCESS OVER
TIME

This section addresses:

Early Stage Delinquency Application and Results

- Segment Profitability Highlights
- Frequency of updates to the early stage delinquency policy

Late Stage Delinquency Application and Results

- Segment Profitability Highlights
- Frequency of updates to the late stage delinquency policy

We combined the prior process design and related score performance insights to manage risk and optimize portfolio yield through a three-year time horizon, from 2007 to 2009 (Figure 12). Two matrices are used—one for early stage consumers (Current, 30 DPD and 60 DPD), and one for late stage consumers (90 DPD and Charge Off).

FIGURE 12

EARLY AND LATE STAGE P&L MATRICES

EARLY STAGE		ACTUAL E	BEHAVIOR		LATE STAGE	ACTUAL BEHAVIOR	
	P&L METRICS	REMAINS CURRENT	CHARGE OFF		P&L METRICS	REMAINS Current	CHARGE OFF
CTED	REMAINS CURRENT	\$200	(\$2,000)	CTED	REMAINS CURRENT	\$175	(\$1,000)
EXPECTED BEHAVIOR	CHARGE OFF	\$0	(\$100)	EXPECTED BEHAVIOR	CHARGE OFF	\$0	(\$50)

- Data is analyzed in the first year, 2007, to optimize the policy and establish the score cuts for each segment for both VantageScore and the benchmark score. These score cuts will then be used for 2008 and 2009 credit policy decisions.
- Accounts are assigned to facilitate a champion-challenger configuration.
 - » Given the KS performance results, VantageScore is established as the "champion" score and the benchmark score is the "challenger" score.
 - » For each segment, the majority of consumers are assigned to the champion score and strategy in order to maximize profit.
 - » To facilitate the ongoing validation of score performance, a small portion of consumers in each segment are assigned to the challenger score and strategy. The objective is to provide a comparative framework to monitor the performance of champion score and strategy against the challenger score and strategy.
- The policy is then applied to the next two years (2008 and 2009) using both VantageScore and the benchmark score.
 - » Profitability by segment using both scores is calculated and compared.

3. RISK
MANAGEMENT
OPTIMIZATION
PROCESS OVER
TIME (Cont.)

EARLY STAGE DELINOUENCY APPLICATION AND RESULTS

The analysis and results of early stage delinquency consumers is portrayed in Figure 13.

FIGURE 13 TIER 1 EARLY STAGE RESULTS

2007 PORTFOLIO OPTIMIZATION: TIER 1 EARLY STAGE										
SEGMENT	VANTAGESCO	RE STRATEGY	BENCHMARK STRATEGY		VS \$	VS %				
SEGMENT	% ACTION TAKEN	PROFIT/ACCOUNT	% ACTION TAKEN	PROFIT/ACCOUNT	IMPROVEMENT	IMPROVEMENT				
1	1.4%	\$183	0.9%	\$182	\$1	1%				
2	16.2%	\$121	19.5%	\$112	\$9	8%				
3	22.3%	\$83	27.2%	\$73	\$11	15%				

SEGMENT PROFITABILITY HIGHLIGHTS:

- "All Current" VantageScore optimizes segment profitability by identifying the riskiest 1.4 percent of the consumers for risk mitigation action. Profitability of \$183 per account is the result. Conversely, the benchmark score affects 0.9 percent of the consumers leading to \$182 per account profitability. In this case, VantageScore results in a 1 percent improvement (\$1) per account.
- "30 DPD Max" VantageScore optimizes the "30 DPD Max" segment at 16.2 percent of the consumers requiring action, leading to total average profitability of \$121. Conversely, the benchmark score affects 19.5 percent of the segment, resulting in profitability of \$112 per account. VantageScore thus increases profitability in this segment by \$9 per account or 8 percent.
- "60 DPD Max" VantageScore optimizes the 60 DPD Max segment at 22.3 percent, or \$83 profitability. The benchmark score affects 19.5 percent of the segment at \$72 per account profitability. VantageScore thus increases profitability in this segment by \$11 per account or 15 percent

Results of this single-year snapshot demonstrate the importance of correctly identifying target consumer populations when developing risk management strategies. Perhaps as important is consideration of the frequency with which this analysis needs to be updated to ensure profitability over time.

HOW FREQUENTLY DOES THE EARLY STATE DELINQUENCY POLICY REQUIRE UPDATING?

As the environment changes from the base timeframe, the effectiveness of risk optimization strategies deteriorates, driving a need to update the policy and score cuts. An ongoing analysis is imperative to understand when shifts are necessary. An effective analysis first compares the magnitude of the deterioration of a policy from prior timeframes with the profitability of a policy that is optimized for a more recent timeframe. A comparison in this manner allows lenders to determine the implications of (or their tolerance for) maintaining a legacy policy or updating that policy using more recent data.

3. RISK
MANAGEMENT
OPTIMIZATION
PROCESS OVER
TIME (Cont.)

Applying the same score cuts to the portfolio in 2008 and 2009 that were defined using the 2007 portfolio reveals the increasing effectiveness of VantageScore for capturing profitability when compared to the benchmark score and strategy (Figure 14).

FIGURE 14
PORTFOLIO OPTIMIZATION FOR 2008 AND 2009, TIER 1 EARLY STAGE

2008 PORTFOLIO OPTIMIZATION: TIER 1 EARLY STAGE USING 2007 CUT SCORES									
SEGMENT	VANTAGESCO	RE STRATEGY	BENCHMARK STRATEGY		VS \$	VS %			
SEUWENT	% ACTION TAKEN	PROFIT/ACCOUNT	% ACTION TAKEN	PROFIT/ACCOUNT	IMPROVEMENT	IMPROVEMENT			
All Current	1.6%	\$179	1.0%	\$177	\$2	1%			
30 DPD Max	19.8%	\$105	21.8%	\$92	\$13	14%			
60 DPD Max	29.3%	\$69	31.7%	\$56	\$13	23%			

2009 PORTFOLIO OPTIMIZATION: TIER 1 EARLY STAGE USING 2007 CUT SCORES										
SEGMENT	VANTAGESCORE STRATEGY		RATEGY BENCHMARK STRATEGY		VS \$	VS %				
SEUMENT	% ACTION TAKEN	PROFIT/ACCOUNT	% ACTION TAKEN	PROFIT/ACCOUNT	IMPROVEMENT	IMPROVEMENT				
All Current	1.6%	\$172	1.0%	\$170	\$2	1%				
30 DPD Max	22.7%	\$79	24.0%	\$62	\$18	28%				
60 DPD Max	32.2%	\$50	34.4%	\$32	\$18	55%				

- Over time, both the absolute per account improvement, and the percent improvement in profitability widens with VantageScore when compared with the benchmark score.
- As the delinquency profile increases, progressing from Current to 30 DPD to 60 DPD, VantageScore retains its predictive strength and thus becomes a progressively more effective account management tool by impacting less of the customer population while delivering superior profitability results.

The analyses demonstrate VantageScore's strong predictive strength over a given time horizon. It is also useful to compare these results against the optimal results discussed in the opening pages of this paper. If the actual results deliver profitability that is close to the optimal for 2008 and 2009, then lenders do not need to comprehensively update the analysis and strategy. This outcome offers lenders additional capacity for other research projects.

3. RISK
MANAGEMENT
OPTIMIZATION
PROCESS OVER
TIME (Cont.)

The tables below illustrate portfolio profitability in 2008 and 2009 when the risk strategies are optimized specifically for each year (Figure 15).

FIGURE 15
VANTAGESCORE WITH BENCHMARK COMPARISON,
OPTIMAL OUTCOMES 2008 AND 2009, TIER 1

2008 PORTFOLIO OPTIMIZATION: TIER 1 EARLY STAGE OPTIMAL 2008 ACTION							
SEGMENT	VANTAGESCO	RE STRATEGY	BENCHMARK STRATEGY		VS \$	VS %	
SEGINIENT	% ACTION TAKEN	PROFIT/ACCOUNT	% ACTION TAKEN	PROFIT/ACCOUNT	IMPROVEMENT	IMPROVEMENT	
All Current	1.7%	\$179	1.5%	\$178	\$1	1%	
30 DPD Max	23.1%	\$105	23.7%	\$93	\$13	13%	
60 DPD Max	31.4%	\$69	34.7%	\$56	\$13	23%	

2009 PORTFOLIO OPTIMIZATION: TIER 1 EARLY STAGE OPTIMAL 2009 ACTION						
SEGMENT	VANTAGESCO	RE STRATEGY	ATEGY BENCHMARK STRATEGY		VS \$	VS %
SEUNIENI	% ACTION TAKEN	PROFIT/ACCOUNT	% ACTION TAKEN	PROFIT/ACCOUNT	IMPROVEMENT	IMPROVEMENT
All Current	2.9%	\$172	2.6%	\$170	\$2	1%
30 DPD Max	32.2%	\$83	46.5%	\$67	\$16	23%
60 DPD Max	40.0%	\$52	48.9%	\$35	\$17	49%

		% OFF 2007 SCORE VS OPTIMAL SCORE		
		VANTAGESCORE	BENCHMARK	
	All Current	0.1%	0.1%	
2008	30 DPD Max	0.3%	0.6%	
	60 DPD Max	0.1%	0.2%	
	All Current	0.2%	0.4%	
2009	30 DPD Max	4.3%	8.2%	
	60 DPD Max	3.8%	7.7%	

- 2008: VantageScore is near its optimal rate for defining policy with minor improvements. All three tiers are within 0.5 percent of their optimal score cut per account profitability while the benchmark score would effectively double the rates at which the study population is impacted.
- 2009: VantageScore is near 4 percent of the optimal score cut target while the benchmark is around 8 percent off the optimal target score cut.

In this consumer segment, VantageScore not only delivers stronger performance results in terms of overall profitability when compared with the benchmark score, but also retains this near optimal performance across an extended time frame.

3. RISK
MANAGEMENT
OPTIMIZATION
PROCESS OVER
TIME (Cont.)

Finally, the same analysis is conducted on the late stage delinquency consumer group and again the effectiveness of VantageScore is compared against the benchmark score to determine the optimal portfolio management strategy for this group.

LATE STAGE DELINOUENCY APPLICATION AND RESULTS

Similar to the analysis of early stage consumers, relative profitability per account among late stage delinquency consumers is examined by comparing the VantageScore strategy with a benchmark strategy (Figure 16).

FIGURE 16 TIER 2 LATE STAGE RESULTS

2007 PORTFOLIO OPTIMIZATION: TIER 2 LATE STAGE						
VANTAGESCORE STRATEGY BENCHMARK STRATEGY VS \$						VS %
SEGMENT	% ACTION TAKEN	PROFIT/ACCOUNT	% ACTION TAKEN	PROFIT/ACCOUNT	IMPROVEMENT	IMPROVEMENT
90 DPD Max	43.0%	\$50	40.8%	\$33	\$17	51%
120+ DPD Max	58.9%	\$25	59.5%	\$11	\$14	122%

SEGMENT PROFITABILITY HIGHLIGHTS

- "90 DPD Max" VantageScore optimizes the 90 DPD Max segment at 43 percent of the consumers with a profitability of \$50 per account. Conversely, the benchmark score affects 40.8 percent of the consumers at \$33 per account profitability. In this case, VantageScore increases profitability by \$17 per account or 51 percent over the benchmark.
- "120+ DPD Max" VantageScore optimizes the "30 DPD Max" segment at 58.9 percent with \$25 per account profitability, while the benchmark score affects 59.5 percent of the segment with \$11 per account profitability, VantageScore thus increases profitability in this segment by \$14 per account or 122 percent.

3. RISK
MANAGEMENT
OPTIMIZATION
PROCESS OVER
TIME (Cont.)

The same score cuts from 2007 were also applied to the 2008 and 2009 timeframes to determine longer-range predictive capabilities of VantageScore (Figure 17).

FIGURE 17 PORTFOLIO OPTIMIZATION FOR 2008 AND 2009, TIER 2 LATE STAGE

2008 PORTFOLIO OPTIMIZATION: TIER 2 LATE STAGE USING 2007 CUT SCORES						
VANTAGESCORE STRATEGY BENCHMARK STRATEGY VS \$					VS %	
SEGMENT	% ACTION TAKEN	PROFIT/ACCOUNT	% ACTION TAKEN	PROFIT/ACCOUNT	IMPROVEMENT	IMPROVEMENT
90 DPD Max	49.2%	\$43	43.7%	\$24	\$20	83%
120+ DPD Max	62.4%	\$22	61.1%	\$10	\$12	117%

2009 PORTFOLIO OPTIMIZATION: TIER 2 LATE STAGE USING 2007 CUT SCORES						
CECMENT	VANTAGESCO	RE STRATEGY BENCHMARK STRATEGY		VS \$ VS %		
SEGMENT	% ACTION TAKEN	PROFIT/ACCOUNT	% ACTION TAKEN	PROFIT/ACCOUNT	IMPROVEMENT	IMPROVEMENT
90 DPD Max	51.1%	\$30	45.7%	\$10	\$20	201%
120+ DPD Max	64.2%	\$14	62.7%	\$8	\$6	67%

- When compared with the benchmark score, the absolute per account improvement in profitability and the percent improvement in profitability with VantageScore widens as time passes. At the same time, the percent of accounts on which action is taken remains consistent.
- As groups are further impacted by delinquent status changes in their profiles, in this case changing the delinquency from 90 DPD to 60 DPD, VantageScore increases its predictive capability to be an effective profit optimizing account management process.

HOW FREQUENTLY DOES THE LATE STAGE DELINQUENCY POLICY REQUIRE UPDATES?

As with the early stage analysis, the optimal frequency for updates to policy should be considered for the higher-risk tier. The magnitude of the deterioration of a policy from prior timeframes with the profitability of a policy that is optimized for the specific timeframe should be considered.

3. RISK
MANAGEMENT
OPTIMIZATION
PROCESS OVER
TIME (Cont.)

As with the early stage population, VantageScore shows stronger process management capabilities over a given time horizon when results from the higher-risk tier are examined. With this information, as mentioned, lenders must then determine the optimal frequency for policy changes to maximize profitability and limit losses. To compare with the 2007 strategy, the tables below show VantageScore's performance over 2008 and 2009 as if it had been optimally calibrated in those years (Figure 18).

FIGURE 18
VANTAGESCORE WITH BENCHMARK COMPARISON,
OPTIMAL OUTCOMES 2008 AND 2009, TIER 2

2008 PORTFOLIO OPTIMIZATION: TIER 2 LATE STAGE OPTIMAL 2008 ACTION						
SEGMENT	VANTAGESCORE STRATEGY BENCHMARK STRATEGY VS \$ VS %					
SEUWENT	% ACTION TAKEN	PROFIT/ACCOUNT	% ACTION TAKEN	PROFIT/ACCOUNT	IMPROVEMENT	IMPROVEMENT
90 DPD Max	47.4%	\$44	48.9%	\$24	\$20	82%
120+ DPD Max	58.0%	\$22	64.0%	\$11	\$12	108%

2009 PORTFOLIO OPTIMIZATION: TIER 2 LATE STAGE OPTIMAL 2009 ACTION						
CECMENT	VANTAGESCO	RE STRATEGY BENCHMARK STRATEGY		VS \$	VS %	
SEGMENT	% ACTION TAKEN	PROFIT/ACCOUNT	% ACTION TAKEN	PROFIT/ACCOUNT	IMPROVEMENT	IMPROVEMENT
90 DPD Max	56.7%	\$31	62.9%	\$16	\$15	98%
120+ DPD Max	61.4%	\$14	65.3%	\$10	\$5	48%

		% OFF 2007 Optimal	
		VANTAGESCORE	BENCHMARK
2008	90 DPD Max	2.3%	2.9%
20	120+ DPD Max	1.8%	5.5%
2009	90 DPD Max	1.0%	35.0%
20	120+ DPD Max	0.0%	11.8%

- 2008: Depending on tier, VantageScore is within 2.3 percent (90 DPD) or 1.8 percent (120 DPD) of an optimal rate of return when defining policy from 2007 for late stage tiers. Conversely, for the same tiers, the benchmark score is 2.9 percent or 5.5 percent off the optimal score cut returns per account.
- 2009: Here the results are more dramatic. In both the 90 DPD and the 120+ DPD segment, VantageScore is within 1 percent of the optimal score cut target while the benchmark score is 35 percent or 11 percent off the optimal target, depending on tier.

VantageScore delivers a stronger performance result in terms of overall profitability and retains this performance over an extended time frame across all stages of a consumer profile.

CONCLUSION

Persistent challenges in the broader economy are causing an increasing number of consumers to slip into progressively more severe levels of delinquency. Default rates for all consumer segments (based on credit profiles) have been rising over the past few years. Although the challenge for lenders has remained constant for many years, the complex forces at work in the present economic environment increase the critical need to find tools that can help effectively navigate the storm.

When applied across a segmented portfolio, VantageScore provides uniformly higher results than an industry benchmark credit score, as demonstrated by the examples used in this study. The results are especially strong for consumers with severe delinquency in their credit profiles. In these increasing states of delinquency, VantageScore drives effective results even in the face of adverse macroeconomic conditions, as demonstrated by the stability of VantageScore during one of the largest consumer credit downturns in recent history.