Adapting Credit Scores to Evolving Consumer Behavior and Data

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ABSTRACT

Credit scores have become an integral component of the credit landscape. As that landscape shifts, credit-score algorithms should adapt to changes in consumer behavior that are reflected in the information that creditors share with credit-reporting agencies. In addition to adjusting the algorithm's mix of characteristics and associated score weights over time, model developers should also evolve the predictive characteristics—those building blocks of the score algorithm—in order to account both for changes in the ways consumers seek and use credit, and for the introduction of new financial products. Through such advances, scientists can develop increasingly predictive scores based on credit information, and they can develop more sophisticated logic that recognizes consumers who manage credit responsibly. This Article discusses three different research studies. The first study focuses on changes made while redeveloping an earlier generation of the FICO Score algorithm. FICO scientists introduced logic to improve the way the algorithm evaluated credit-inquiry information, making it more appropriate to consumers who were rate shopping for the best loan. The second research study discusses how credit-utilization calculations were modified to account for flexible spending accounts—a new type of credit card that possesses both a charge and a revolve feature. This enhancement was incorporated into the current suite of FICO Scores. The final research study examines whether, in future versions of the FICO Score algorithm, mortgage short sales should penalize scores less than foreclosures do.

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I. INTRODUCTION

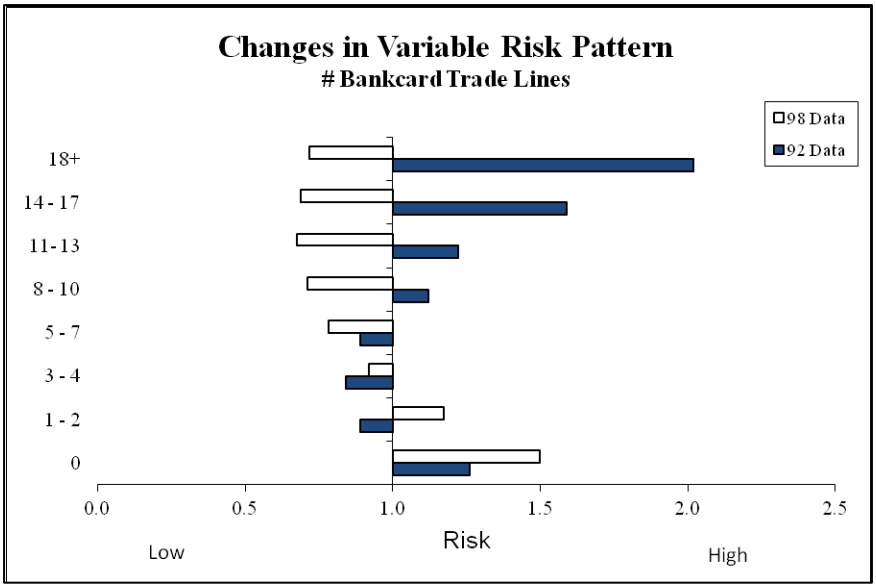
Credit scores are a vital element of the lending ecosystem, providing lenders with an objective means to assess a consumer's creditworthiness. Broad-based credit scores, such as the FICO Score, are redeveloped periodically to capture changes in consumer risk patterns, leverage improvements in the reporting of information to the Credit Reporting Agencies (CRAs), and incorporate new technological enhancements into the score algorithm.[1]

To demonstrate how consumer risk patterns have changed over time, we might consider the number of credit cards a consumer has. The earliest incarnations of the FICO Score typically incorporated a predictive variable that measured the number of credit cards a consumer possessed. In the nascent days of FICO Scores, having many credit cards was risky and having few credit cards actually represented good risk. Over time, the risk pattern associated with that variable fundamentally changed.

In Figure 1, we observe a noticeable change in the number of credit cards and associated risk. In 1992, having many credit cards indicated a high level of credit risk; in fact, a consumer with eighteen or more credit cards was twice as risky as the total population. In 1998, consumers with many credit cards were actually slightly better credit risks than the total population. In both time periods, having no credit cards indicated a greater degree of credit risk, but elsewhere the risk pattern fundamentally changed. While most predictive characteristics employed by credit scores demonstrate more stable risk patterns, this is one example that demonstrates the benefit of redeveloping scores periodically in order to account for changing risk patterns.

1. Broad-based, or generic, credit scores like the FICO Score are designed to be used across a wide variety of applications and products. On the other hand, custom credit scores are frequently designed with a more specific or narrow focus—for example, originations for a specific type of credit product. Custom credit scores can also be developed for a specific lender's portfolio.

Figure 1—Risk Pattern for Number of Bankcard Trade Lines Over Time



The vertical axis represents the number of bankcard trade lines on consumer credit reports. The horizontal axis measures normalized risk. Risk values are calculated by taking the bad rate observed for a given attribute, and dividing that by the bad rate observed for the total population. Risk values greater than one indicate that the attribute is riskier than that of the total population. For example, consumers who had zero bankcards in 1998 were 1.5 times *riskier* than the total population. But in 1998, consumers with eight to ten bankcards were 0.71 times *less risky* than the general population. This analysis was conducted by FICO during a redevelopment of the FICO Score in the early 2000s.

In addition to redeveloping the scores to accommodate for changing risk patterns, the building blocks of the score—the characteristics and the treatment of the primitive data elements—should also evolve. This Article presents three different examples of how the predictive characteristics of the score evolved to adapt for changes in the credit landscape. The first study focuses on enhancements introduced to an earlier generation of the FICO Score, released in the early 2000s. The second study focuses on enhancements that were incorporated into the FICO 8 models. The last study focuses on research that determines whether short sales and other codes signifying different types of mortgage stress events should be treated less harshly by the FICO Score.

II. CHANGING INQUIRY ASSESSMENT TO MORE EFFECTIVELY ACCOMMODATE RATE-SHOPPING

Credit inquiries have long served as predictors in credit-scoring models. Although they contribute a relatively small percentage to the predictiveness of the final score, credit inquiries often attract a disproportionate amount of attention from consumers. This presumably has been due to the prominence they receive on credit reports. Since the mid-1990s, FICO Scores have employed logic in the treatment of inquiries that recognizes the presence of rate-shopping behavior. There are two components of this logic, a buffer and a deduplication window. The purpose of the buffer is to bypass any auto or mortgage inquiries made within the last thirty days. This prevents very recent auto or mortgage inquiries from influencing any current applications for credit. The deduplication window is a rolling timeframe in which multiple auto or mortgage inquiries, posted to the credit report during the deduplication window, will be counted as a single inquiry.

The following table illustrates the general concepts behind the earlier inquiry logic. In this example, all of the auto inquiries occur within the last thirty days and are ignored. The two mortgage inquiries fall outside of the thirty-day buffer, and are eligible to be counted. However, since both mortgage inquiries fall within fourteen days of each other, only one inquiry will be counted. Even though the department-store inquiry occurs within fourteen days of the first mortgage inquiry, it is counted separately; only auto and mortgage inquiries are deduplicated. In this example, an earlier version of the FICO Score would count two inquiries.

Figure 2—Example of Earlier Inquiry Logic

Type of Inquiry	Number of Days Ago	Treatment
Department Store	68	Counted as one inquiry
Mortgage	65	Counted as one inquiry (deduplicated within fourteen days)
Mortgage	56	
Auto	17	Not counted (ignored within thirty days)
Auto	9	
Auto	8	

With the beginning of consumer score disclosure in 2000, the launch of MyFICO.com in the early 2000s, and the increase in financial advice to consumers through news media and the Internet, consumers became more aware of the benefits of shopping for the best rate. At the same time, lenders

began to offer a wider array of credit products enabled by risk-based pricing.[2] As consumers became more financially savvy, their search for the best interest rates on a mortgage or auto loan often took longer than fourteen days. FICO suspected that consumers who were attempting to find the best rate could be penalized and that the inquiry logic could be improved upon. The company's scientists revisited the model's inquiry logic to determine if a fourteen-day deduplication window remained ideal for risk prediction. If the fourteen-day window was too short, too many inquiries were being counted, excessively penalizing the consumer and yielding slightly fewer predictive characteristics.

To investigate the merits of broadening the deduplication window, FICO varied the length of the window and measured the resulting impact to predictiveness. In general, a longer deduplication window was proven to be more effective in evaluating inquiry information. Information value—a statistic that measures how well a given characteristic separates goods from bads—was used to determine if a change in the deduplication window was merited.[3]

Figures 3 and 4 represent internal FICO research that assesses the analytic merit of different deduplication windows. They demonstrate that by expanding the length of the deduplication window, the characteristic is marginally better at predicting risk. Figure 3 is based on the performance of all credit accounts on the consumer's file. Figure 4 is based on the performance of new accounts. Inquiries can be more relevant in an originations context, so the same analysis was repeated based on the performance of new accounts—accounts opened within the six months following the scoring date. The patterns are fairly consistent in both contexts.

2. Risk-based pricing is the practice of setting credit terms according to a consumer's credit-risk profile.

3. For a characteristic with bins i = 1,…q, factored counts are defined by:

n_g = Number of Goods in the population; n_b = Number of Bads in the population

n_{gi} = Number of Goods in bin i; n_{bi} = Number of Bads in bin i

Empirical frequency distribution versions of these counts are defined by:

$$f_g(i) = 100\frac{n_{gi}}{n_g};\ f_b(i) = 100\frac{n_{bi}}{n_b}$$

Information value of a binned variable is defined as:

$$IV = \sum_{i=1}^{q} \frac{f_g(i) - f_b(i)}{100} \log\left[\frac{f_g(i)}{f_b(i)}\right]$$

Figure 3—Varying the Length of the Deduplication Window (Performance on All Accounts)

Information Value Calculation						
	Length of Deduplication Window					
	14	21	30	45	60	90
Total	0.466	0.469	0.472	0.475	0.476	0.476
Derogatory	0.200	0.202	0.204	0.208	0.208	0.211
Clean	0.304	0.307	0.308	0.308	0.308	0.306

The column headings indicate the length in days of the potential deduplication window. The rows indicate values for three different populations: the total population; the population of people with derogatory events on their credit files; and the population with clean credit files (no derogatory events). In the table, larger values indicate a more predictive characteristic based on consumers' performance on all categories of credit accounts.

Figure 4—Varying the Length of the Deduplication Window (Performance on New Accounts)

Information Value Calculation						
	Length of Deduplication Window					
	14	21	30	45	60	90
Total	0.369	0.373	0.373	0.376	0.377	0.379
Derogatory	0.163	0.167	0.167	0.169	0.171	0.176
Clean	0.291	0.294	0.294	0.297	0.296	0.294

In this second table, larger values indicate a more predictive characteristic based on consumers' performance only on new credit accounts.

For the total population, increasing the deduplication window leads to a slightly stronger characteristic. However, we found there is an upper limit to the length of the deduplication window. The improvement gained in using a sixty- or ninety-day deduplication window is marginal. For the clean population (roughly 70% of all consumers), the ideal deduplication window is approximately forty-five days when looking at performance metrics for both all accounts and new accounts separately. Interestingly, we see that the ideal deduplication window for the rest of the population—those who have at least one derogatory event on their credit history—may be greater than forty-five days. This is intuitive because consumers with blemished credit histories may require more time to find and secure credit.

Only one deduplication window could be selected—it would be impractical and confusing to consumers if differing deduplication windows were used to assess inquiries. Ultimately, a forty-five-day window was selected. The forty-five-day window was more predictive than the status-quo window of fourteen days. The information value associated with a sixty- and ninety-day window was not discernibly stronger than the forty-five-day window. Additionally, for

subpopulations with no credit blemishes, a slight reversal in the predictiveness of the characteristic was observed with a sixty- and ninety-day window. This observation was notable because inquiry information is slightly more predictive for this pocket of the population.

In this way, FICO was able to introduce an enhancement to the FICO Score that provided a more effective methodology to evaluate inquiry information. Given that this characteristic is designed to measure the true number of unique searches for credit by the consumer, it is not surprising that increasing the deduplication window to better reflect how long it takes a consumer to shop for a loan can make the characteristic more predictive.

III. ADAPTING TO NEW CREDIT PRODUCTS

As the credit-card industry becomes more competitive, issuers introduce new products in an effort to grow their portfolios. As an example, they introduced flexible spending cards in the mid-2000s. Flexible spending accounts are hybrid accounts with a revolving component as well as a charge component. These accounts have no preset spending limits but do have revolving limits. Thus, amounts charged in excess of the revolving limit need to be paid in full at the next billing cycle. Flexible spending accounts have also been referred to as no-preset spending limit accounts, Signature Cards, or World Accounts.[4]

From a credit-reporting perspective, flexible spending accounts represent a challenge as they carry both revolving and charge features. Reporting guidelines from the Consumer Data Industry Association (CDIA) indicate that flexible spending accounts should be reported as a revolving card, and that the limit reported should reflect the revolving-limit component of the card.[5] Because utilization characteristics can have significant importance for FICO Scores, issuers of flexible spending accounts were concerned that FICO Scores should evaluate flexible spending accounts appropriately in characteristics measuring credit-card utilization.[6] In particular, they were concerned about instances where the balance exceeds the limit for the revolving portion of these accounts. They felt that the risk associated with the overutilized flexible spending account is not reflective of traditional revolving accounts that are over the limit. This suggested that flexible spending accounts should be treated

4. It is important to note that in the context of credit scores, the flexible spending accounts referenced here are not the tax-exempt healthcare spending accounts that companies offer to their employees.

5. *See* CONSUMER DATA INDUS. ASS'N, 2006 CREDIT REPORTING RESOURCE GUIDE 156 (2006) (on file with author).

6. Utilization characteristics measure outstanding balances in relation to credit limits or loan amounts. Within the FICO Score, credit-card-utilization calculations are very influential predictors. Credit-card utilization can be calculated by taking the sum of the credit-card balances and dividing by the sum of the credit-card limits.

differently by the FICO Score, or should be represented on the credit report in a different manner. This hypothesis is supported by the observation that users of flexible spending accounts are encouraged and authorized to exceed the assigned credit limit, whereas traditional revolving products are not allowed to go over the limit without an authorization.

During the development of the FICO 8 Score, research was conducted to determine the best way to factor flexible spending accounts into utilization characteristics. To better understand the relationship between risk and utilization characteristics, the analysis population was narrowed to only those consumers who possessed at least one flexible spending account. The study was performed on a database consisting of approximately four million consumer records. The database was based on two archives: April 2005 and April 2007. As of April 2005, consumers with a flexible spending account represented approximately 0.2% of the scoreable population.

The focus of the study was to evaluate alternative treatments for flexible spending accounts and utilization characteristics. Utilization characteristics are variables used by the FICO Score to evaluate the indebtedness dimension of a consumer credit report. The research focused on the following utilization characteristics: highest utilization on bankcard; highest utilization on credit card; bankcard utilization; and credit card utilization.[7]

For each of these utilization characteristics, five different versions were generated. Each version represented a specific treatment for flexible spending accounts.

- Version 1 – Benchmark; No special treatment for flexible spending accounts
- Version 2 – Bypass flexible spending accounts from utilization calculation
- Version 3 – Use the high balance as the limit for flexible spending accounts
- Version 4 – Use the high balance as the limit for flexible spending accounts when the balance is greater than the limit
- Version 5 – Use the maximum of the balance and the limit for flexible spending accounts

To evaluate the predictive merit associated with each variation, information value was calculated across each version for each characteristic. Because of the smaller proportion of flexible spending accounts relative to *traditional* credit cards, analyzing the predictiveness on the aggregate level would dilute the impact of each variation. For that reason, the analysis population focused on consumers with flexible spending accounts.

7. Bankcards are a subset of credit cards. Bankcards are credit cards issued by a bank. Finance companies, credit unions, and other financial institutions can also issue credit cards. Other variations of utilization calculations look at the highest utilized credit card on file. For example, if a consumer has a credit card with a $500 balance and a $1000 limit, and another credit card with a $9000 balance and a $10,000 limit, the highest utilization for that consumer will be 90%.

As summarized in Figure 5, Version 2 yields a lower information value than Version 1 for three of the four utilization characteristics. This indicates that bypassing flexible spending accounts from utilization characteristics generally results in a weaker predictive characteristic. The result is intuitive as it illustrates the potential loss of predictiveness from indiscriminately removing valuable information from the characteristic calculation. The results also suggest that versions of the characteristics show promise when they mitigate utilization calculations in scenarios where the balance exceeds the credit limit.

Figure 5—Measuring Predictiveness for Different Utilization Calculations (CRA #1)

	Information Value				
	Version 1	Version 2	Version 3	Version 4	Version 5
Highest Utilization on Bankcard Trade Line	1.308	1.285	1.373	1.407	1.411
Highest Utilization on Credit Card Trade Line	1.367	1.308	1.409	1.443	1.446
Bankcard Utilization	1.262	1.183	1.318	1.331	1.328
Credit Card Utilization	1.308	1.189	1.397	1.406	1.407

This table measures how predictive each version of the characteristic is, based on our analysis of data provided by a major CRA. Higher values indicate a stronger, more predictive characteristic.

The results of the analysis indicate that changing the treatment of flexible spending accounts could lead to a more predictive way of assessing utilization for this population. In three of four characteristics, Version 5 yields the greatest information value, indicating that it is the most predictive variation. These results suggest utilization characteristics that mitigate overutilized flexible spending accounts are more predictive than the current methodology.

Of particular interest are the results associated with the information value for characteristics that measure highest utilization. Highest utilization is calculated by identifying the highest utilization level for each credit card separately. For purposes of illustration, consider a consumer who has two credit cards, one with a balance of $750 and a limit of $1000, and the other with a balance of $5000 and a limit of $10,000. The highest utilization on a credit card for this consumer is 75%. Comparing Versions 2 through 5 to Version 1, the

difference in predictiveness in the highest utilization characteristics is more pronounced. This should not come as a surprise because these variations are the ones that will have the largest impact caused by flexible spending accounts where the balance is greater than the reported credit limit. Unlike the variations that look at utilization across the sum of all credit card balances and credit card limits, the highest utilization characteristics cannot be watered down by multiple accounts, so the impact is more noticeable.

This research was repeated at another major CRA and the conclusions outlined in Figure 6 were similar: Utilization characteristics employed by the FICO Score can be modified to better assess flexible spending accounts.

Figure 6—Measuring Predictiveness for Different Utilization Calculations (CRA #2)

	Information Value				
	Version 1	Version 2	Version 3	Version 4	Version 5
Highest Utilization on Bankcard Trade Line	1.418	1.35	1.502	1.524	1.521
Highest Utilization on Credit Card Trade Line	1.485	1.487	1.556	1.583	1.586
Bankcard Utilization	1.479	1.294	1.564	1.578	1.536
Credit Card Utilization	1.500	1.393	1.581	1.586	1.554

Figure 6 is similar to Figure 5 but represents a separate analysis of data from a different CRA. As before, higher values indicate a stronger, more predictive characteristic.

Ultimately, Version 5 was selected. Though both Version 4 and Version 5 represent improvements over the status quo, Version 5 was selected because Version 4 calculations can be susceptible to an isolated spike in the high balance. When the new scoring model encountered an overutilized flexible spending account, the utilization would be capped at 100% for scoring purposes. It is important to note this treatment assumes that the account is reported according to CDIA guidelines. If the account is not reported appropriately, then it is possible for the account not to receive the specialized treatment associated with this particular type of account.

IV. THE MORTGAGE CRISIS AND REVISITING THE CLASSIFICATION OF SHORT SALES

The aftermath of the mortgage crisis created an unprecedented wave of stress in the housing market. Depressed housing values and increased unemployment continue to strain homeowners. When homeowners find they have no choice but to default on their mortgages, they may consider various options from loan modifications to foreclosures, short sales, and deeds in lieu of foreclosure. Some may want to better understand the credit-scoring consequences of their options. In general, foreclosures, short sales, and deeds in lieu are all treated in a similar manner by the FICO Score. As a result, there is no substantial difference in the impact to the FICO Score between a foreclosure, short sale, and a deed in lieu. Each of these events, in and of itself, is considered derogatory by the FICO Score and the specifics of how the event is reported can lead to subtle differences in its treatment by the score. For example, short sales without a reported deficiency balance could have a slightly smaller impact than a foreclosure.

Observers sometimes ask whether it remains appropriate for a short sale to be treated in a manner similar to a foreclosure. Some critics assert that a short sale should be substantially less punitive than a foreclosure. They argue that because short sales do not cost the bank as much money as foreclosures, the penalty to a credit score should be commensurate with the financial impact on a lender. Some also suggest that a willingness of the borrower to work with the lender should have a positive effect on the borrower's credit risk.

Additionally, as the mortgage crisis evolved many lenders used loan modifications as a remediation strategy for distressed homeowners. From a credit-reporting perspective, no existing codes were available to lenders for clearly differentiating loan modifications from other events. The CDIA introduced new reporting codes to allow lenders to accurately account for those events.[8] All newly introduced loan-modification codes received no special treatment by the FICO Score. The FICO Score cannot provide them with any special treatment until an empirical study can determine the relationship between the presence of these new codes and credit risk. Figures 7 through 10 highlight FICO's internal research into the appropriate treatment for these codes.

Figure 7 documents the frequency of various mortgage-stress-related events over time. Each column represents the number of consumers whose credit report contains a reporting code for a specific event (foreclosure, short sale, deed in lieu, etc.) on a mortgage trade line for a given year. The table is based on a random sample of 10 million consumer credit reports over time. The

8. *See* Bulletin for Systems Update from Credit Reporting Agency (May 29, 2009) (on file with author).

descriptions in the table are self-explanatory but two merit additional commentary. Events such as "paying under a partial payment agreement" are typically reported for mortgages that are in the trial period of renegotiated or refinanced loans, or are referenced in Making Home Affordable, Fannie Mae/Freddie Mac, and other loan forbearance programs. Events that are reported as "account paid for less than the full balance" are typically associated with the reporting of short sales.

Figure 7—Frequency of Mortgage Reporting Codes Over Time

	# of Consumers with Specific Mortgage Trade Line			
Event:	**2005**	**2007**	**2009**	**2011**
Paying under a partial payment agreement	9,771	13,449	48,368	23,022
Foreclosure	43,907	47,721	66,328	96,796
Forfeit of deed in lieu of foreclosure	461	787	1,682	3,223
Account paid for less than the full balance	5,346	6,934	22,187	52,436
Account paid after foreclosure started	4,320	6,021	8,107	9,725
Making payment - foreclosure was initiated	2	3	1	1
Foreclosure process started	38,498	60,824	12,9043	140,356
Loan modified under a federal government plan	0	0	0	43,968
Loan modified	0	0	0	52,447
Account in forbearance	0	0	0	0

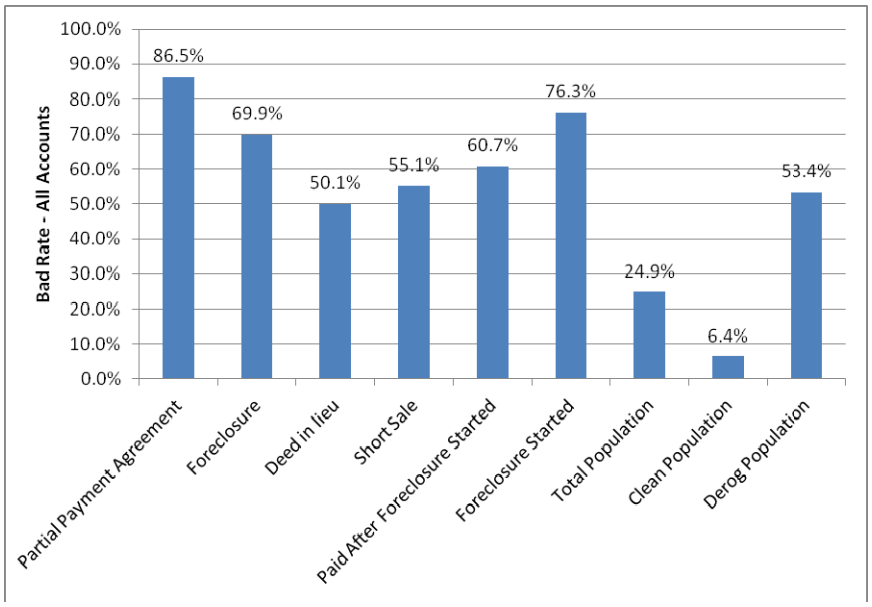
Not surprisingly, there is a dramatic increase in the number of consumers who experienced a distressful event regarding their mortgage between 2005 and 2011. In particular, reported short sales are nearly ten times more prevalent in 2011 than they were in 2005. Deeds in lieu are seven times more common than they were in 2005. When it comes to foreclosures, codes indicating that a foreclosure process has started are more than 3.5 times more common in 2011 than they were in 2005.

As noted, loan-modification codes were introduced in the wake of the mortgage crisis, and were not observed on credit-report data available to FICO until 2010. In terms of scale, it is interesting to observe that nearly twice as many loan modifications—government and nongovernment—were reported in

2011 compared to short sales. All of the listed events demonstrate a consistent increase over time, with the exception of "paying under a partial payment agreement."

The next phase of the analysis is to understand the risk associated with each of these reported events. The analysis population was based on an observation snapshot of October 2009 and a performance snapshot of October 2011. For each of the events in question, the borrowers' subsequent payment behavior over the two-year performance window was observed. Figure 8 depicts the "bad rates" observed following each of the events. A "bad" is defined as any consumer who experienced a delinquency of ninety days or longer past due on any reported credit obligations during the two-year performance window.

Figure 8—Bad Rates for Mortgage-Related Codes (Performance on All Accounts)



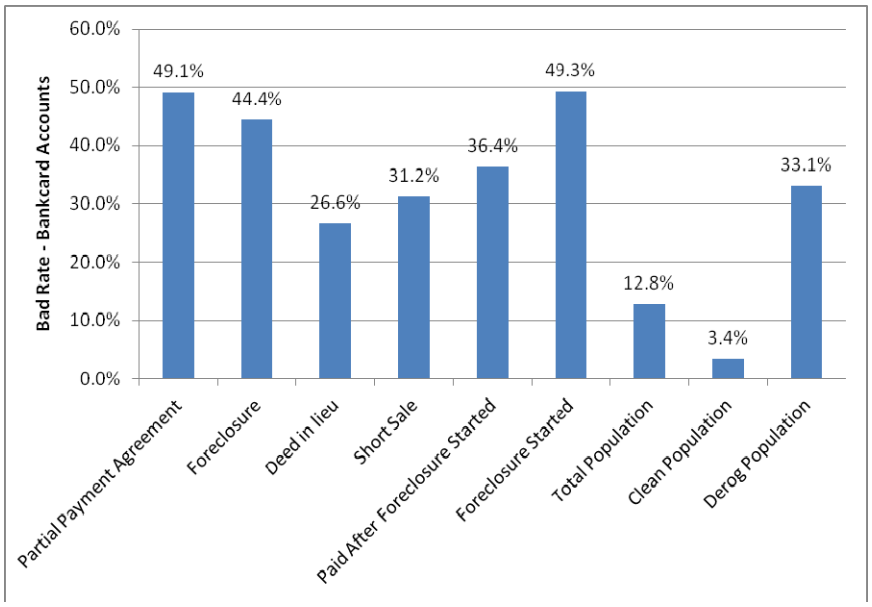
This chart displays the percentage of people with different events on their credit reports who go on to default on one of their credit obligations during the two-year performance window. For example, people with evidence of a short sale on their credit report go on to default on one of their credit obligations 55.1% of the time.

All of the mortgage-stress events represent a substantially greater degree of risk than that posed by the total population. All of these events are currently classified as derogatory items by the FICO Score, and could result in a negative impact to a consumer's score. The three columns on the far right in Figure 8 represent different benchmark populations. The first column represents the aggregate population, the second represents "clean" consumers with no severe

derogatory information, and the third column represents consumers with some severe derogatory information on file.[9] Reporting codes associated with short sales (account paid for less than full balance) remain extremely risky; they are slightly better risks than foreclosures, but are at least twice as risky compared to the total population. Consumers with short sales also perform no better when compared to consumers who have a derogatory item on file.

Figure 8 looks at the performance on any trade line, including any mortgage trade lines opened at the time of scoring. What if we examined the consumers' subsequent payment behavior on bankcards alone, a credit obligation far removed from the consumers' mortgage obligations? Figure 9 indicates that there remains a strong link between poor bankcard-payment behavior and consumers who experience one of the mortgage-stress events.

Figure 9—Bad Rate for Mortgage-Related Codes (Performance on Bankcard Accounts)



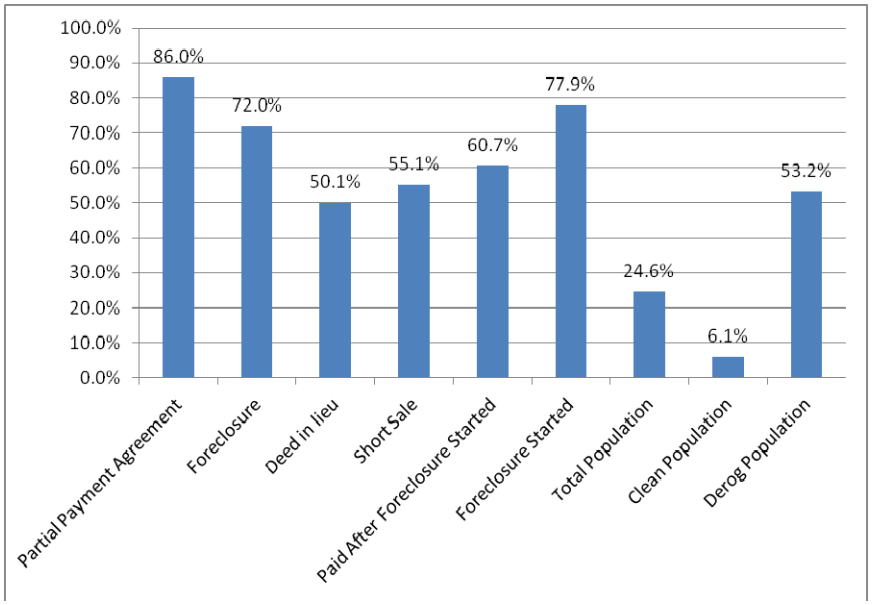
Unlike the previous chart, this chart displays the percentage of people who go on to default specifically on one of their bankcard obligations. The previous chart addressed those who default on any of their credit obligations, including auto loans, student loans, bankcards, and so on. For example, people with evidence of a foreclosure starting on their credit report go on to default on one of their bankcards 49.3% of the time.

One of the arguments for revisiting the scoring model's treatment of these mortgage-stress events is that the mortgage crisis was unprecedented; consumers, who would have otherwise paid responsibly, were now making

9. A derogatory file is a credit report with the presence of severe delinquency (90+ days past due), a collection, or a derogatory public record.

decisions that theoretically were not representative of their true risk. This premise was tested by isolating more recent occurrences of these events by identifying records that contained one of these reporting codes in 2009, but did not contain one in 2007. For example, of the 66,328 records with a reported foreclosure in 2009, the analysis focused on the 18,607 records (66,328 – 47,721) with a foreclosure in 2009, but not in 2007. This analysis produced the results in Figure 10. Comparing it to Figure 8 yields no discernible difference. The same conclusion is drawn: All of the reported mortgage-stress events represent a greater degree of credit risk when compared with the general population.

Figure 10—Bad Rate for Mortgage Related Codes
(Performance on All Accounts)



This chart displays the percentage of people whose mortgage-stress events first appear on their credit reports between 2007 and 2009, who go on to default on one of their credit obligations. For example, people with recent evidence of a deed in lieu on their credit report go on to default on one of their credit obligations 50.1% of the time.

Not quite enough time has passed to provide a twenty-four-month performance window for analyzing the predictiveness of the codes representing loan modification. If there is empirical evidence demonstrating that consumers with a reported loan modification perform substantially worse in repaying their credit obligations, future credit-scoring models will be modified to appropriately classify those codes.

V. CONCLUSION

Credit-scoring models are periodically redeveloped to account for changing risk patterns. To build the most effective credit scores, scientists may need to go beyond reoptimizing the scorecard weights given to predictive characteristics based on recent data. The building blocks of the credit scores, the predictive characteristics, may need to evolve with the model as well. This evolutionary innovation ensures the components of the model adapt to changes in consumer credit behavior and produce the most consistently predictive score.

Various market forces can influence how consumer repayment behavior relates to the predictive characteristics used in calculating credit scores. For example, the combination of making scores available to consumers, plus a wealth of financial-literacy information on the Internet, has made consumers more aware of the benefit of shopping for the best interest rates. Research has demonstrated that the logic used in assessing the predictive value of inquiry information could be updated to better recognize the actual risk associated with rate-shopping behavior.

New credit products can also create the need for predictive characteristics to evolve. In the mid-2000s, flexible spending accounts that incorporated revolving and charge properties for the cards were introduced. Because of the properties of the card and the lenders' target markets, the risk associated with flexible spending accounts when the balance was greater than the revolving limit was not great when compared to the risk of traditional revolving products. Mitigating the treatment of utilization rates for flexible spending accounts improved the model's ability to assess indebtedness.

Lastly, the mortgage crisis raised interest in how the FICO Score treated various events relating to mortgage stress. Of particular interest was whether it remained appropriate for short sales to be classified as derogatory items, similar to foreclosures. Evaluating the credit performance following these various mortgage events validated the derogatory classification by the scoring model. Consumers with short sales on their credit reports continue to represent considerable credit risk, and scoring models need to continue representing that risk appropriately.

Reporting codes for loan modification are relatively new to the databases of CRAs. Currently, these codes are not classified as derogatory indicators by the FICO Score. As time passes and the credit risk associated with these consumers over a twenty-four-month performance window can be evaluated, their classification in the scoring model may change. If it is determined that the credit risk associated with these accounts is substantially greater than that of the total population, it is possible that future scoring models will treat these events as negative items. As credit data evolves and reflects changing consumer behavior, FICO Scores will also evolve to adapt to the ever-changing credit landscape.