THE FAIR CREDIT REPORTING ACT:

ACCESS, EFFICIENCY, & OPPORTUNITY

PART II

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Contents

1. EXECUTIVE SUMMARY & KEY FINDINGS

The following report confirms the findings put forward in Part I of "Access, Efficiency, and Opportunity: The Economic Importance of Fair Credit Reauthorization." In Part I, we found a clear link between the strengthened federal preemptions that were amended to the FCRA in 1996, and the raft of benefits currently enjoyed by consumers in the markets for mortgage debt and credit cards.

A key component of the first part of this study concerned the effect that data restrictions, stemming from a loss of federal preemption, would have on the ability of credit grantors to assess the risk of a loan. It was found that a loss of preemption would lead to a deterioration of the ability of credit grantors to distinguish "low" credit risks from "higher" ones. In turn, this loss in predictive capability would cause consumer loan acceptance rates to decline, or the price of those loans would rise. A thorough reading of Part I is necessary to fully understand the context of the findings from Part II.

In Part I, we arrived at these conclusions by simulating the effect that a range of data restrictions would have on the performance of four generic commercial scoring models and two credit card models. In Part II, we examine the degradation in predictive power of a generic commercial scoring model, even when that model is "re-optimized" or "retooled" to account for the simulated data restrictions.

This report finds that the scoring model examined in this study, even when re-optimized to maximize performance given a restricted data set, still demonstrates markedly less predictive power than the original scoring model deployed on credit files without the data restrictions. In other words, we confirm the findings of Part I which holds that our full-file national credit reporting system, as governed by the FCRA, is a key factor in maintaining consumer credit access and keeping credit prices affordable.

Several key findings fall out of this analysis, including:

- Even when a retooled model is used, between 80% and 90% of consumers could expect to see a change in their credit scores if the FCRA's preemptions are modified or allowed to expire. In general, the vast majority of consumer credit scores would decrease using a retooled scoring model, as compared with the original model in a full-file national credit reporting system.
- Roughly 6.3 million borrowers, who would have been approved for credit under the current full-file national credit system, would be denied credit if Congress fails to reauthorize the FCRA's preemptive provisions.
- Countless millions of borrowers will receive less favorable terms as a result of the degradation of scoring models that will result if Congress fails to reauthorize the FCRA's strengthened preemptive provisions.
- Those most likely to be affected are the "near-prime" and "non-prime" borrowers – the vast majority of Americans whose credit is neither perfect nor atrocious. Under the scenario of data restrictions considered in this report, the ability of lenders to assess the risk of extending credit to members of this group would decline by an average of more than 44%, and by an average of 31% using a re-optimized model.
- If the preemptions expire and lenders have less data on which to base lending decisions, the resulting increase in delinquencies would cost credit card issuers an additional $3.3 billion a year. If these were passed along to American consumers, it would cost the average household $44 per year

2. BACKGROUND: NEW LEARNING IN FOLLOW-ON RESEARCH

The first component of this research (June 2003) presented incontrovertible evidence that failure to renew the Fair Credit Reporting Act's strengthened preemptive provisions would impact many Americans' credit scores – nearly 9 in 10 under one potential scenario – and that the ability of lenders to predict risk would be substantially diminished.[1] Additional evidence demonstrated that the consumers most likely to be impacted were minorities, younger Americans, and the economically disadvantaged – precisely the groups that have most benefited from the national credit system as governed by the FCRA during the past 30 years.

This second component of the Information Policy Institute's research on the economic significance of the FCRA has a slightly different focus, one that supplements and extends the original research in three important ways.

1. Re-tooled Commercial Model Used in Analysis: Both parts of this exercise take as their starting point that should the FCRA's strengthened preemptions lapse, or be modified in ways consistent with various state proposals, the quantity and quality of the data available in credit reports will deteriorate. Our earlier analysis examined existing commercial scoring models developed for use under the uniform national data standards of today's FCRA. In that analysis, we examined the degradation in predictive power of those existing scoring models that would occur if the quality and quantity of the data in credit reports deteriorates. In this analysis, we recognize that credit reporting agencies (CRAs or credit bureaus) and financial institutions will retool their scoring models to minimize the loss in predictive power resulting from poorer data. *In short, this analysis presents data comparing the performance of an existing commercial scoring model under given the current national data standards with that of a retooled model assuming certain data restrictions.*

2. Loan Type and Risk Tier Examined: Whereas the original research examined the value of uniform national data standards on a pool of 3.5 million credit reports, the follow-on analysis provides a higher level of granularity. This analysis examines a smaller pool of 230,000 credit reports, and also assesses the impact on different types of loans (revolving and installment) and various risk portfolios (prime, near-prime, non-prime, and sub-prime). Despite the smaller sample size, this level of detail strongly supplements the socio-demographic analysis conducted in the original study, and enhances the general understanding of precisely which types of borrowers are most likely to be impacted by a failure to renew FCRA preemptions.

3. METHODOLOGY

The analytical framework below was developed by the Institute to assess the possible impact of failure to renew the FCRA's strengthened federal preemptions:

Defining the scenarios. Removing federal preemption would undoubtedly trigger a flood of legislative initiatives at both the state and local levels that would ultimately lessen both the quality and quantity of information contained in consumers' credit reports. In our analysis, we classified these potential initiatives into two broad categories:

- Initiatives that would induce behavioral changes that reduce the *quantity* of data reported (for example, increasing the liability of reporting agencies may reduce reporting rates).
- Initiatives that would directly affect the *types* of data reported (for example, eliminating the reporting of 30 day delinquencies.)

The four scenarios selected for our analysis—which are described in Table 1—represent specific examples of what could happen under these two types of legislative actions.

> Author's Note: While all four scenarios are considered in part 1 of this report, the following analysis limits itself to scenario D only. However, for the sake of thoroughness, all scenarios considered in part 1 are discussed here. The number of credit files in our sample given in the descriptions of Scenarios A and B below reflect analysis conducted in part 1. Our sample is larger for the present analysis.

Scenarios A and B represent the impact of legislation that would likely affect the quantity of data reported by imposing additional obligations and liabilities on data furnishers, as currently proposed in California and Illinois.[2]

- In Scenario A we assume that two major data aggregators drop out of the system. These third-party data processors collect information primarily from credit card issuers. These card issuers vary by size, and include large issuers as well as community banks and credit unions. The data no longer available from these lenders would affect nearly 266,000 credit files in our sample of 3.5 million credit files. Each of these files contains an average of 9.3 trade lines (credit information, for example, the balance on an open credit card account). In the group of credit files affected, 315,000 trade lines—or about 13 percent—would be no longer be available as a result of the data restrictions modeled in Scenario A.
- In Scenario B, eight randomly selected major credit providers drop out of the system. Unlike Scenario A, however, the data affected in Scenario B captures a broad swath of credit types, including revolving credit and non-revolving credit. The loss of these data furnishers would affect 1.9 million credit files out of the 3.5 million credit files analyzed. In the group of credit files affected, 3.8 million trade lines—or about 21% of the trade lines in this group—would no longer be reported.

Although it is impossible to predict how increased reporting liability will affect the behavior of different credit reporters, both scenarios assume that all current, historic, and inactive trade lines provided by a reporting agency will be purged from the system once that agency decides to drop out.

Scenarios C and D consider restrictions on the kinds of information that can be included in the consumer's credit report. The "moderate" scenario (Scenario C) assumes that late payments can only be reported after 90 days; that all public record data must be purged after 3 years; that all negative information must be purged after 5 years; and that inquiries clustered within a 30-day period count only once, as currently proposed in North Dakota, New York, and Rhode Island, respectively.[3]

The more "severe" scenario (Scenario D) assumes that late payments can only be reported after 120 days; that all public record data pertaining to a late payment must be purged upon settlement of debt; that all adverse information – including bankruptcy – must be purged after 4 years; and that all inquiries, whether initiated by the consumer or not, must be purged if they are less than 60 days old.[4] These restrictions reflect recent proposals in the New York and California legislatures.

It should be noted that the results from these scenarios also apply to cases in which similar restrictions are enacted at the federal level, even if the more restrictive law preempts state legislation.

Table 1: Scenarios

	Reductions in the Number of Data Furnishers		Restrictions on the Type of Data Reported	
Criteria	Scenario A	Scenario B	Scenario C "Moderate"	Scenario D "Severe"
Limitations on reporting of delinquent accounts			Purge trades with 30- or 60-day delinquencies	Purge trades with 30-, 60-, or 90-day delinquencies
Limitations on reporting of paid public record items			Purge at 3 years	Purge when paid
Limitations on reporting of all adverse information			Purge all adverse information at 5 years	Purge all adverse iinformation at 4 years
Limitations on use of inquiries in models			All 30 day clustered inquiries count as one (?)	Purge all but one inquiry less than 60 days
Reduction of trade-line availability due to imposition of obligations or liability on furnishers	Two data aggregators stop reporting	8 major credit issuers stop reporting		

Modeling the Data Restrictions: Scorex, an Experian company, agreed to participate in our analysis as part of the Institute's ongoing research. In this report, the objective of the analysis is two part: first, to simulate the effect of data restrictions on the performance of a scoring model similar to those currently in use; and second, to see if the degradation of the model's performance could be ameliorated by re-optimizing the model to account for those restrictions.

Unfortunately but unsurprisingly, re-tooling a scoring model in such a fashion involves considerable effort and expense. The cost of re-optimizing a model for all four of the scenarios was prohibitive. For the purposes of this research, Scorex has retooled a single generic scoring model to provide the Institute with quantitative data regarding the impact of Scenario D, which reflects proposed legislation introduced in the two most populous states, California and New York.

Scorex, uses a standard set of aggregated attributes (STAGGS) in its modeling and analytical work. This set of aggregated attributes facilitates the meaningful interpretation of raw credit data. The complete set contains approximately 500 attributes capturing a broad range of information from an individual's credit file. The set includes account or trade counters, measures of delinquency and derogatory payment behavior, balance and credit limit totals and utilization ratios, measures of credit file age, inquiry counters, and public record counters. A number of the attributes target the timing of certain behavior such as recent delinquency, recent inquiry of credit, or recent account opening.

The raw credit data used for the analysis was a random sample of 230,000 anonymized records from Scorex's Cool Stuff Database©. The database contains the credit profiles of five million consumers from the Experian credit bureau.

The first step was to simulate the effect of the data restrictions described in Scenario D. Scenario D represents the impact of significant limitations on the type of data reported to credit bureaus. The legislative changes envisioned in Scenario D assume the following: late payments can only be reported after 120 days, all public record information pertaining to late payment must be purged upon debt settlement, all adverse information must be purged after 4 years, and all inquiries must be counted as 1 if aged less than 60 days.

In order to simulate these changes, the set of STAGGS attributes—attributes through which raw credit data is interpreted--was altered. A limited set of attributes was created by combining existing characteristics—for example, regarding delinquencies under 90 days as "satisfactory."

While most of these changes could be modeled by modifying STAGGS attributes in this fashion, one of the data restrictions called for in Scenario D required that the raw credit data be modified prior to attribute aggregation.

Unfortunately, one of the proposed changes described in Scenario D could not be approximated precisely using either of these methods. One of the components of the legislation imagined in Scenario D is a requirement to purge adverse information—such as charge-offs and delinquencies--in a consumer's credit file if that information was older than 4 years. This legislation could not be modeled precisely because the STAGGS attributes only categorize delinquency and derogatory information at 6, 12, and 24-month intervals. Therefore, it was impossible to capture the precise effect of having delinquencies purged after 4 years.

To get around this, Scorex created two schemes. The first scheme (D1) restricts the adverse information to 2 years on all accounts. This scheme also includes adverse information on trade lines opened less than 3 years ago, although clearly this does not capture all of the adverse data prior to the three-year-old mark. However, this was the best that could be achieved given the limitations of the STAGGS attributes.

The second scheme (D2) considers all adverse information available on a consumer's file. Adverse information is generally purged after seven or ten years, depending on the type of information. The notion was to best capture the effect of the restrictions described in Scenario D, and the hope is that the effects of a four-year restriction on adverse information would likely fall between the two schemes described.

It should also be noted that when we simulated the effects of data restrictions on the original scoring model in the following research, the D1 scenario was employed. So, if one is to index the Scenario D results against the Scenario D results conducted in part 1 of our research, it should be considered that the data restrictions modeled here are more severe. That is, all adverse information is purged after 24 months in the scenario D below, except for the adverse information captured by including adverse information on trade lines less than three years old.

A chart below describes the exact structure of the modifications undertaken to simulate the data restrictions. In the left-hand column is the type of data restriction; in the middle, the specific restrictions to what sort of data could be reported or maintained in credit reports; and in the final column, the fashion in which that data restriction was simulated.

Table 2: Data Modifications to Simulate Limitations

Criteria	Scenario D	CRA Data Modification
Limitations on reporting of delinquent accounts	Purge trades with 30-, 60-, or 90-day delinquencies	Within STAGGS, 30-,60-, and 90-day delinquencies were considered "satisfactory" along with current trades.
Limitations on reporting of paid public record items	Purge when paid	Only STAGG attributes for unpaid/unsatisfied public records were used.
Limitations on reporting of all adverse information	Purge all adverse information at 4 years	STAGG attributes currently capture delinquency and derogatory information in the past 6, 12 and 24 months. In order to approximate the effect of purging adverse information at four years, two scenarios were tested. Scenario D1: In the first version of Scenario D, derogatory data was limited to 24 months. Additionally, variables considering trades opened in the last 36 months that contained adverse information were included. Scenario D2: In the second version of Scenario D, all adverse information available was used. Adverse information currently stays on file a maximum of 10 years.
Limitations on use of inquiries in models	Purge all but one inquiry less than 60 days	The raw data was modified prior to the inquiry variables being computed.
Reduction of trade-line availability	N/A for research below, this applies to Scenarios A and B only	N/A for research below, this applies to Scenarios A and B only

Simulating a Re-optimized Model: Next, it was necessary to ascertain the impact of these data restrictions on a commercial scoring model. First, a master model was selected. This scoring model was built to utilize all available credit data currently on file. This model is highly comparable in terms of performance and score distribution to other commercial scoring models in use and under development.

The original scoring model is designed to determine a "good credit risk" based on the information in a consumer's file. That is, a high score produced by the model would indicate that the consumer is unlikely to default or be late on a trade.

The master model was the benchmark for comparison in this research. To simulate the effect of the data restrictions called for in Scenario D, the master model was applied to the restricted sets of attributes. For example, if the master model scored on the basis of the attribute, "Number of trades 30 or more days past due," under the restrictions of Scenario D only 120-day delinquent and derogatory trades would be scored. In other words, trades 30, 60, or 90 days past due would normally have a downward impact on score, however, here these delinquencies were not scored.

Next, the restricted set of attributes was used to build re-estimated models in hopes of maintaining their ability to distinguish a "good credit risk", even with the less predictive data available under Scenario D. Each model in the analysis contained 15 characteristics. This exercise was intended to simulate the activity of firms who would no doubt recalibrate their models to minimize the impact resulting from a loss in the quality of data.

The random sample used for the modeling analysis consisted of reports requested in connection with individual trades opened within several months of August 2000 and reflect the credit history at the time the consumer applied for the account. The credit profiles as of August 2000 were used to create the full and limited sets of aggregated characteristics for modeling. The performance of these trades from account opening through August 2002 was then used as the dependent variable in all of the analyzed models. Simply put, the performance observed of the actual trades in August 2002, was compared with the predictions that the original and re-optimized models made against the August 2000 data present in the consumer's files.

4. Results Summary: Analysis on Industry-Wide Sample

The following tables illustrate the effects of the data limitations on both the master scoring model and on the retooled models that were re-estimated to based on the proposed changes in data availability.

Impact on Scores

The following two tables show the percent of credit scores that would be affected under Scenario D as well as the effect the changes would have on the distribution of credit scores. Table 3A breaks the score distribution into fixed 50-point bands. Table 3B considers the score distribution as twentiles—in other words, approximately 5% of the sample in each row, using the credit score produced by the original model.

The first column of tables shows the current distribution of credit scores based on the full-file data. The second column shows the impact of Scenario D (or rather, D1, as noted earlier) on the original scoring model. This second column therefore refers to the effect of data limitations without any model adjustment. The final two columns depict the impact of the data limitations when the models are re-optimized to minimize the loss of performance.

Two calculations were used to determine the percentage of scores affected by the data restrictions. The first calculation considered a significant score change, or "delta," to be more than two points higher or lower than the original existing score. The second calculation was stricter, considering a one-point delta to be significant.

TABLE 3A: IMPACT ON CREDIT SCORES (50 POINT DISTRIBUTION FORMAT)

		Restrictions on Type of Data Reported (%)		
		Original Scoring Model	Re-Estimated Scoring Models	
	Current Full-File Reports (%)	Scenario D	Scenario D1 (Limited Derogatories)	Scenario D2 (Unlimited Derogatories)
Percent of Scores Affected				
(|delta| > 2)	NA	31.87	79.7	82.12
(|delta| > 1)	NA	33.4	87.41	89.9
Distribution of Scores				
< 400	3.1	1.43	2.13	2.92
400 – 449	0.74	0.43	1.11	1.16
450 – 499	0.9	0.59	1.24	0.92
500 – 549	1.06	0.81	1.24	1.12
550 – 599	1.3	1.07	1.51	1.33
600 – 649	1.53	1.35	1.62	1.64
650 – 699	1.89	1.71	2.33	1.85
700 – 749	2.28	2.07	2.38	2.2
750 – 799	3.01	2.76	3.99	3.26
800 – 849	4.5	4.35	4.26	4.84
850 – 899	7.77	7.8	6.88	6.68
900 – 949	16.37	16.99	15.06	15.45
950+	55.55	58.63	56.24	56.62

TABLE 3B: IMPACT ON CREDIT SCORES (TWENTILE DISTRIBUTION)

		Restrictions on Type of Data Reported (%)		
		Original Scoring Model	Re-Estimated Scoring Models	
	Current Full-File Reports (%)	Scenario D	Scenario D1 (Limited Derogatories)	Scenario D2 (Unlimited Derogatories)
Percent of Scores Affected				
(|delta| > 2)	NA	31.87	79.7	82.12
(|delta| > 1)	NA	33.4	87.41	89.9
Distribution of Scores				
< 510	4.94	2.6	4.68	5.21
510-685	5.03	4.28	5.86	5.21
686-787	4.97	4.55	6.17	5.13
788-846	5.02	4.81	4.81	5.42
847-882	4.97	4.92	4.31	4.15
883-907	4.95	5.04	4.4	4.4
908-925	4.95	5.03	4.36	4.73
926-939	4.96	5.17	4.77	4.58
940-949	4.68	4.96	4.4	4.55
950-957	4.91	5.23	4.81	5.1
958-963	4.78	5.12	4.66	5.34
964-968	4.94	5.17	5.38	6.02
969-972	4.96	5.28	5.77	6.47
973-975	4.55	4.72	5.91	6.44
976-977	3.69	3.79	4.92	5.53
978-979	4.42	4.62	5.77	6.55
980-981	5.41	5.68	6.31	7.6
982-983	6.66	7.05	5.99	5.61
984-985	6.56	6.99	4.27	1.81
986+	4.66	4.97	2.46	0.16

The impact of Scenario D on the credit scores of consumers is significant. The results of this analysis are consistent with those of the previous Institute analysis, in that 33% of consumers would expect to see a change in their credit scores as a result of the data restrictions using the original scoring model. This result is comparable to the analysis conducted in part 1. That analysis showed that changes to the quality or quantity of the data available would generally change the scores of 5 to 35 percent of consumers, depending on the scoring model employed (one model even yielded a result where 88% of consumers would see their score change).

Here we find that the effect of the data restrictions on the current scoring model is a generally upward shift in scores; consumers' scores increase as minor delinquency and aged derogatory data no longer negatively impacts their scores. If scoring models are re-optimized to reduce this upward shift, the percent of consumers affected significantly increases to between 80% and 90%, most of whom then suffer a downward shift in their scores.

Impact on Predictive Power

Table 4 illustrates the effects of Scenario D on the original scoring model's predictive power. Additionally, the table examines whether re-optimizing the models restores any of the lost predictive power. Predictive power is captured by the models' Komogorov-Smirnov or 'K-S' Statistic, a commonly used measure of a model's ability to distinguish between two different groups -- in this case, performing and non-performing accounts, based on the absence or presence of one delinquency of 90 days or more. Each of the K-S statistics has been scaled to equal 100 when the scoring model is based on full-file data.

TABLE 4: IMPACT ON PREDICTIVE POWER – KS STATISTICS

		Restrictions on Type of Data Reported (%)		
		Original Scoring Model	Re-Estimated Scoring Models	
	Current Full-File Reports (%)	Scenario D	Scenario D1 (Limited Derogatories)	Scenario D2 (Unlimited Derogatories)
Original Scoring Model	100	96.4	96.1	97.1

The proposed data limitations under Scenario D reduce the ability of the original model to separate high and low credit risks. Since the re-optimization of the model under Scenario D1 did not improve on the loss in KS, and thus on the model's predictive power, the restriction of adverse information to two years is the most significant factor in the reduction of predictive power.

The decrease in predictive power in the current analysis is not great as in the Institute's first analysis. This is likely due to the broad range of accounts and risk levels in the sample. The data sample used in this analysis contains a number of both extremely high-risk ("sub-prime") and extremely low-risk ("prime") markets. The presence of a relatively high number of both prime and sub-prime borrowers in the sample permitted the models to perform relatively well in spite of the fact that access to adverse information was restricted. The natural separation between these groups in their credit characteristics is sufficiently profound that attributes such as file history, number of accounts, and utilization allow the models to do a reasonably good job of distinguishing between borrowers whose behavior places them at these two extremes of risk, even though data restrictions are in place.

However, as will be detailed below, the model performance degrades substantially as a result of data restrictions when observed solely at the near-prime or non-prime level (which of course, represents the majority of borrowers.)

Impact on the Overall Cost and Availability of Credit: Tradeoffs

Assuming that the FCRA's preemptive provisions sunset, and at least one state enacts legislation comparable to that contained in Scenario D, this study finds that consumers would face a general downward shift in their credit scores. This means that some consumers who were previously classified as Prime borrowers under the full-file system will be reclassified as Near-Prime borrowers in a post-FCRA world. Similar results would occur across all risk tiers, from Near-Prime to Non-Prime, and from Non-Prime to Sub-Prime. While such migrations will negatively impact the terms of credit offered to consumers, and force a readjustment in terms for millions of current borrowers, many Subprime borrowers are likely to be denied access to credit altogether.

The logic is straightforward. When lenders face a shift in their applicant population, acceptance strategies have to be changed. These changes are made to maintain delinquency or acceptance levels given a decline in model performance. If a lender chooses to maintain approval rates, the risk is an increased number of delinquent and loss accounts. On the other hand, choosing to maintain risk levels will result in a decline in acceptance rates. Many lenders choose to modify their strategies by using a combination of these methods. For example, lenders will use risk-based pricing methods in order to accept higher risk applicants by structuring the terms of a loan in order to offset the costs associated with the risk of delinquency.

Tables 5 and 6 illustrate the trade-offs associated with the simulated decline in credit information. Table 5 shows that the number of serious delinquencies associated with a given acceptance rate usually rose (however, at 30% and 40% acceptance rates the increases were minor, which is unsurprising given that this would limit acceptances to the least risky borrowers) when Scenario D limitations were simulated. For example, considering a 70% acceptance rate, which is typical of the industry, serious delinquency rates would rise from 2.7% to 3.0%—an increase of more than 11%—as the data moves from a full-file system to a restricted system. Additionally, the re-estimated models do not improve upon the increase in risk; a 70% approval rate would result in a 3.0% delinquency rate regardless of model refinement.

The projected 11% increase in delinquency rates will result in higher losses for creditors. In 2001, the credit card industry sustained approximately $30 billion in charge offs.[5] As such, the resultant increase in delinquencies resulting from the data restrictions analyzed in this report would cost credit card issuers an additional $3.3 billion per annum[6]. Given the competitive nature of the industry, as creditors take precautions and price according to risk, the higher observed delinquency rates will lead to higher interest rates and less appealing loan terms for higher risk consumers. As will be discussed below, those most likely to be impacted are consumers with a reasonable (not perfect, and not horrible) credit history. This is intuitive, as those consumers with either very high or very low scores will be less impacted by various individual data restrictions, as those consumers are easier to categorize even when access to adverse data about them is restricted.

TABLE 5: SERIOUS DELINQUENCY BY TARGET ACCEPTANCE RATES

		Restrictions on Type of Data Reported (%)		
		Original Scoring Model	Re-Estimated Scoring Models	
Acceptance Rate	Current Full-File Reports (%)	Scenario D	Scenario D1 (Limited Derogatories)	Scenario D2 (Unlimited Derogatories)
30%	0.6	0.7	0.6	0.7
40%	0.8	0.9	0.8	0.9
50%	1.2	1.3	1.3	1.4
60%	1.8	2.0	1.9	2.0
70%	2.7	3.0	3.0	3.0

Table 6 weighs the potential reduction in acceptance rates if a lender chooses to maintain current delinquency rates. For example, if a lender currently maintains a 6% delinquency rate, approval rates would be expected to decline by 5% as a result of the proposed data limitations. Re-optimizing the models to minimize the negative impact of the proposed data limitations does not improve the lender's situation in this example.

Assuming a target delinquency rate of 3%, under the current full-file national credit reporting system, using the model examined in this study approximately 73 percent of loan applicants would be approved for credit. Assuming the world changed in ways consistent with Scenario D, the acceptance rate declines by 3.4% using the original model, and by 3.7% using the re-optimized model in Scenario D2.

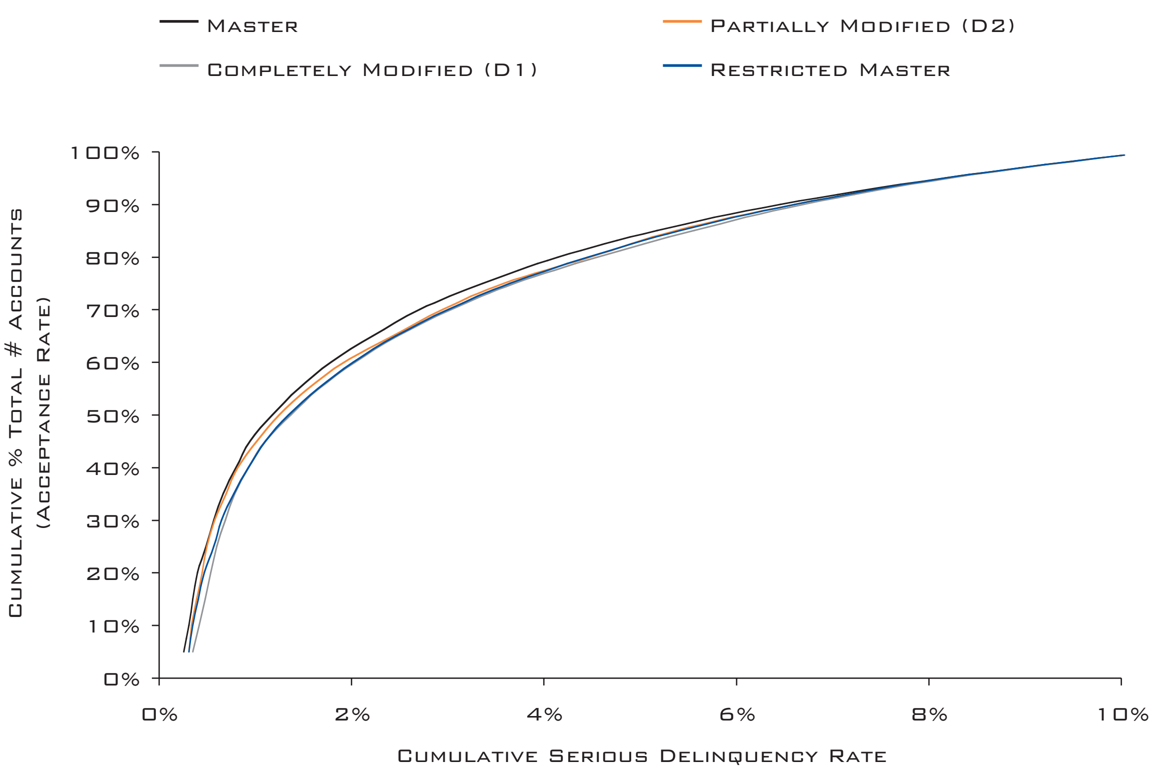
As discussed in our original study, general-purpose credit card issuers acquire about 170 million new accounts each year. Of this, 2 million are first time borrowers, 32 million are acquiring an additional card, and 138 million are changed accounts, presumably to take advantage of the better terms of the new card over the old one. *Based on the findings of this analysis, roughly 6.3 million borrowers who would be approved for credit under the current full-file national credit system, would be denied credit should Congress fail to reauthorize the FCRA's preemptive provisions*[7].

TABLE 6: ACCEPTANCE RATES BY TARGETED DELINQUENCY RATE

		Restrictions on Type of Data Reported (%)		
		Original Scoring Model	Re-Estimated Scoring Models	
Incidence of Serious Delinquency	Current Full-File Reports (%)	Scenario D	Scenario D1 (Limited Derogatories)	Scenario D2 (Unlimited Derogatories)
2%	62.4	60.0	60.0	60.2
3%	72.6	70.1	70.1	69.9
4%	80.0	77.5	77.6	77.6
5%	85.0	82.5	82.5	82.8
6%	92.5	87.5	87.4	87.5

Graph 1 depicts the trade-offs between acceptance and delinquency rates across the entire credit sample. The graph shows that lenders will sacrifice little with the low risk consumer; delinquency rates do not increase significantly for the top scoring 40% of consumers. In the middle ground – acceptance rates of 40% to 80% -- the graph shows that lenders will expect delinquency levels to rise (assuming a fixed acceptance rate) under the data limitations.

GRAPH1: TRADE-OFF ANALYSIS – ACCEPTANCE RATES VS. DELINQUENCY RATES



Rates

The proposed limitations in the credit reporting system under Scenario D will greatly impact lenders' portfolios. Lenders will have to choose whether to maintain current risk levels—thereby turning away numbers of applicants—or to maintain approval rates. In maintaining approval rates, lenders will accept greater losses and will likely in turn adjust pricing to compensate for those losses. In maintaining delinquency rates, lenders will have to turn away consumers who would have otherwise been approved. The consumers will suffer as many are turned away from credit offers and others who are approved may face increased charges to acquire the credit.

5. RESULTS SUMMARY: ANALYSIS ON SIMULATED PORTFOLIOS

Financial institutions often offer a wide range of credit products – mortgages, auto loans, credit cards—targeting specific risk-based consumer segments—Subprime, Non-prime, Near-Prime and Prime. Each of these portfolios tracks performance and acceptance data independently from the other portfolios. For example, if Bank A offers a Subprime bankcard, a prime bankcard, a Subprime auto loan and a prime mortgage, Bank A will measure each of these portfolios independently. If all four portfolios are rolled into one pool for measurement purposes, the results would be skewed as the Subprime portfolios would have higher delinquency rates than the prime portfolios. The first analysis presented in this report considered a broad credit sample containing many products and credit risk tiers – much like rolling all four of Bank A's portfolios into one analysis group. Due to the inherent separation between risk tiers (Prime vs. Subprime) and products (mortgage vs. bankcard), the performance of the credit model was maintained even under the limited credit data scenario. Similarly, the trade-offs between approval and delinquency rates may not represent the most drastic effects of the proposed data limitations.

A secondary analysis was completed in order to simulate the effects of the data limitations on specific credit industries. This analysis considers separate products (bank installment loans and revolving accounts) as well as multiple risk tiers across products. The risk tiers -- Prime, Near Prime, Nonprime and Subprime -- were assigned according to a C&RT analysis where segments were created based on a risk score (not the master scoring model used in this analysis). Accounts were assigned to the portfolios, Bank Installment and Revolving, by a business code on the file. Accounts were considered Revolving if they were from the Bankcard or Retail sectors. Bank Installment included all installment loans except those from the Loan Finance industry.

Impact on Predictive Power

Table 7 illustrates the effects of Scenario D on the existing model's predictive power per simulated credit portfolio. Additionally, the table examines whether re-optimizing the models with the limited data restores or minimizes any lost power. The KS statistics have been normalized to 100 so that the difference from the full file result indicates the power lost or gained as a result of data limitations and model re-estimation.

TABLE 7: IMPACT ON PREDICTIVE POWER PER PORTFOLIO – KS STATISTICS

		Restrictions on Type of Data Reported (%)		
		Original Scoring Model	Re-Estimated Scoring Models	
Simulated Portfolio	Current Full-File Reports (%)	Scenario D	Scenario D1 (Limited Derogatories)	Scenario D2 (Unlimited Derogatories)
Revolving Prime	100	91.3	92.5	98.0
Revolving Near-Prime	100	64.2	70.4	79.9
Revolving Nonprime	100	47.1	72.2	62.3
Revolving Subprime	100	93.3	99.0	84.5
Installment Prime	100	90.1	91.7	101.2
Installment Near-Prime	100	61.4	56.7	64.3
Installment Nonprime	100	52.6	75.3	67.2
Installment Subprime	100	89.5	109.1	114.2

The results in Table 7 indicate that model performance suffers the greatest loss according to risk tier rather than account type. For both Revolving and Installment portfolios, the middle tiers of Near Prime and Nonprime suffer significant model degradation as a result of the limitations under Scenario D. In these risk tiers, re-estimation of the models improves upon the lost performance, however the residual degradation is pronounced. Thus, rather than declining by an average of nearly 44% in Scenario D using the original model, the predictive power of the retooled model still declines by an average of more than 31% in both Scenarios D1 and D2. The degradation in either case is substantial, and the resulting reduction in access to credit, higher cost of credit, and worsening of terms for Near-Prime and Non-Prime borrowers will be pronounced.

The middle tiers are relatively more dependent on delinquency data related to 30 to 90 days past due in order to distinguish risk. With the 30 to 90 day delinquencies removed from the credit file, the re-estimated models still suffer in terms of performance. The greatest difference between the Nonprime and Near-Prime groups exists in the adverse or derogatory information on the account holders' files. In the Nonprime segments, more than 70% of account holders had an adverse item on file; two-thirds of these had an adverse item occurring in the last 24 months. Thus, the time restriction on adverse information is not a great impact to this group as illustrated in the re-estimation model D1 outperforming the re-estimation D2. In the Near Prime segment, the number of account holders with an adverse item drops to 40%. About half of these files had an adverse item occurring within the last 24 months. As demonstrated in the KS results for the re-estimated models, aged derogatory information is important to the Near Prime risk tier.

The Prime segments are least affected by the proposed data limitations. Only a 10% decrease in power is observed in the master model when the data restrictions are in place. The sustained performance is due to the nature of the Prime segments. Prime segments consist of the cleanest credit profiles; most account holders have few if any delinquent accounts. If adverse or derogatory information exists on file, it is likely aged indicating consumers have improved their credit behavior. However, the presence of any derogatory item – new or old – is an important indication of risk. This is substantiated by the result of the re-estimated models where all derogatory items were considered; the performance of the D2 scenario is greater than the D1 scenario for both prime segments.

On the other extreme, the Subprime segment consists of the highest credit risk consumers. The majority of the simulated Subprime population (about 90%) has adverse information on file. In fact, the adverse information often dominates the file. For example, in the Revolving Subprime simulated portfolio, 24% of the account holders had 90% or more of their trades reported adversely. The limitations under Scenario D cause some degradation in performance for the existing model. Re-estimating the models significantly improves performance in this risk segment at times surpassing the initial model performance. Because this population is high risk with large quantities of adverse information, restricting the negative attributes in the models to the derogatory trades (as opposed to relying on delinquent payment behavior) actually improves identification of the riskiest accounts.

Under all versions of Scenario D considered here, the mid-tier lenders would suffer the most with degraded model performance. While their models could be re-estimated and improved, performance will still fall well below today's standards. As the majority of lenders have offerings that fall into this wide range of mid-tier risk products, the degradation is significant. The ultimate impact on borrowers, in turn, is contingent upon the strategies adopted by lenders with respect to access to and the price of credit.

Impact on the Overall Cost and Availability of Credit

Analysis was completed to consider the trade-offs in approval and serious delinquency rates resulting from the data limitations under Scenario D for simulated industry segments. As the quality of data and power of models decline, lenders will be faced with lower acceptance rates or higher delinquency rates depending on how existing strategies are adjusted. *Trade-offs in acceptance and delinquency rates will vary depending on portfolio type.*

The results in table 7 show that model degradation is a significant issue for the Near-Prime and Nonprime markets under Scenario D. As the trade-offs were also most significant for these groups, the Revolving Near-Prime and Revolving Nonprime results are presented here. Trade-off results for these risk tiers in the Bank Installment industry were similar.

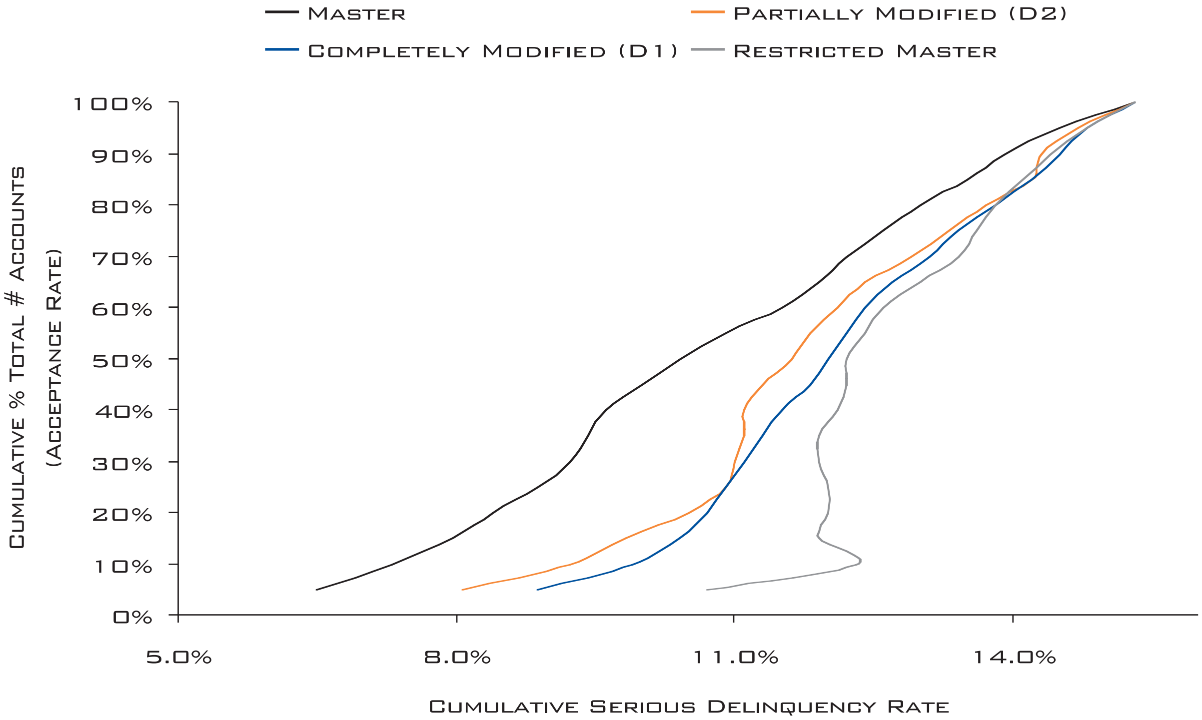
The simulated Revolving Near-Prime population is greatly impacted by the data limitations under Scenario D. Table 8 illustrates the expected delinquency rates per given acceptance rate for this segment. Given a 40% approval rate, under the full file scoring, a lender could expect a 9.6% serious delinquency rate. If the 40% approval rate is maintained when data restrictions are in place, the lender would see delinquency rates rise to 12.1% if no model adjustment is made. If the model is re-estimated, the lender will see a modest improvement from the worst-case scenario, but *delinquency rates will remain nearly 20% higher than the lender is accustomed to.* If delinquency rates are to be maintained, a lender would experience a 75% decrease in approval rates from 40% to 10% in order to maintain a 9.6% delinquency rate. The analysis shows that the approval rate would fall even lower if models are not re-estimated.

Table 8: Revolving Near Prime - Serious Delinquency by Target Acceptance Rates

		Restrictions on Type of Data Reported (%)		
		Original Scoring Model	Re-Estimated Scoring Models	
Acceptance Rate	Current Full-File Reports (%)	Scenario D	Scenario D1 (Limited Derogatories)	Scenario D2 (Unlimited Derogatories)
10%	7.3	12.3	9.9	9.2
20%	8.4	12.0	10.7	10.5
30%	9.2	11.9	11.1	11.0
40%	9.6	12.1	11.5	11.1
50%	10.4	12.2	12.0	11.6
60%	10.9	12.6	12.4	12.1
70%	12.2	13.4	13.1	12.9

Who Will be Impacted and How: Revolving Near-Prime -- For the Revolving Near-Prime lender, the effects of the proposed data limitations translate into increased losses due to increased delinquency rates or reduced profits due to approving fewer accounts. The data limitations will definitely impact the bottom line for the Revolving Near-Prime lender. For consumers, the data limitations will result in less access to credit at low interest rates. The Near-Prime Consumer is a good credit consumer. They have thinner credit history than Prime consumers and some late payments, but are overall a low to moderate credit risk. Under Scenario D, these consumers will have access to credit but under different terms. The high risk Near-Prime consumer will have the credit available to them under the Nonprime segment's higher interest rates. The moderate risk consumer may have access to Near-Prime segment interest rates but with lower credit limits. Scenario D will have a direct effect on revolving account lenders and consumers in the Near-Prime risk tier.

GRAPH 2: TRADE-OFF ANALYSIS – ACCEPTANCE VS. DELINQUENCY RATES



Graph 2 illustrates the trade-offs in approval and delinquency rates across the entire score distribution for the Revolving Near-Prime segment. That is, an expected delinquency rate can be found on the x-axis for every fixed approval rate shown on the y-axis for each of the scenarios. The graph clearly shows delinquency rates would increase substantially under each data limitation scenario for every fixed acceptance rate. The graph also shows all approval rates would be expected to fall 10 percentage points if strategies are adjusted to maintain delinquency rates.

Who Will be Impacted and How: Revolving Nonprime—The Nonprime Revolving industry would also suffer business losses resulting from the restricted credit information. Table 9 illustrates the expected delinquency rates per given acceptance rate for this segment. Under the restricted data scenarios, if a 30% approval rate is held constant, major delinquency rates could rise from 24.0% to 29.3% if the current model is used. Model re-estimation improves the situation but delinquency rates would still be expected to be approximately 3.5% higher than current rates. If delinquency rates are maintained, approval rates could fall from 70% to 10% if no model adjustments are made. Even if models are re-estimated, approval rates would be expected to fall from 40% or 50% to 10% given a 25% to 26% delinquency rate. Lenders in the Nonprime Revolving market would have to seriously consider the trade-offs between increased delinquency and lower approval rates if the FCRA preemptions are removed.

TABLE 9: REVOLVING NONPRIME - SERIOUS DELINQUENCY BY TARGET ACCEPTANCE RATES

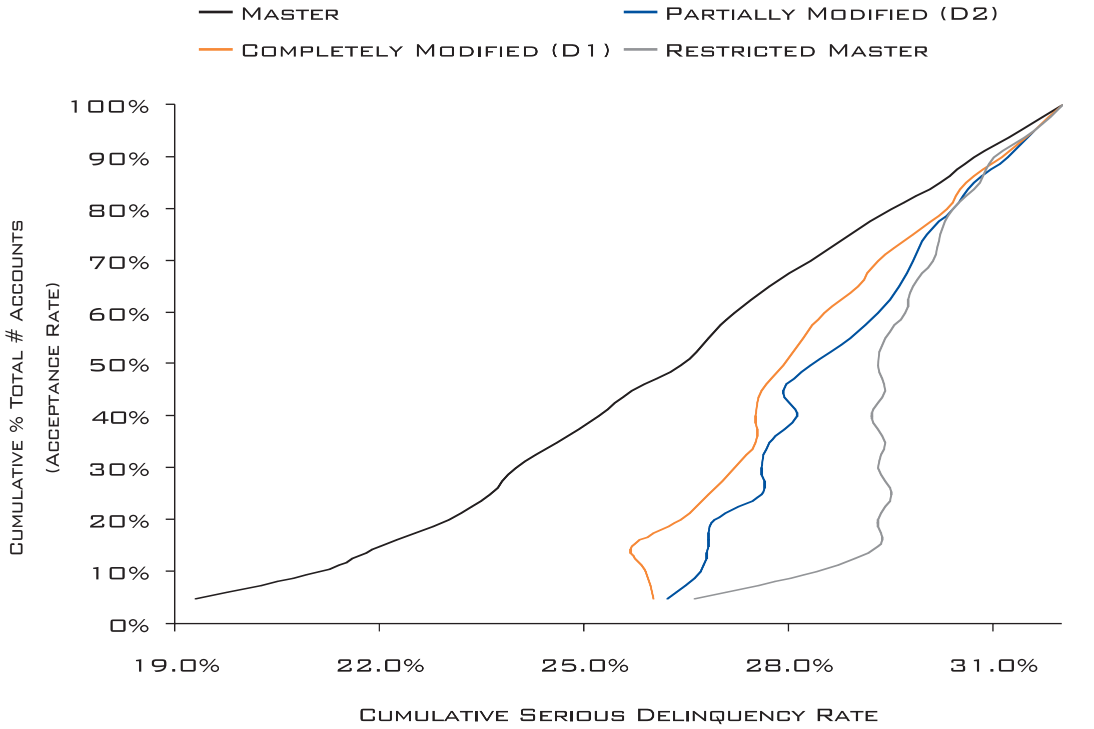
		Restrictions to Type of Data Reported (%)		
		Original Scoring Model	Re-Estimated Scoring Models	
Acceptance Rate	Current Full-File Reports (%)	Scenario D	Scenario D1 (Limited Derogatories)	Scenario D2 (Unlimited Derogatories)
10%	21.1	28.4	25.9	26.7
20%	23.0	29.3	26.4	26.9
30%	24.0	29.3	27.2	27.6
40%	25.2	29.2	27.5	28.1
50%	26.4	29.3	27.9	28.3
60%	27.2	29.7	28.5	29.3
70%	28.3	30.1	29.3	29.8

Graph 3 further illustrates the trade-offs between delinquency rates and approval rates under Scenario D. Clearly the original or "master" model under the full file scenario outperforms the other models by reducing delinquency in the higher score ranges (lower approval rate ranges). Using the master model under full file conditions allows for a 50% approval rate associated with the lowest delinquency rate attainable under the other conditions. *Another striking observation is that the original model under the Scenario D data restrictions cannot distinguish differences in risk given approval rates 15% to 55%* (see light gray area above). That is, a lender using the master model under restricted data conditions cannot decrease approval rates within this range in order to manage delinquency levels. The lender may have to reduce approval rates to below 15% in order to impact portfolio delinquency rates.

As in the Near-Prime Revolving analysis, lenders and consumers will face difficulties under the proposed data limitations. Delinquency rates for all Nonprime lenders will likely increase regardless of model adjustments or strategies involving reduced approval rates. As a result of the increased delinquency rates, lenders are likely to increase the interest rates for the higher risk applicants in order to compensate for the additional costs.

For example, lenders with portfolios that average a 28% delinquency rate may be able to maintain delinquency rates *by managing approval rates. The trade-off for these lenders would be a reduction in approval rates from 70% to 50% or less* (see dark gray area above). The significant reduction in approval rates by these lenders translates into a loss of credit for some consumers. Some of these consumers that will be turned away from Nonprime credit offerings may find available credit within the Subprime market—but at a significantly increased cost. The possible data restrictions under Scenario D would greatly impact the Nonprime Revolving market. Consumers and businesses alike will face increased costs of credit.

GRAPH 3: TRADE-OFF ANALYSIS – ACCEPTANCE RATES VS. DELINQUENCY RATES



6. Endnotes

1 Turner, Michael A. The Fair Credit Reporting Act: Access, Efficiency & Opportunity – The Economic Importance of Fair Credit Reauthorization. New York and Washington, D.C., The Information Policy Institute and the National Chamber Foundation. June 2003.

2 See CA AB 800 and IL HB 3334.

3 See ND SCR 4019, NY SB 356, and RI HB 5820

4 See NY SB 1530 and CA AB 3

5 The Nilson Report. Number 760, March 2002. Pages 6-7.

6 An 11% increase (reflecting the rise from 2.7% to 3% delinquencies) to the $30 billion charge-offs recorded in 2001 gives us $3.3 billion additional charge-offs.

7 3.7% of the 170 million new accounts each year yields 6.3 million borrowers who would be denied credit.

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