GIVE CREDIT WHERE CREDIT IS DUE

Increasing Access to Affordable Mainstream Credit Using Alternative Data

Political and Economic Research Council
The Brookings Institution Urban Markets Initiative

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EXECUTIVE SUMMARY

Despite the vast accomplishments of the American credit system, approximately 35 million to 54 million Americans remain outside the credit system. For a variety of reasons, mainstream lenders have too little information on them to evaluate risk and thereby extend credit. As a result, those in most need of credit often turn to check cashing services and payday loan providers, with effective interest rates as high as 500 percent. The lack of reliable credit places them at a great disadvantage in building assets (such as homes, small businesses, or loans for education) and thereby improving their lives.

This study offers a feasible market solution to bring those outside the mainstream credit fold within it. Mainstream lenders can use "alternative" or "nontraditional" data, including payment obligations such as rent, gas, electric, insurance, and other recurring obligations, to evaluate the risk profile of a potential borrower.[1] Our findings indicate that alternative data, if widely incorporated into credit reporting, can bridge the information gap on financial risk for millions of Americans. More concretely, considering that many of these millions outside the credit mainstream are poorer, less advantaged Americans, the information can direct markets toward a faster alleviation of poverty in this country.

We examined a sample of approximately 8 million TransUnion credit files with a strong focus on consumers outside of the credit mainstream. The consumers include populations with thin credit files (fewer than three sources of payment information, or trade lines) on payment timeliness, as well as "unscoreable" segments whose risk cannot be determined owing to insufficient information. The credit report files, which contained alternative or nontraditional utility and telecommunications payment information, were applied to models used by lenders to make a variety of credit decisions. The scores, or predictions, of these models were then compared with payment/bankruptcy outcomes observed during the following year.

Key findings include:

• ***Those outside the credit mainstream have similar risk profiles as those in the mainstream when including nontraditional data in credit assessments.*** The evidence suggests that most individuals in this segment are not at high risk in terms of lending. Using nontraditional data lowered the rate of serious default by more than 20 percent among previously unscoreable populations. The risk profile of the thin-file/unscoreable population—after energy utility and telecommunications data sets are included in their credit files—is similar to that of the general population (as measured by credit score distribution).

• ***Nontraditional data make extending credit easier.*** Including energy utility data in all consumer credit reports increases the acceptance rate by 10 percent, and including telecommunications data increases the acceptance rate by 9 percent, given a 3 percent target default rate.

• Minorities and the poor benefit more than expected from nontraditional data.

Including alternative data was especially beneficial for members of ethnic communities and other borrower subgroups. For instance, Hispanics saw a 22 percent increase in acceptance rates. The rate of increase was 21 percent for Blacks; 14 percent for Asians; 14 percent for those aged 25 or younger; 14 percent for those aged 66 older; 21 percent for those who earn $20,000 or less annually; and 15 percent for those earning between $20,000 and $29,999. In addition, renters (as opposed to homeowners) saw a 13 percent increase in their acceptance rate, and those who prefer Spanish as their primary language saw a 27 percent increase in their acceptance rate.

• Nontraditional data decrease credit risk and increase access.

The addition of the alternative data moves 10 percent of the analysis sample from being unscoreable to scoreable. Sizable segments would see their credit scores improve—22.4 percent in the utility sample and 11 percent in the telecommunications sample. Most remarkable is that two-thirds of both the thin-file utility sample (60.3 percent) and the thin-file telecommunications sample (67.7 percent) become scoreable when alternative data are included in their credit files. Preliminary evidence strongly suggests that the inclusion of alternative trade lines in conventional credit reports improves access to mainstream sources of consumer credit. In a one-year observation period, 16 percent of thin-file borrowers whose credit report included nontraditional data opened a new credit account compared with only 4.6 percent of thin-file borrowers with only traditional data in their credit reports.

• Nontraditional data have little effect on the credit mainstream.

One worry is that including nontraditional data will be counterproductive, harming more in the mainstream that helping those now excluded. The results of simulations reported here suggest that little will change for the mainstream population.[2]

• More comprehensive data can improve scoring models.

This migration greatly affects the performance of examined scoring models. For example, in our study, in one set of calculations we assume that creditors interpret little or no credit information as the highest risk. As a result, when fully reported utility or telecommunications trade lines are added to credit reports, we see a significant rise in the KS statistic—an industry gauge to measure the model performance. Specifically, we see a 300 percent rise for a sample of thin-file consumers, and a nearly 10 percent rise for the general sample. In the most conservative case, in which the general sample is used but unscoreable credit files are excluded from the calculations, we still find a modest 2 percent improvement in model performance with the addition of alternative data.

• More data can reduce bad loans.

Including fully reported energy utility and telecommunications trade lines (i.e., different accounts) in traditional consumer credit reports measurably improves the performance of loans for a target acceptance rate. For example, by integrating fully reported energy utility data, a lender's default rate (percentage of outstanding loans 90 days or more past due) declines 29 percent, given a 60 percent target acceptance rate. Similarly, adding telecommunications data reduces the default rate by 27 percent. These reductions allow lenders to make more capital available and improves their margins, capital adequacy, and provisioning requirements. Such improvements could have further positive economywide effects.

In summary, nontraditional data promise to bring millions into the credit mainstream and improve their chances of building assets. Although using alternative data in consumer credit reports affects how the data appear in a host of credit scoring models, nothing about the data subjects has changed. What has changed is the availability of information. Whenever an information gap exists, markets fail to thrive. The use of alternative data in consumer (and commercial) credit reports can close an information gap that has negatively affected the lives of millions of thin-file and unscoreable Americans who reside in urban areas and elsewhere.

The benefits of using nontraditional data will not be instantaneous. Information must first be gathered and implemented, new models optimized for such data must be built and old models modified. Some models must be altered to not treat utilities and telecommunications accounts as a financial trade. The steps, while few, are important. Simply bringing the information online will spur many of the steps; without it, there is no incentive to take them. Public officials can play a positive role by removing barriers to reporting where they exist. ■

OVERVIEW

- **Section I** provides a brief overview of the impact of the U.S. credit system, those left behind, and the role of information in bringing those outside the credit mainstream into accessible, affordable credit channels.
- **Section II** describes the objectives, data sources, and methodology of the study.
- **Section III** shows how the addition of utility and telecommunications trades has affected consumers' credit profiles, focusing on the number of consumers who can be scored and the resulting distribution of credit scores.
- **Section IV** compares the number and size of new accounts that were opened by consumers with an existing utility or telecommunications trade (the "analysis" sample) to the number and size of new accounts that were opened by otherwise similar consumers without such trades (the "validation" sample).
- **Section V** examines the impact of utility and telecommunications trades on the predictive power of several scoring models and the implications for both the cost and availability of credit.
- **Section VI** examines the demographic groups that would most likely be affected by a more systematic reporting of utility and telecommunications data.
- **Section VII** summarizes the empirical results and concludes with a discussion of their implications for public policy.
- **Section VIII** offers directions for future research.

Appendix A describes the analysis sample in more detail and assesses the extent of potential biases. **Appendix B** presents the complete results of our model simulations. ■

I. INTRODUCTION

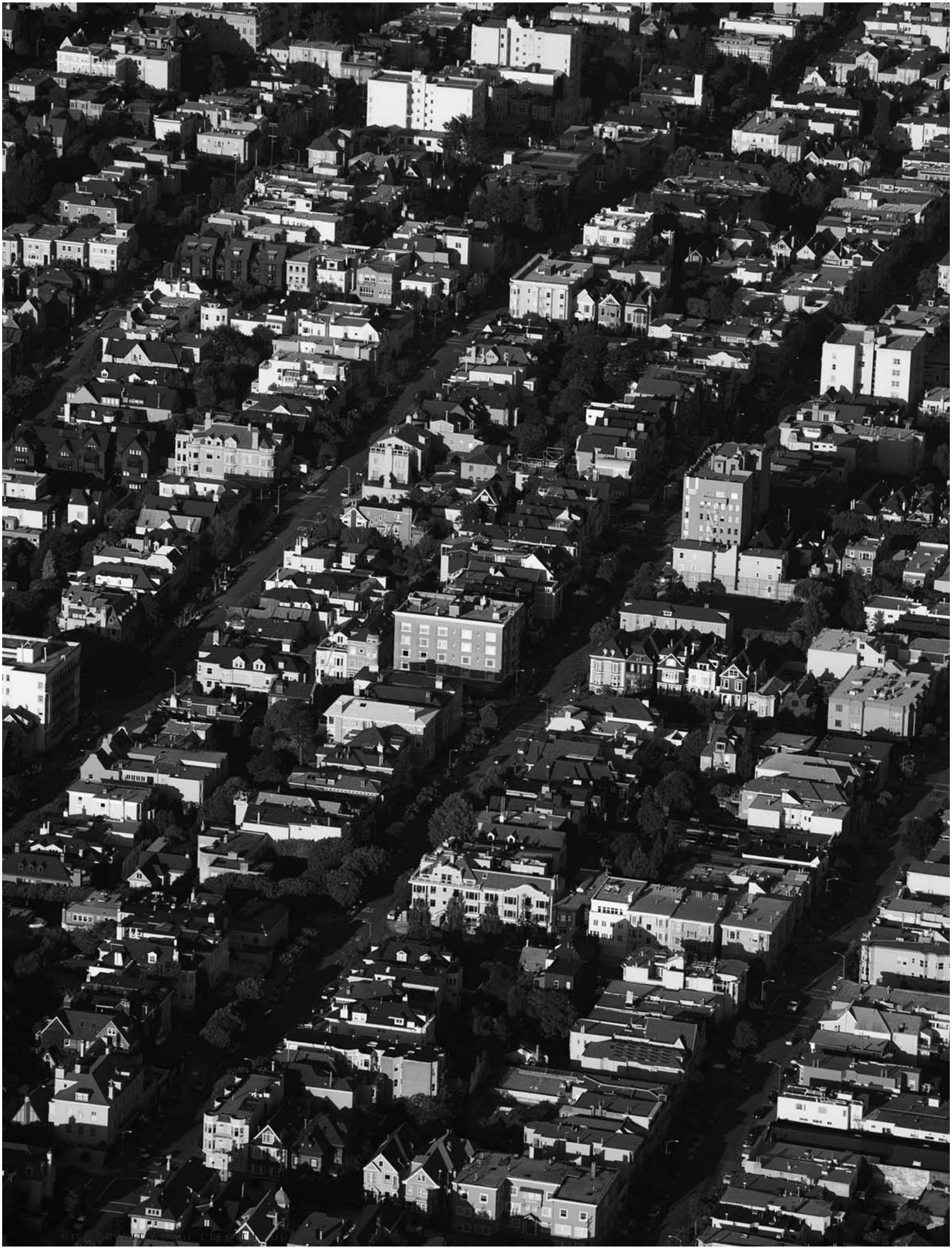
EXCLUDED FROM THE MIRACLE

The American credit system is in many ways the envy of the world.

The steady development of information-sharing, automated credit scoring, and easy entry by new competitors have extended credit to tens of millions of Americans. In the years since the financial services industry began using standardized payment information for scoring, homeownership rates have grown and credit has become available to those for whom credit was reserved for the elite.

The national credit reporting system has become the basis for "automated underwriting," a practice that has become so successful that former Federal Trade Commission Chairman Tim Muris referred to it as "the miracle of instant credit." The former Federal Reserve Board Chairman Alan Greenspan said that such a system and technologies using it had "a dramatic impact...on consumers and households and their access to credit in this country at reasonable rates." This success ranges from those applying for a home mortgage loan or refinancing an existing mortgage to those applying for a credit card or a retail store card. Thus, the national credit reporting system touches the lives of millions of Americans each day. The robust and full-file data maintained by consumer reporting agencies have contributed to a significant expansion in consumer and small-business lending without increasing risk in the national credit system.

Despite the impressive track record of the national credit system under the Fair Credit Reporting Act—record homeownership, fairer lending across all segments of society, a democratization of access to credit—an estimated 35 million to 54 million Americans remain outside of the mainstream national credit system. This group is excluded from instant credit because there is little or no credit information in their credit files. As a result, mainstream lenders, lacking sufficient information for automated underwriting tools, equate a lack of information with unacceptably high credit risk.



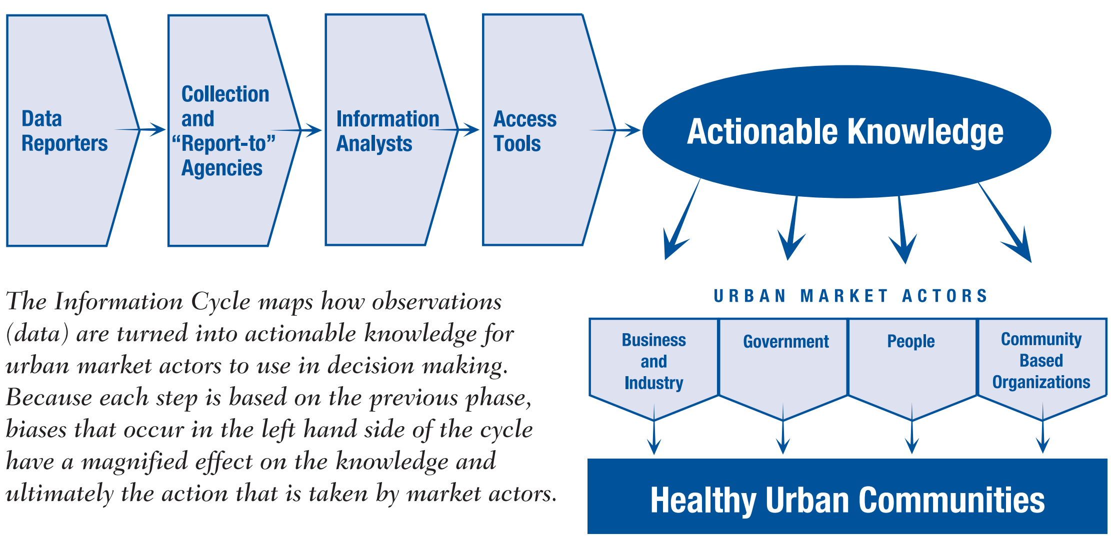
THE INFORMATION CYCLE

In one sense, those outside the mainstream credit system are trapped in a catch-22 by their lack of a credit history: how does one build a credit history when denied access to credit? Lenders currently lack the right tools to adequately assess the credit risk, credit capacity, and credit-worthiness of tens of millions of "thin-file" (that is, those with little credit history) and "unscoreable" Americans. The lack of tools stems from a gap in adequate information on which to make credit decisions about these individuals.

Identifying information gaps, developing solutions to bridge them, and educating decision makers in new ways to better understand underserved credit markets requires a clear understanding of the process of knowledge creation, or the information cycle.[3] Although decision makers begin with raw data, they must analyze it, or add value to it, to make it useful *information*. Prior to 1970, lenders gained information by assessing the capacity, collateral, credit, and character of borrowers. In today's world of automated credit underwriting, data are turned into information by external consultants—consumer credit bureaus. Consumer credit bureaus have become powerful information sources and "translators" of the potential of consumer credit markets.

The Information Cycle

Knowledge spurs action in urban markets



The Information Cycle maps how observations (data) are turned into actionable knowledge for urban market actors to use in decision making. Because each step is based on the previous phase, biases that occur in the left hand side of the cycle have a magnified effect on the knowledge and ultimately the action that is taken by market actors.

In credit decisions, lender's analytic teams and modeling capabilities provide a customized understanding of the market context to use in turning the information they receive into *knowledge* on which to act. Although automation has enabled a deeper penetration of some markets, it customarily overlooks the thin-file and unscoreable populations. The lack of data and information on these populations can lead to "knowing-doing" gap: the gap between a lender's perception of a particular individual's potential and the reality of his or her credit risk, credit capacity, and credit-worthiness.[4] Many lenders, who are aware that this is not the case, are often forced to treat these borrowers as excessively risky simply for want of better information.

NONTRADITIONAL DATA CAN BRIDGE THE INFORMATION GAP

One potential solution to the credit Catch-22 is pervasive reporting of nontraditional or alternative data in consumer credit reports.[5] In this study, PERC singled out energy utilities (gas, electric, heating oil, water) and telecommunications as the most promising data sets to help bring consumer outliers into the fold. These two data sets ranked highest along three metrics—coverage, concentration, and being credit-like. They were also likely to yield results for a large segment of the 35 million to 54 million thin-file/unscoreable individuals, as the penetration rates for these services are frequently 90 percent or more. The utility and telecommunications industries are relatively concentrated, making data collection more feasible. Finally, exchanges in these two industries involve "credit-like" transactions—that is, a good or service is provided in advance of a payment, and the payments are made in regular installments.

Other alternative data sets—such as auto insurance, remittance payments, and rental data—did not score as highly as utility and telecommunications data. These sets may have value, but their near-term promise for the thin-file/unscoreable population is not as evident. For simplicity's sake, throughout the course of this study, the terms "alternative data" and "nontraditional data" refer exclusively to utility and telecommunications data, unless otherwise specified.

This study tests the hypothesis that including utility and telecommunications data in consumer credit reports can achieve the following results:

(1) Increased ability of mainstream lenders to adequately assess credit risk, credit capacity, and credit-worthiness of the thin-file/unscoreable population;

(2) Increased access to affordable mainstream credit for thin-file/unscoreable population;

(3) Thin-file/unscoreable individuals will derive the greatest benefit from including alternative data, while the credit effects on "thicker-file" individuals will be less evident; and,

(4) Increased fairness in lending, especially for minority communities and younger borrowers.

THE CRITICAL ROLE OF CREDIT FILES

Information contained in consumers' credit files plays a critical role in determining both the amount and the terms of credit that they receive. Behind this simple fact is an issue of considerable importance, for the claim can be extended to "and thereby shape the ability of individuals to build assets and thus alter their life chances." The use of information in credit decisions, especially via automated models, has extended credit to millions, increasing homeownership rates, access to education, and small business formation. This payment information therefore plays a significant role in shaping the social fortunes of individual Americans. In general, consumers who have demonstrated a history of timely payments on several different accounts, or trade lines, are more likely to be granted credit at more favorable terms than those with spotty payment records or with little, if any, established credit.

Unfortunately, those with *no* credit histories and those with *poor* credit are often treated similarly. The net effect is that millions of Americans remain outside the credit mainstream and are consequently handicapped in their ability to access credit and improve their lives. Moreover, many are forced to turn to providers who charge as effective rates as high as 500 percent.

Alternative or nontraditional data offer one possible solution to the problems posed by no credit histories. The financial services industry has long recognized the need to find alternative ways of evaluating the creditworthiness of thin-file consumers. For example, some in the mortgage industry now accept a "nontraditional credit report" based on the consumer's demonstrated performance in meeting such ongoing obligations as rent, utilities, and telephone bills.[6] Although such payments are not credit obligations in the traditional sense, they are generally believed to reflect a consumer's willingness and ability to repay credit-like obligations.

A recent report by the Information Policy Institute examined the feasibility of collecting these and other types of nontraditional credit data on a widescale basis. Of the different sources considered, utility and telecommunications trades again appeared to be most promising, for among other reasons, the concentration of the data. Relatively few data furnishers must be engaged, unlike with rental information, which is widely dispersed among diverse landlords. Although some utility and telecommunications companies currently report data to credit bureaus, the majority do not. In fact, in some states, the reporting of such data is prohibited by law or regulation, and in many others, uncertainty about the reaction of regulators inhibits utilities from reporting.

None of this is to suggest that other types of alternative payment information—auto insurance, rents, and so forth—are of less value, just that utility and telecommunications data may be one effective way of folding in those outside the credit mainstream. From a standpoint of practicality, utility and telecommunications payment data may be the fastest way to extend credit to underserved communities.

The promise is that new data sources can help tens of millions of Americans take a step toward asset formation. Considering that many of these millions are poorer, less advantaged Americans, the information can help alleviate poverty in this country. That is, it promises a market solution to problems of credit access. What follows is an attempt to measure that promise.

II. METHODS

OBJECTIVES

This report examines the impact that the broader reporting of telecommunications and utility trades could have on consumers' access to different types of credit. In our analysis, "utility" trades include payments for electricity, gas, and heating oil, while "telecommunications" trades refer to traditional telephone service (i.e., land lines) and mobile phones. Although precise statistics are difficult to assemble, the number of consumers who would likely be affected by the reporting of these trades is undoubtedly very large, as the consumption of these services is nearly universal.

It should be noted that there have been previous attempts to encourage the utilities to report to the credit bureaus. Yet, to date, the scale of the impact remained one without measurement. This study aims to fill that gap and to provide clear estimates of the impact of reporting. In doing so, industry and policy makers can assess what is at stake and chart viable courses to assist those who have poor or no access to mainstream credit.

Increasing the reporting of utility and telecommunications trades could affect consumers in at least two different ways:

- ***First, it would increase the number of consumers who can be scored, and who thereby can access credit.*** Although the industry has developed several alternative approaches for evaluating the credit-worthiness of thin-file borrowers, many traditional scoring models require at least one valid trade. All of the models used in this study require just one trade to produce a score. Nonetheless, using a representative sample of credit files, we found, 13 percent of credit files had no payment histories, and 19.4 percent had only one or two payment trade lines. Because the systematic reporting of utility and telecommunications data should add one or more trade lines to the credit profile of the typical consumer, the number of potential borrowers with thin credit files should be reduced. By increasing the number of trade lines that can be used to score consumers, the predictive power of scoring models should be improved, which in turn should lead to higher acceptance rates, lower costs, or a combination of the two.

- ***Second, the systematic reporting of utility and telecommunications trades could affect the distribution of credit scores.*** Depending on the consumer's payment record and overall credit profile, the impact on an individual's score could be positive or negative. Although the impact on consumers with well-established credit histories would likely be minimal, the impact on consumers with little or no established credit could be large.

To the extent that this information leads to better lending, we might also expect reductions in the average price of credit. We do not, however, undertake a direct measure of this expected reduction, but rather estimate changes in the performance of portfolios, which

Table 2.1. Distribution of Consumers by Number of Telecommunications and Utility Trades: 2005 Analysis Sample

Number of Trades	Consumers with Utility Trades		Consumers with Telecom Trades	
	No.	%	No.	%
1	5,076,811	67.5	545,826	92.4
2	1,414,501	18.8	38,127	6.5
3	608,502	8.1	5,025	0.9
4+	419,206	5.6	1,817	0.3
Total	7,519,020	100.0	590,795	100.0

are a major component of loan pricing. The research presented in this report has been designed to estimate the probable magnitude of these different effects and to identify the types of consumers who are most likely to be affected.

Although not quantified in this study, another benefit of including alternative data in consumer credit reports is that the uncertainty associated with a given credit score should decline. For example, a lender deciding whether to extend credit to two individuals with identical credit scores—the first of which uses alternative data in addition to traditional credit data—will be more likely to lend to the first applicant, all else equal, because the additional data reduces uncertainty about the credit score. The lender may even prefer to extend credit to an individual with a more accurate but lower credit score than to an individual with a less accurate but higher credit score. As is evidenced in this and other studies, adding predictive information to a credit scoring model reduces the uncertainty of credit scores. It is therefore reasonable to expect that lenders would extend credit more deeply[BR1] than the estimates generated in this study. This may be particularly true for those with thin credit files. A lender may be more likely to lend (and at better rates) to an individual of a given risk level if they know that risk level with greater certainty.

THE DATA FOR THE SIMULATIONS

Our analysis uses a data set constructed by TransUnion from the detailed credit reports of two mutually exclusive samples of consumers:

- An analysis sample of approximately 8.1 million consumers with at least one "fully reported" utility (gas, electric, or fuel) or telecommunications trade (wireless or land line) as of March 31, 2005.

- A validation sample of approximately 4 million randomly selected individuals designed to represent the broader population of consumers with no fully reported utility or telecommunications trades on March 31, 2005.

"Fully reported" trade lines include information on the timely payment of bills as well as any derogatories (e.g., delinquent accounts referred to collection agencies.) Although most utility and telecommunications companies routinely report collections, the reporting of *timely* payments is far less common.

Table 2.1 shows the number and distribution of consumers in the analysis file by the number of utility and telecommunications trades. As shown in the chart, most of the records in the analysis file have a utility as opposed to a telecommunications trade. Just over 7.5

million consumers in the analysis file have at least one fully reported utility trade, and about one-third have more than one (for example, consumers who use a combination of gas and electricity in their homes.) In contrast, only 591,000 consumers in the analysis file have a fully reported telecommunications trade, and only 8 percent have more than one. Because there is relatively little overlap between the two groups (only about 1,500 records have both a utility and a telecommunications trade), they are treated separately throughout this report.

We collected detailed information from the consumers' credit reports for both the analysis and the validation samples at two points in time: March 31, 2005 (the date that was used to generate the samples) and March 31, 2006. The intervening year is the "performance period," during which the predictions of the model were evaluated. We augmented the credit bureau data in two ways:

- We used a variety of credit scoring models to score each consumer in the sample with and without his or her utility and telecommunications data.

- We sent the data to an independent service provider, who appended information on the individual's race, ethnicity, age, and household income.[9]

The resulting data set contains a wealth of information on the credit profiles of consumers, their demographic characteristics, and the effect of any reported utility and telecommunications trades on a variety of credit scores.

We took deliberate steps to ensure the privacy and confidentiality of individual consumers. Specifically, the data contain no identifying information of individual consumers (that is, no names, addresses, social security numbers, or account numbers). Once the demographic data were merged with the credit reports, we purged all identifying information from the file.

APPROACH

This study examines the impact of including alternative data in consumer credit reports on credit scoring models and on credit access by various communities. Specifically, the analysis focuses predominantly on the 35–54 million Americans outside the credit mainstream. Attention is paid to the credit profiles and score distributions of this group as well as access to credit with and without alternative data. Then credit scoring model performance, as measured by the Kolmogorov-Smirnov (K-S) statistic, is examined. Several commercial grade scoring models were analyzed to determine model predictiveness. Finally, credit access is probed through a comparative analysis of new accounts opened by those with and without alternative data and an examination of acceptance rates for various communities.

The next step in the analysis examined the impact of removing the telecommunications and utility trades on the consumer's credit score. This analysis used a "VantageScore," a generic scoring model recently introduced by the three national credit bureaus (Experian, Equifax, and TransUnion). We used the model to derive a credit score for each consumer, with and without the utility or telecommunications trades. We then compared the distribution of these hypothetical scores with the score based on the consumer's existing credit file (that is, including the telecommunications and utility trades).[10]

The third step in the analysis focused on the impact that utility and telecommunications data would have on consumers' access to credit. We also compare the actual experiences of the consumers in the analysis and the validation files over a 12-month time period: March 31, 2005 (the date that the samples were drawn) and March 31, 2006 (the end of the performance period.) In particular, we compared the number and size of new accounts that were opened by consumers with an existing utility or telecommunications trades (the analysis sample) with the number and size of new accounts opened by otherwise similar consumers without such trades (the validation sample.)

That is, does this information impact credit behavior?

We then examined how the reporting of utility and telecommunications trades would affect the predictive power of several generic and industry-specific scoring models, and estimated the impact that this would have on both the availability and cost of credit.[11] Credit scores are the principal means by which credit is allocated in the United States to consumers. The scoring models considered in this report include:

- VantageScore, which predicts the probability that a consumer will have at least one 90-day delinquency on a new or existing account over a two-year period;
- TransRisk New Account, which predicts the probability that a consumer will have at least one 90-day delinquency on a new account over a two-year period;
- Two separate bankruptcy scores (one from a large financial institution and one from TransUnion[12]), which predict the probability that a consumer will declare bankruptcy in a two-year period; and
- A mortgage screening model developed by a major lender that exclusively relies on credit bureau data and predicts the probability that a consumer will have at least one 60-day delinquency on a mortgage account over a two-year period.[13]

We used these different models to score consumers with and without their utility and telecommunications trade line(s), and test the extent to which the resulting scores accurately predict consumer performance over a 12-month period: April 1, 2005 to March 31, 2006.[14] In general, if the presence of utility and telecommunications trades helps to improve the models' accuracy, this should ultimately lead to higher acceptance rates, lower delinquency rates, or a combination of the two.

The final step in the analysis explored how different demographic groups are likely to be affected. We first estimated the relative importance of energy utility and telecommunications trades for different demographic groups by examining each group's share of total trades. We next estimated the probable impact of such trades on acceptance rates within each group. The impact on acceptance rates again reflects the extent to which the predictive power of scoring models improves with the addition of utility and telecommunications trades.

LIMITATIONS

The analysis has a few limitations that should be noted. Most relate to the underlying characteristics of the analysis sample and the scoring models.

SAMPLING ISSUES

Because of the local nature of both utility and telecommunications providers, we knew from the start that the analysis sample would not be representative. In fact, 84 percent of our data on consumers with utility trades is concentrated in the three states—Illinois, Wisconsin, and Pennsylvania—where several large local utilities have begun to report their data. Likewise, 81 percent of the records with telecommunications data were from Pennsylvania and Texas.

The validation sample was designed to test the extent to which the analysis file is representative in other ways, for example, the number of trades in the consumer's files *excluding* telecommunications and utilities. The results of this analysis are presented in Appendix A. As discussed there, the analysis file appears to be broadly representative of all consumers in terms of their overall credit profiles and demographic mix. In general, however, consumers with utility or telecommunications trades seem to have stronger credit profiles than the general population, although this is less true for consumers with telecommunications trades.

The analysis sample is also limited in two other respects. The analysis file is necessarily restricted to consumers with either a utility or telecommunications trade. As a result, the findings they cannot be used to make inferences to the broader population, which includes an unknown number of consumers with neither a utility nor a telecommunications account. In addition, consumers in our analysis file are unlikely to have *all* of their utility and telecommunications trades reported. Despite the fact that many consumers pay both a utility and telephone bill, there is relatively little overlap between the two trade accounts in our sample. Furthermore, the telecommunications data are dominated by wireless accounts and may therefore underestimate the full effects of reporting both land lines and cell phone accounts. As a result, our analysis will likely underestimate the potential impact of full reporting.

MODELING ISSUES

It is important to recognize that many of our findings are based on the current versions of existing scoring models. In the event that utility and telecommunications data were more broadly reported, many scoring models would undoubtedly be optimized to reflect this important change. However, on the basis of an earlier analysis of a similar issue,[15] we believe that any biases introduced by this simplification will not affect our overall conclusions regarding the probable impact of full reporting. This limitation likely means our findings will tend to err on the side of caution, attenuating the actual impact we would expect with increased reporting of alternative trades.[16] ■

III. IMPACT ON CONSUMERS' CREDIT PROFILES

The full reporting of utility and telecommunications data would clearly affect the credit profiles of most consumers by adding one or more trade lines to their files. Logically, consumers with little, if any, "traditional" forms of credit would have the most to gain. (Simulations below suggest that this is in fact the case.) This section details the results of our estimation of the potential magnitude of these effects by examining the impact of the utility and telecommunications trades on the consumer's total number of trade lines as well as their credit score.

Table 3.1 compares the distribution of consumers by their total number of trade lines, with and without any utility or telecommunications trades.[17] The first two columns refer to the sample of 7.5 million consumers with an existing utility trade. Column 1 shows the distribution of these consumers on the basis of the total number of trades that currently appear in their credit files (that is, including any utilities.) Column 2 presents the counterfactual, the distribution of these same consumers when their utility trades are excluded. The last two columns present comparable information for the sample of 590,795 consumers with at least one fully reported telecommunications trade. Column 3 shows the distribution of these consumers based on the information currently appearing in their files (i.e., including any telecommunications), while column 4 illustrates what this distribution would have looked like had the telecommunications trades not been reported.

As shown in Table 3.1, the reporting of both utility and telecommunications trades has a sizable impact on the credit profiles of the consumers in our sample. For example, when utilities are included in consumers' credit reports (column 1), about 12 percent of the sample can be classified as having a thin credit file (fewer than three established trades). However, when the utility trades are removed from their credit records (column 2), the proportion of thin-file borrowers rises to 17 percent, and about 10 percent of the sample have no reported trade lines at all.[19]

The impact of adding the telecommunications trades is similar, although the impact on the share of consumers with no established trade lines is more pronounced. For example, when their telecommunications trades are reported (column 3), about 18 percent of the sample would be classified as having a thin credit file. However, when their telecommunications trades are removed (column 4), the share rises to 23 percent, and 14 percent of the sample would have had no established trades.

Table 3.1. Impact of Utilities and Telecom Trades on Total Number of Trades[23]

Total Number of Trades	Consumers with Utility Trades: Including Utilities (#1) (%)	Consumers with Utility Trades: Excluding Utilities (#2) (%)	Consumers with Telecom Trades: Including Telecoms (#3) (%)	Consumers with Telecom Trades: Excluding Telecoms (#4) (%)
Thin-File				
0	-	9.6	-	14.0
1	7.7	4.0	13.4	4.9
2	4.1	3.4	5.0	4.1
Thick-File				
3	3.5	3.2	4.1	3.7
4	3.2	3.1	3.8	3.5
5	3.1	3.1	3.5	3.3
6	3.1	3.1	3.4	3.2
7+	75.2	70.5	66.8	63.3
All Consumers	100.0	100.0	100.0	100.0
Sample Size	7,519,020	7,519,020	590,795	590,795

Data Source: March 31, 2005 Credit Files for Analysis sample.

Differences in the impact of telecommunications and utility trades most likely reflect underlying differences in the populations with such trades. For example, a comparison of the underlying credit profiles of the two groups of consumers (columns 2 and 4) suggests that consumers with telecommunications trades have a smaller number of traditional trade lines than consumers who are responsible for utility payments. In this respect, consumers with telecommunications trades appear to be more similar to the general population than do consumers with utility trades (see Appendix A). Because it is easier to get a cell phone than to rent or buy a home, this pattern makes sense.

Figures 3.2c and 3.2d show the impact of adding the utility and telecommunications trades to the consumer's VantageScore. (This score ranges from 501 to 990, with higher scores signifying lower credit risks). Figures 3.2a and 3.2b show the distribution of consumers by the change they experience when adding their utility and telecommunications trade lines to their scores. In general, a change of more than 25 points in the VantageScore, or a change from an "unscoreable" to a "scoreable" situation, should be viewed as a significant change. Where along the score range the change occurs is also important. For instance, a consumer gaining 50 points and moving from 900 to 950 may gain little in practical terms relative to a consumer also gaining 50 points but moving from 650 to 700.

One would expect the reporting of utility and telecommunications data to increase the number of consumers who could be scored by increasing the their trade lines. However, there is no a priori reason to expect that the reporting of utility or telecommunications data will change a consumer's existing credit score in one direction as opposed to another. Although a good payment history on a larger number of trades will tend to increase a consumer's score, a poor payment history on additional trades would most likely reduce it.

Figure 3.2. Impact of Utilities and Telecommunications Trades on VantageScore
All Consumers

Figure 3.2a Impact of Utility Trades on VantageScore Change

Figure 3.2c Impact of Utility Trades on VantageScore

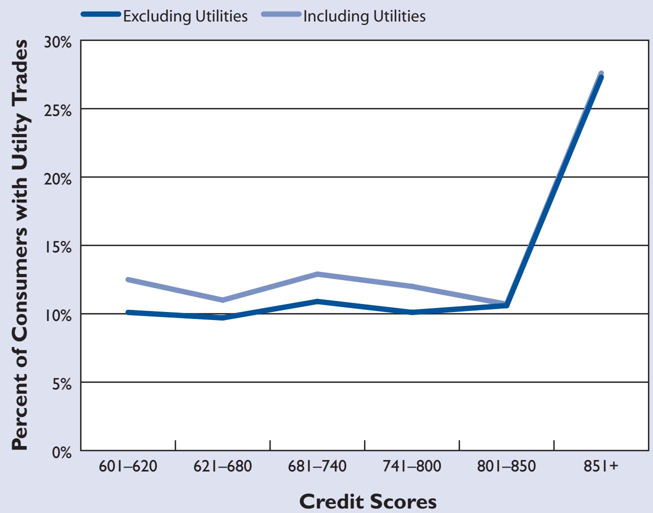


Figure 3.2b Impact of Telecom Trades on VantageScore Change

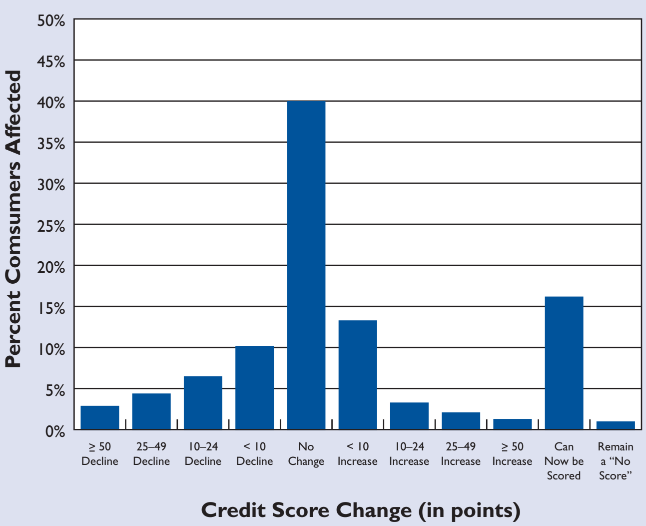
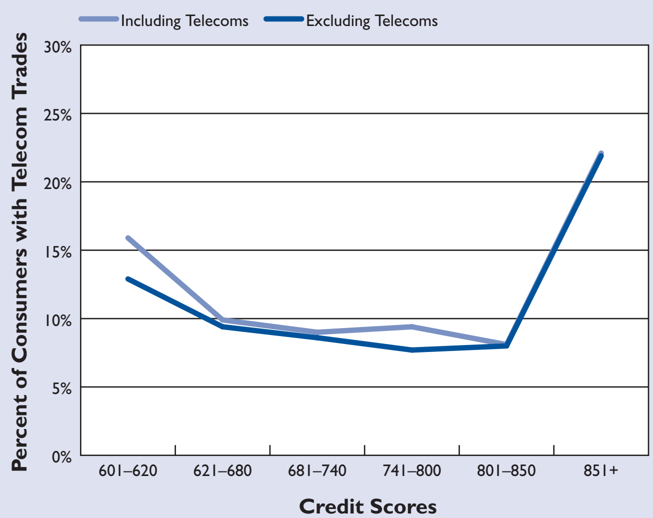


Figure 3.2d Impact of Telecom Trades on VantageScore



Source: March 31, 2005 Credit Files for Analysis sample.

"The impact of adding utility and telecommunications trades is considerably greater for thin-file consumers than for the population at large."

Adding utility data to the consumer's credit report decreases the proportion of consumers who cannot be scored, from about 12 percent to 2 percent. However, among consumers who could be scored without their utility trade lines, the share whose score increased by more than 25 points with the addition of the utility trades (4.6 percent) was about the same as the share whose score decreased by more than 25 points (5.2 percent). In fact, the inclusion of the utility data had little or no significant effect on about 69 percent of the sample, resulting in no change or changes less than 10 points. It should be kept in mind that lenders often place unscoreable consumers among the highest risk. That is, a share of the 12 percent would be treated as belonging to the lowest-risk tiers, given that they have little on which to base their decisions. (Some lenders of course will attempt to collect information to get a better sense of the applicant's risk, but this track is far more costly.)

Figure 3.3. Impact of Utilities and Telecommunications Trades on VantageScore Consumers with Less than 3 Traditional Trades

Figure 3.3a Impact of Utility Trades on VantageScore Change (Consumers with Less than 3 Traditional Trades)

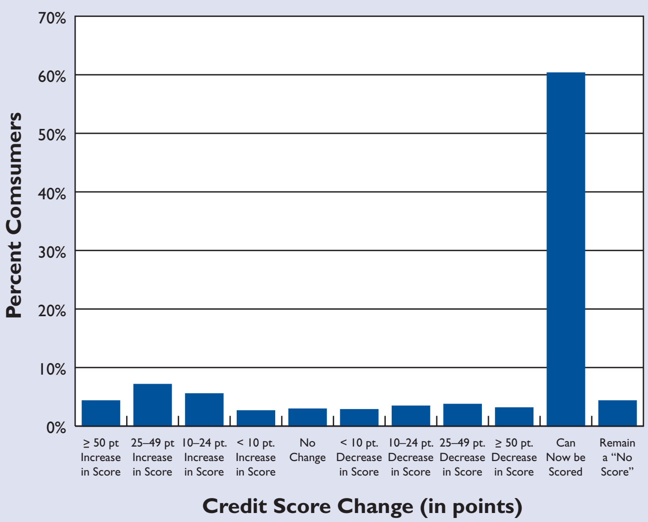


Figure 3.3c Impact of Utility Trades on VantageScore

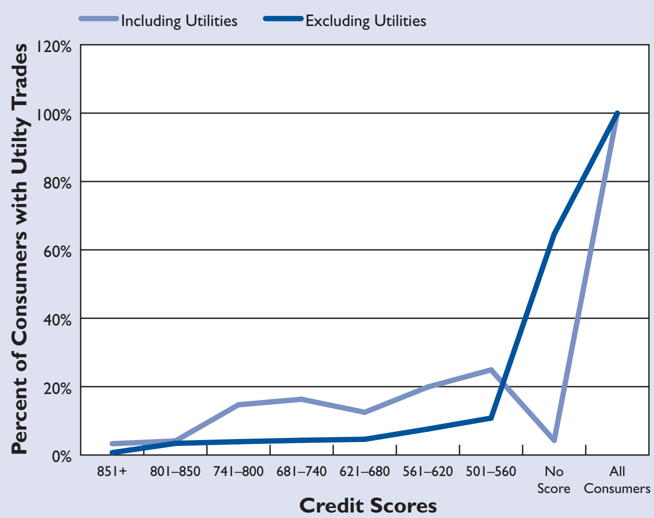


Figure 3.3b Impact of Telecom Trades on VantageScore Change (Consumers with Less than 3 Traditional Trades)

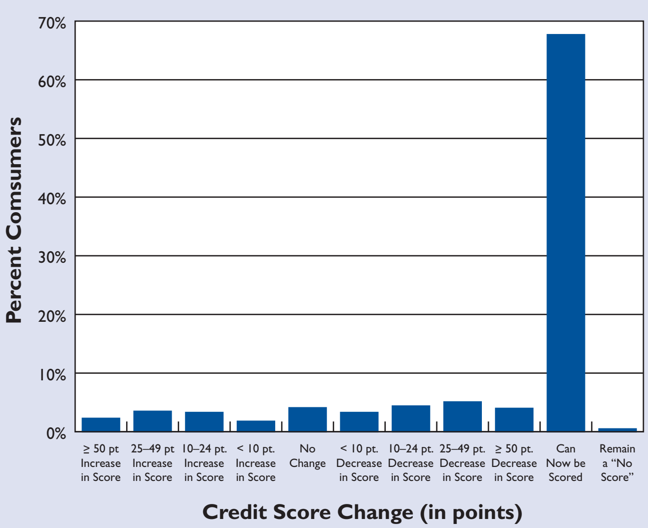
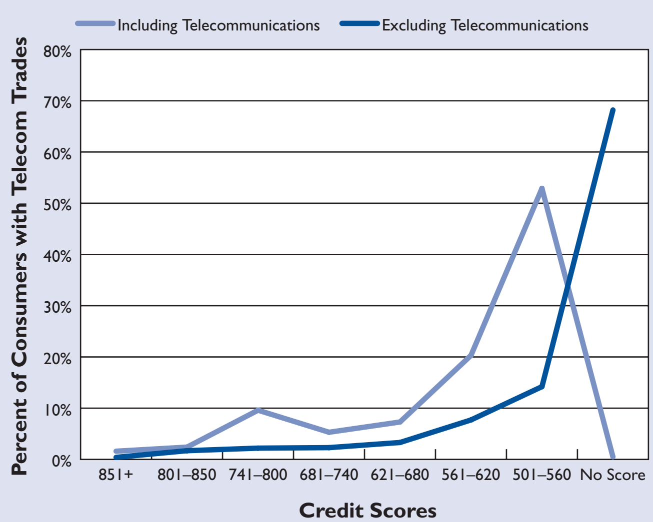


Figure 3.3d Impact of Telecom Trades on VantageScore



Source: March 31, 2005 Credit Files for Analysis sample.

Roughly comparable patterns can be observed in the sample of consumers with telecommunications data. Again, the primary impact of including telecommunications data appears to be on the proportion of consumers who cannot be scored, which drops from 17 percent to 1 percent. However, among the consumers who could be scored without their telecommunications data, the share who experienced an increase of more than 25 points in their score (3.2 percent) was only about one-half the proportion of consumers who experienced a decline (7.1 percent.) Although the number significantly affected was higher than it was for the utility data, telecommunications data had little or no effect on the credit scores of about 63 percent of the population.

Figure 3.3 presents comparable statistics for borrowers with less than three traditional trades (or more precisely, less than three trades, excluding any telecommunications and utility accounts.) This segment represents the population of most interest, as many of these borrowers have difficulty accessing mainstream credit. As expected, the impact of adding utility and telecommunications trades is considerably greater for thin-file consumers than for the population at large, and the primary effect is to increase the percentage of consumers who can be scored. For example, adding utility data reduced the percentage of thin-file consumers who could not be scored from about 65 percent to just 4 percent. The reporting of telecommunications data had an even greater effect, declining from 68 percent to less than 1 percent. ■

“The primary effect [of using alternative data] is to increase the percentage of consumers who can be scored”

IV. OBSERVED DIFFERENCES IN ACCESS TO CREDIT

All else equal, one would expect that the full reporting of utility and telecommunications data would increase access to credit by reducing the proportion of consumers with thin credit files and increasing the proportion of consumers who can be scored. Although we the impact on consumers with a well-established credit history is relatively modest, the impact on consumers with less than three traditional trades was quite pronounced.

To estimate the potential impact of the utility and telecommunications trades on the consumer's access to credit, we compare the actual experiences of consumers in the analysis and validation files over a 12-month period beginning April 1, 2005 and ending on March 31, 2006. Because consumers in the validation sample have no reported utility and telecommunications trades, they provide a convenient, although imperfect "control" for assessing the potential effects of full reporting.[20]

The results of this analysis are presented in Table 4.1. In addition to comparing the proportion of consumers who opened a new account within this period, we also looked at other indicators of credit use, including the average change in the consumer's total outstanding credit balance (i.e., credit use) and the average change in the consumer's aggregate credit limit. The first three columns in Table 4.1 describe the results for the three populations groups. The last three columns restrict the analysis to thin-file consumers.

Table 4.1. New Credit Accounts Opened February 2005 to January 2006

	All Borrowers			Thin-File (<3 *Traditional* Trades)		
	Consumers with Utility Trades (#1)	Consumers with Telecom Trades (#2)	Validation Sample (#3)	Consumers with Utility Trades (#4)	Consumers with Telecom Trades (#5)	Validation Sample (#6)
Pct with new accounts	50.92%	48.73%	42.21%	16.44%	16.42%	4.61%
Ave. no. trades opened	1.14	1.07	0.93	0.27	0.26	0.05
_ Total outstanding balance	+ $3956	+ $1466	+ $8489	+ $1972	+ $891	- $402
_ Total available credit	+ $6973	+ $3192	+ $12309	+ $2466	+ $1094	- $382
Sample size	6,211,323	504,481	3,785,681	1,036,396	113,240	1,030,357

Data Source: March 31, 2005 and March 31, 2006 Credit Files for Analysis Sample

In general, widespread reporting of utility and telecommunications data increases consumer access to credit. Although the proportion of consumers who opened a new account over the observation period was higher for all consumers with a fully reported utility or telecommunications trade, the impact was significantly greater for thin-file borrowers. For example, only about 5 percent of thin-file borrowers in the validation sample (column 6) opened a new account between April 1, 2005, and March 31, 2006, compared with 16 percent of thin-file consumers who had either a reported utility or telecommunications trade (columns 4 and 5, respectively).

Compared with thin-file consumers without such trades, those with a fully reported utility or telecommunications trades also experienced greater increases in their use of and access to credit. In fact, thin-file consumers with utility and telecommunications data increased their credit limits by about $2,500 and $1,100, respectively, over the 12-month period, while thin-file consumers without such trades experienced a small decline ($382). However, the pattern for all consumers shows the opposite effects, with larger increases observed for consumers in the validation sample. ■

"Thin-file consumers with utility and telecommunications data increased their credit limits"

V. IMPACT ON SCORING MODELS

Another way to assess the probable outcome of full reporting is to examine its impact on the reliability or ability to rank risk within the scoring models. In general, reporting utility and telecommunications trades should affect consumers' access to credit if the additional information provided improves the ability of credit issuers to identify a good credit risk. As shown in prior research, greater accuracy in estimating credit performance should lead to lower credit costs for lenders, higher acceptance rates, or some combination of the two.[21] Moreover, if better performance reflects better capacities of borrowers to pay, it limits over-indebtedness.

IMPACT ON PREDICTIVE POWER

To examine these potential effects, we relied on several commercial scoring models, including the VantageScore model; a generic new account model; two bankruptcy models; and a mortgage screening model Although none of these models specifically distinguishes telecommunications or utility trades from other types of accounts, the scores of each model will be affected by the consumer's performance on all reported trade lines, including any utility or telecommunications accounts.

We began by scoring consumers in the analysis file with and without their reported telecommunications and utility trades. We then used the resulting scores to rank consumers according to their predicted risk, and compared the different rankings with consumers' performance over a 12-month period (April 1, 2005, to March 31, 2006). The accuracy of the various scores was summarized by their Kolmogorov-Smirnov (K-S) statistic, a commonly used metric designed to capture a model's ability to distinguish between two different groups, in this case, performing and nonperforming accounts.[22] The K-S statistic ranges from 0 to 100, with higher values signifying a greater ability to distinguish between good and poor credit risks.

In calculating the KS statistics, we first assumed that consumers who could not be scored would be treated as a higher risk than consumers with the minimum applicable score. In reality, however, some credit issuers, primarily those lending for mortgages, would attempt to validate the credit-worthiness of no-score applicants by examining nontraditional sources of credit. Our analysis, therefore, may oversimplify the decision-making process of credit-issuers in some instances, such as for mortgages, and overstate the benefits that arise when consumers move from unscoreable to scoreable.

Table 5.1. Impact of Utilities and Telecommunications Trades on K-S Statistics: General Population Models

	Consumers with Utility Trades		Consumers with Telecom Trades	
Model	Including Utilities (#1)	Excluding Utilities (#2)	Including Telecoms (#3)	Excluding Telecoms (#4)
VantageScore	1.098	1.000	1.085	1.000
TransRisk new account	1.051	1.000	1.048	1.000
TransRisk bankruptcy	1.135	1.000	1.214	1.000
Bankruptcy model II	1.138	1.000	1.262	1.000
Sample size	6,211,323	6 ,211,323	504,481	504,481

Data Source: March 31, 2005 and March 31, 2006 Credit Files for analysis sample.

With these caveats in mind, Table 5.1 shows the estimated impact of adding the utility and telecommunications trades on the predictive power of the various models (For reasons described below, the mortgage model has been treated separately.) To protect the proprietary nature of the models, the K-S statistics for each of the models has been scaled to equal 100 when the utility and telecommunications trades are excluded from the consumers' credit files. Values above 100 when the utility or telecommunications trades are included indicate a relative improvement in the model's predictive power.

As shown Table 5.1, adding utility and telecommunications data increases the overall accuracy of the scoring models by a significant amount.[23] For example, adding the data to the VantageScore model increases its overall K-S statistic by 9.8 percent and 8.5 percent, respectively. Results for the other general population models are similar, ranging from a 5 percent increase for the second generic model to nearly a 14 percent increase for the bankruptcy scores in the utility sample and increases of more than 20 percent for the bankruptcy scores in the telecommunications sample.

The improvement in the model's predictive power with the addition of the utility and telecommunications trades appears primarily to be driven by the greater ability to score previously unscoreable consumers, rather than to a better risk-ordering of those who can be scored without the addition of the alternative data. This is evident from comparing the results in Table 5.1 and 7, which are based on calculations from samples composed of only those who can be scored with or without the alternative data, and thus only captures the reordering effect from the addition of the new data. The greater lift (that is, increase in the KS statistic) in Table 5.1 when previously unscoreable consumers are scored and moved out of the greatest risk category. This reflects the fact that the average rate of serious delinquencies among such consumers is relatively low compared with the scoreable consumers at the bottom of the score distribution. Hence, these consumers do not belong (as a group) in the highest-risk category. For example, consumers who were unscoreable without their utility trades had a delinquency rate of 14 percent, which is only slightly greater than the rate observed among consumers with scores in the 680 to 740 range of the VantageScore, and well below the rates observed among consumers with lower scores (whose delinquency rates ranged between 33 percent and 60 percent).

As mentioned, also calculated changes in the K-S statistic for samples of consumers who could be scored with and without the alternative data. These calculations, thus, make no assumptions regarding how those with no score should be classified, but they do exclude those who would most benefit from the inclusion of the alternative data. Nonetheless, it is useful to explore

Table 5.2. Impact of Utilities and Telecommunications Trades on K-S Statistics: Excluding Unscoreables[24]

	Consumers with Utility Trades		Consumers with Telecom Trades	
Model	Including Utilities (#1)	Excluding Utilities (#2)	Including Telecoms (#3)	Excluding Telecoms (#4)
VantageScore	1.022	1.000	1.012	1.000
TransRisk New Account	1.025	1.000	1.010	1.000
TransRisk Bankruptcy	1.005	1.000	0.987	1.000
Bankruptcy Model II	1.008	1.000	1.003	1.000
Sample Size	5,439,844	5,439,844	421,915	421,915

how the models' performance is affected when including alternative data for those who can be scored without it. These results are shown in Table 5.2.

Table 5.2 makes it clear that for those who can already be scored without the alternative data, we should expect, on average, only a modest improvement in score model performance (at least with current nonoptimized models). This should be expected given that, for instance, more than three-quarters of the consumers in the utility subsample used had seven or more traditional trade lines. Therefore, the addition of another (alternative) trade line for the average consumer should have little effect.

Because the purpose of the study is to determine whether and how the addition of alternative data in credit files can benefit those traditionally underserved by the mainstream financial sector, we now look at model performance for those with little or no traditional trade lines—the thin-file consumers.

As before, we first treated those with no score as the highest-risk consumers (they were placed at the bottom of the score distribution). In the absence of the utility and telecommunications data, only 36 percent and 32 percent, respectively, of such consumers registered a score for the VantageScore model. With the addition of the data, the number of no-scores declined to a minimal amount, and the model's ability to predict the credit performance of thin-file consumers increased dramatically.

As shown in Table 5.3, the K-S statistic for VantageScore model rose by more than a factor of 3 with the addition of the utility data and by more than a factor of 4 with the addition of the telecommunications trades. The results for the other models are roughly the same order of magnitude. These findings underscore the critical nature of such trades in evaluating the credit performance of thin-file borrowers.

Table 5.4 shows the change in model performance when scoring thin-file consumers who are scoreable with and without utility and telecommunications data, that is, when scoring consumers with one or two traditional trade lines. We see a larger average lift with the addition of the alternative data for the thin-file consumers than for the general sample results in Table 5.2, reflecting the greater importance of additional trade lines to consumers (and those trying to estimate their level of risk) with few trade lines. Again, we should expect a lift from adding utility and telecommunications data to the credit files of the thin-file consumers when the scoring models are optimized for such data.

Table 5.3. Impact of Utilities and Telecommunications Trades on K-S Statistics: Thin-File Borrowers Only

	Consumers with Utility Trades		Consumers with Telecom Trades	
Model	Including Utilities (#1)	Excluding Utilities (#2)	Including Telecoms (#3)	Excluding Telecoms (#4)
VantageScore	3.294	1.000	4.281	1.000
TransRisk New Account	2.932	1.000	4.993	1.000
TransRisk Bankruptcy	3.358	1.000	5.297	1.000
Bankruptcy Model II	3.595	1.000	6.783	1.000
Sample Size	1,280,553	1,280,553	137,256	137,256

Data Source: March 31, 2005 and March 31, 2006 Credit Files for Analysis Sample

Table 5.4. Impact of Utilities and Telecommunications Trades on K-S Statistics: Thin-File Borrowers Only, Excluding Unscoreables

	Consumers with Utility Trades		Consumers with Telecom Trades	
Model	Including Utilities (#1)	Excluding Utilities (#2)	Including Telecoms (#3)	Excluding Telecoms (#4)
VantageScore	1.078	1.000	1.021	1.000
TransRisk New Account	1.061	1.000	1.024	1.000
TransRisk Bankruptcy	1.035	1.000	0.978	1.000
Bankruptcy Model II	1.050	1.000	0.971	1.000
Sample Size[26]	369,903	369,903	36,506	36,506

These findings are consistent with what one would expect with the addition of alternative data; namely, that (1) the largest impact would be for those who become scoreable after adding the new data; (2) thin-file consumers who were scoreable without the new data would experience a smaller, but noticeable, impact; and (3) consumers with thick files would see relatively little change.

MORTGAGE SCREENING MODEL

Although the results are quite robust for the generic scoring models, applying the same approach to the mortgage screening models proved problematic. Because mortgage screening models are designed to predict the incidence of 60+ days mortgage delinquencies, the samples we used to estimate the K-S statistics were limited to consumers with mortgage trades at the beginning of the performance period. Not surprisingly, all of the consumers in these subsamples had at least one established traditional trade (their mortgage), and the great majority had thick credit files. For example, 95.6 percent of mortgage holders in the utility sample had seven or more traditional trades (i.e., excluding utility trades), compared with 70.5 percent in an overall sample of consumers. Likewise, fewer than 1 percent of mortgage holders in the utility sample had thin credit files compared with about 17 percent in the overall sample.

Given that including utility and telecommunications data had relatively little impact on a model's ability to predict the performance of thick-file borrowers, it is therefore not surprising that these data had relatively little impact on the K-S statistics of the mortgage screening models, *on the basis of the observed performance of consumers with mortgages.* In fact, the addition of the utility data led to a 0.4 percent decline in the K-S statistic of a mortgage screening model designed for homebuyers, while the telecommunications data led to 0.9 percent decline.[27]

To gain a better understanding about how utility and telecommunications data could enhance a mortgage lender's ability to identify credit-worthy borrowers, we recalculated the K-S statistics for the mortgage screening models using an alternative performance measure: the incidence of any 90+ day delinquency. We based this analysis on the entire sample of consumers, whether or not they had a mortgage trade. The results of this analysis were similar to the generic scoring models. In particular, we found that utility and telecommunications data increased the K-S statistics of the homebuyers model by 13.4 percent and 3.2 percent, respectively. Although these results should be interpreted with caution—mortgage models are specifically designed to predict mortgage performance not performance across all trades—they nevertheless suggest that the improvements observed for the generic credit models are likely to apply to models specifically designed for mortgage loans.

ADDITIONAL RESULTS ON THE PREDICTIVE POWER OF ALTERNATIVE DATA

We would expect that alternative payment data would contain some information useful in predicting future payment outcomes. If an individual has been making his or her utility or telecommunications payments on time for a period of time, we would expect they would be more likely to make timely payments (in the present and the future) on a variety of their obligations compared with someone who had fallen behind on payments. That we see a rise in the K-S statistic in the overall samples or in the thin-file samples, and including or excluding the unscoreable populations, points to this. In addition, and more simply, we could look at the correlations between a serious delinquency on an alternative trade and a serious delinquency on a traditional trade.

Specifically, using the sample of consumers with utility trade lines who also had traditional trade lines, we calculated the correlation between a serious delinquency (90+ days) on a utility trade and on a traditional trade line between March 2004 and March 2005. We similarly calculated serious delinquencies for telecommunications trade lines. The respective correlations were .288 and .292 and, not surprisingly given the very large sample sizes, they were statistically significant.[28] The results indicate that a serious delinquency on either a utility or telecommunications trade is weakly to moderately correlated with a serious delinquency on a traditional trade. These results refute any notion that utility and telecommunications payments are unrelated to traditional payments. The correlation does not, however, explain whether alternative payments are a good predictor of future payments.

Table 5.5. Regression Results, Dependent Variable: Whether a Consumer Had a Serious Delinquency on Any Trade During March 2005 and March 2006 (Standard Errors in Parentheses)

	Consumers with Utility and Traditional Trades		Consumers with Telecom and Traditional Trades	
Variables	(#1)	(#2)	(#3)	(#4)
Constant	.082	.106	.110	.130
	(.0001)	(.0002)	(.0006)	(.0006)
Whether a Traditional (90+ DPD) Delinquency, March 04-March 05	.412	0.511	.424	0.485
	(.0004)	(.0004)	(.0014)	(.0014)
Whether a Utility (90+ DPD) Delinquency, March 04-March 05	.410			
	(.0005)			
Whether a Telecom (90+ DPD) Delinquency, March 04-March 05			.247	
			(.0017)	
R-Squared	0.3009	0.2136	0.2506	0.2143
Sample Size	5,631,146	5,631,146	436,140	436,140

The correlation between having a serious delinquency on a utility trade during March 2004 and March 2005 and having such a delinquency on any trade the following year is 0.42. Such a correlation for telecommunications delinquencies during is 0.32. The correlation for delinquencies on a traditional trade is 0.46. The correlation between a consumer's serious delinquency and serious delinquencies on a traditional trade, a utility trade, or a telecommunications trade are quite similar.

It could be the case that the predictive information alternative trades embody is already captured in the information from traditional trades, and therefore adding such alternative trades to traditional trades may not add any predictive power. To test this, we ran regressions to determine whether adding alternative trade information would improve predictability.

The results in Table 5.5 indicate that with the addition of the utility data, the predictive power or goodness of fit of this admittedly crude model rises by 40% as measured by the R-squared. With the addition of the telecommunications data, the goodness of fit of the model rises by 17% also as measured by the R-squared.[29]

Of course, this is only suggestive of how the addition of utility and telecommunications payment information would affect model fit in a reoptimized commercial-grade scoring model. A commercial model would be more sophisticated, take into account much more detailed information, and do a much better job of predicting. Nonetheless, it appears that utility and telecommunications payment data contain information that could be useful in predicting future payment outcomes.

IMPACT ON DELINQUENCY AND ACCEPTANCE RATES

In a competitive market, consumers could benefit from an increase in the accuracy of scoring models in two different ways. On the one hand, credit issuers could increase their acceptance rates and keep the rates that they charge the same. Increasing their acceptance rate without increasing rates and fees is possible because the default rate associated with a given acceptance rate will necessarily decline with an improvement in the model's predictive power. Alternatively, lenders could maintain their existing acceptance rates but lower their rates and fees. Again, a price reduction would be possible because the default rate that is associated with a given acceptance rate will decline with improvements in the model's predictive power. In short, the trade-off between the size of the lender's market and the performance of their portfolios becomes less steep.

Although it is difficult to predict the market outcome, the types of trade-offs that credit issuers face with full reporting of utility and telecommunications trades are illustrated in Tables 5.6 and 5.7. Although the data in the tables are based on the VantageScore model, results for the other models are generally similar and are presented in Appendix B. As before, we have assumed that lenders would put consumers who cannot be scored in the highest-risk category.[30] This assumes that the unscoreable population is essentially excluded from consideration (given that they are put at the bottom of the risk distribution) but nonetheless count as potential borrowers/consumers (their presence is felt in the numerator of the acceptance rate).

Table 5.6 shows how the performance associated with a given acceptance rate could improve with the addition of utility and telecommunications data.[31] For example, suppose that a credit issuer wished to maintain an acceptance rate of about 50 percent, a rate that is more or less in line with the current acceptance rates among credit card issuers. With this target acceptance rate, serious delinquencies would fall by about 22 percent (from 2.3 to 1.8 percent) with the

Table 5.6. Serious Delinquencies by Target Acceptance Rates: VantageScore Model

	Consumers with Utility Trades		Consumers with Telecom-Telecommunications Trades	
Acceptance Rate	Including Utilities (#1)	Excluding Utilities (#2)	Including Telecoms-Telecommunications	Excluding Telecoms-Telecommunications
30%	0.90%	1.10%	1.10%	1.30%
40%	1.20%	1.50%	1.70%	2.20%
50%	1.80%	2.30%	3.30%	4.60%
60%	3.00%	4.20%	7.40%	10.10%
70%	5.40%	8.10%	12.40%	16.20%
80%	9.50%	13.80%	15.90%	20.90%
90%	13.80%	17.70%	18.20%	21.60%

addition of utility data, and by about 28 percent (from 4.6 to 3.3 percent) with the full reporting of telecommunications accounts. In a highly competitive market, the savings associated with these declines would ultimately be passed through to consumers in the form of lower rates.

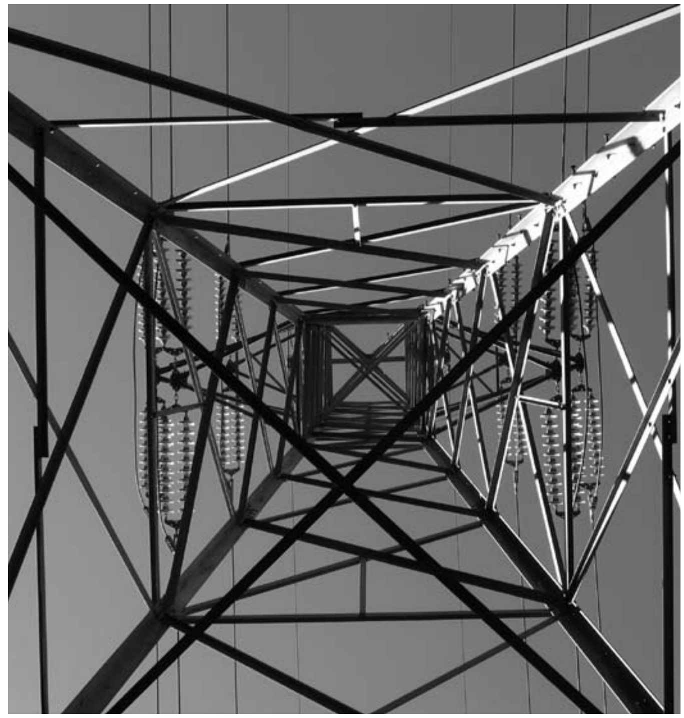


Table 5.7 takes the opposite perspective, and shows what would happen to acceptance rates if issuers wished to maintain their current level of risk (as measured by the incidence of serious delinquencies) and expand their business base. For example, acceptance rates could rise from 54.9 to 60.4 percent with the addition of utility data using a targeted delinquency rate of about 3 percent—the approximate average for credit cards. With the addition of the telecommunications data, acceptance rates could rise from about 44.9 to 49.0 percent without increasing projected losses.

As noted earlier, many credit issuers attempt to create alternative credit histories for thin-file borrowers by turning to non-traditional credit sources. As a result, the findings presented in Tables 5.3 and 5.4 may tend to overestimate the actual impact on acceptance rates, but they may do so only slightly. Nevertheless, our analysis clearly illustrates the potential impact of such reporting, and the value it can bring to underserved markets. ■

Table 5.7. Acceptance Rates by Targeted Delinquency Rates: VantageScore Model

	Consumers with Utility Trades		Consumers with Telecom Trades	
Delinquency Rate %	**Including Utilities (#1)**	**Excluding Utilities (#2)**	**Including Telecoms (#1)**	**Excluding Telecoms (#2)**
2	52.4	47.2	43.4	38.8
3	60.4	54.9	49.0	44.9
4	65.4	59.6	52.6	48.4
5	69.1	63.1	55.3	51.0
6	72.0	65.7	57.4	53.3
7	74.5	67.9	59.4	55.0

VI. DEMOGRAPHIC IMPACTS

Figure 6.1 shows how changes in acceptance rates would vary across different demographic groups[32] assuming that the risk tolerance of lenders remains the same. To simplify the presentation, we again present our results for just one model—the VantageScore model— and use a "targeted" delinquency rate (3 percent) that approximates the average for credit cards. However, as before, the results are much the same when other models or risk cut-offs are used.[33]

In general, minorities, lower-income groups, and younger (18 to 25 years old) and older (66+ years) consumers are most affected by the addition of utility and telecommunications data. Again, although the results are roughly similar for the utility and telecommunications trades, the largest impact is associated with the addition of the utility data. The addition of the utility trades would increase acceptance rates for both black and Hispanic borrowers by about 21 percent, more than twice the increase observed for whites (see Figure 6.1a). Likewise, acceptance rates would rise by about 25 percent for consumers earning less than $20,000 per year (see Figure 6.1b), by about 13 percent for consumers under the age of 25, and by 14 percent for those over age 65 (see Figure 6.1c). We were curious whether the 65+ group was evidence of "widow effect," where a widow is left with little credit history because bills had been in her husband's name. We did not, however, find any difference by gender.

Figure 6.1. Impact on Acceptance Rates by Demographic Group:

(assumes 3 percent serious delinquency rate)

Figure 6.1a Consumers by Race with Utility Trades (Assumes 3 percent Serious Delinquency Rate)

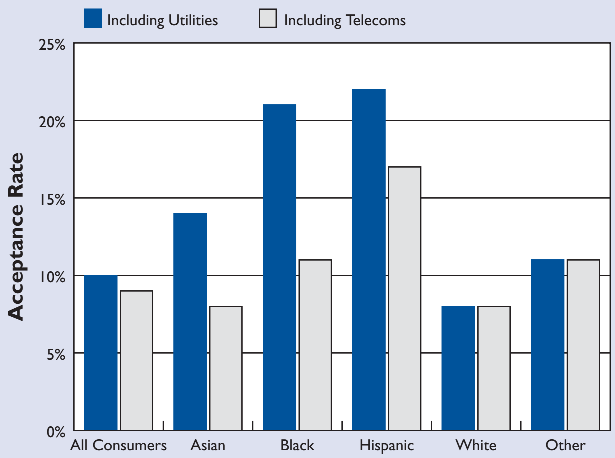


Figure 6.1c Consumers by Age with Utility and Telecom Trades (Assumes 3 percent Serious Delinquency Rate)

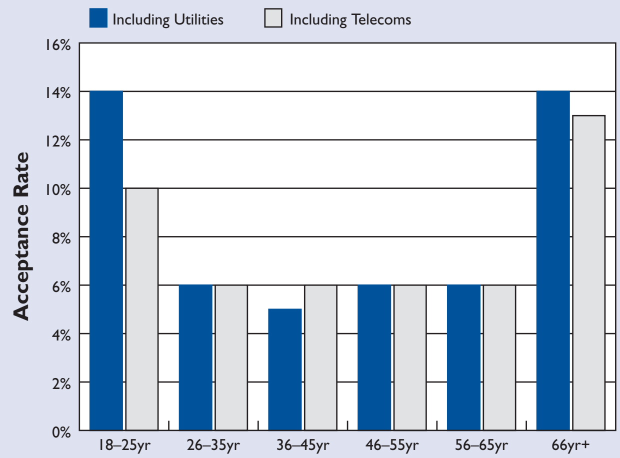


Figure 6.1b Consumers by Income with Utility Trades (Assumes 3 percent Serious Delinquency Rate)

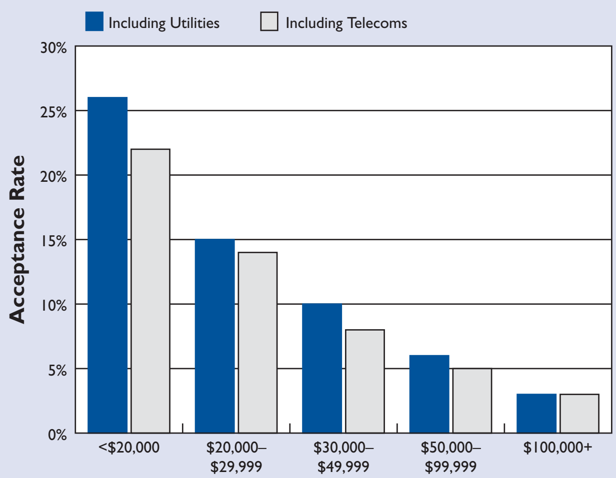


Figure 6.1d Consumers by Homeowner Status with Utility and Telecom Trades (Assumes 3 percent Serious Delinquency Rate)

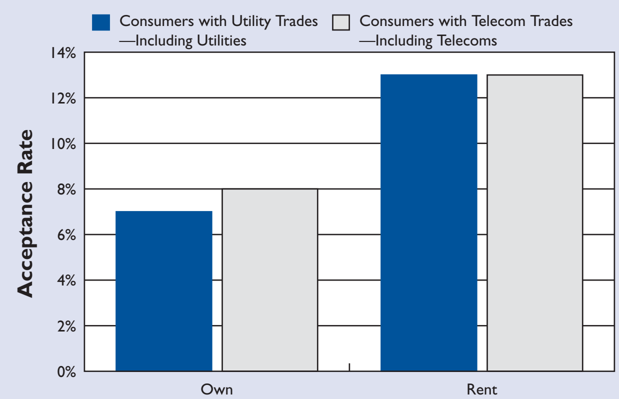
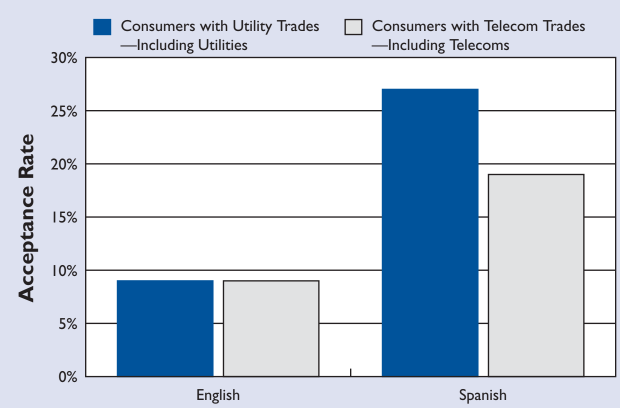


Figure 6.1e Consumers by Language Preference with Utility and Telecom Trades (Assumes 3 percent Serious Delinquency Rate)



Source: March 31, 2005 Credit Files for Analysis sample.

Table 6.2. Reported Trades by Borrower Characteristics

	Consumers with Utility Trades			Consumers with Telecom Trades		
	<3 traditional trades (%)	Mean Number of Trades	Utilities as Percent of Total Trades	<3 traditional trades (%)	Mean Number of Trades	Telecoms as Percent of Total Trades
All	17%	17.32	9%	23%	15.04	7%
Race						
Asian	20%	17.02	8%	18%	17.54	6%
Black	28%	12.46	11%	48%	7.91	13%
Hispanic	32%	13.24	11%	40%	10.16	11%
Other	16%	18.12	9%	20%	16.21	7%
White	14%	18.35	9%	19%	16.21	7%
Gender						
F	14%	18.19	9%	22%	15.33	7%
M	12%	18.44	9%	16%	16.74	7%
Age						
18–25	24%	11.11	13%	36%	8.88	12%
26–35	10%	19.19	9%	18%	16.29	7%
36–45	9%	21.57	8%	13%	18.85	6%
46–55	9%	20.81	8%	12%	19.21	6%
56–65	8%	20.19	8%	10%	19.39	6%
66+	18%	13.43	11%	18%	13.25	8%
Income						
<$20,000	31%	11.01	14%	38%	9.13	12%
$20,000–29,999	20%	13.92	11%	24%	12.49	9%
$30,000–$49,999	13%	16.88	9%	16%	15.51	7%
$50,000–$99,999	7%	20.89	8%	8%	20.54	5%
$100,000+	4%	24.22	7%	4%	24.24	5%

"Minorities, lower-income consumers, and the young and the old are more likely to be thin-file borrowers."

Renters, who presumably are less in the financial mainstream than homeowners, saw their acceptance increase at nearly twice rate as homeowners with the addition of the utility data. Renters may also find improving their credit files particularly important if they hope to become eventual homeowners.

Finally, language preference reveals that those who prefer Spanish as their primary language experience a 27 percent increase in their acceptance with the addition of the alternative data. This is probably a better measure than ethnicity of the underserved immigrant population from Latin America. Although similar patterns for all conditions are observed for the telecommunications data, the estimated impact were not as large.

Differences in the estimated impact on different demographic groups reflect differences in their underlying credit profiles. As shown in Table 6.2, minorities, lower-income consumers, and the young and the old are more likely to be thin-file borrowers. As a result, the addition of utility and telecommunications trades to their credit records will have a larger effect on their overall credit profiles. ■

VII. SUMMARY AND POLICY IMPLICATIONS

The results of our analysis lend strong support to the suggestion that the systematic reporting of telecommunications and utility trades would benefit consumers and increase their access to low-cost credit. Assuming that our sample is reasonably representative of all consumers with such trades, the impact is likely to be large.

The primary effect of fully reporting energy utility and telecommunications data appears to be on the number of consumers who could be scored. Based on the tri-bureau VantageScore model, the percentage of unscoreable consumers would decline from 13 percent to 2 percent when adding utility data. Likewise, adding telecommunications data reduces the number of unscoreable consumers from about 17 percent to 1 percent.

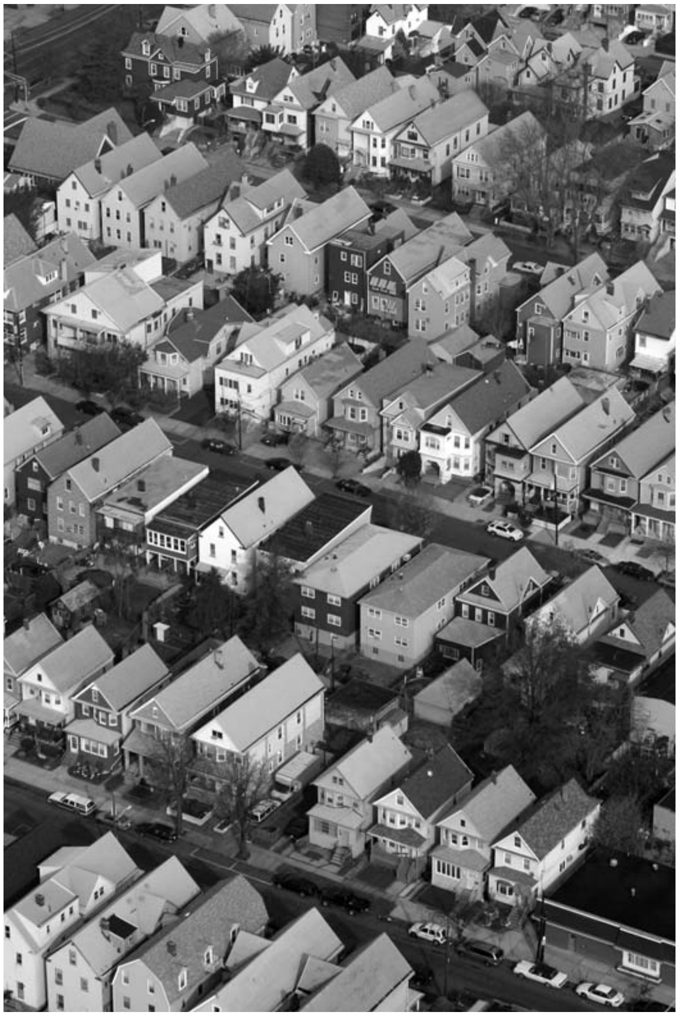
Scoring models and credit scores are relatively unaffected by additional information on utility and telecommunications trades for consumers who can be scored without them. In other words, for consumers with a relatively thick credit files, the addition of these trade lines has little, if any, effect—either positive or negative—on their credit scores or their access to credit. As a result, it seems safe to assert that relatively few consumers would be harmed by the full reporting of such data.

In contrast, the impact on otherwise unscoreable consumers would be significant. For example, based on the VantageScore model, we estimate that overall acceptance rates could rise by as much as 10 percent with the full reporting of utility and telecommunications trades. Significantly larger gains would go to minorities, low-income groups, and consumers at the two extremes of the age continuum—the relatively young (18 to 25 years) and the relatively old (over 65).

ENCOURAGING ALTERNATIVE DATA REPORTING

In our view, these findings provide a strong public policy rationale for encouraging the full reporting of utility and telecommunications payment data to consumer reporting agencies. The net result of full reporting should be positive for consumers and business alike. Thin-file consumers would stand to gain by having a more accurate assessment of their credit-worthiness, and credit issuers would stand to gain by enhancing their ability to expand their markets without a concurrent increase in risk.

PERC surveyed the members of the National Association of Regulated Utility Commissions (NARUC) in 2005, and identified four states where the transfer of customer data to third parties was statutorily prohibited. Although these laws were written with other concerns in mind—in most cases they are privacy rules—they clearly preclude sharing customer data with consumer reporting agencies (CRAs). We believe that lawmakers in those states should carefully review those laws in light of the findings reported here. Any privacy concerns should be carefully weighed against the demonstrated social and economic



benefits. Specifically, we encourage state lawmakers in those few states to carve out an exemption in existing law for reporting payment data—not detailed account information such as customer proprietary network information or CPNI—to accredited consumer reporting agencies.

The NARUC survey identified regulatory uncertainty as the primary policy barrier to sharing energy utility and telecommunications data with CRAs. Given that the majority of states have no law on the books either precluding or permitting data sharing with CRAs, and given an environment of heightened sensitivity to data privacy and data security concerns, regulators are unwilling to provide energy utility and telecommunications firms with explicit permission (especially written permission) to share customer payment data with CRAs. In fact, in some cases, despite the absence of a statutory prohibition, some regulators have told inquiring energy utility and telecommunications firms that they were not permitted to share customer payment data with CRAs. In these states, we advocate the passage of a law clearly permitting the sharing of customer data with CRAs.

PRESERVE VOLUNTARY REPORTING

When considering data-sharing legislation, it is important to preserve the voluntary nature of the national credit reporting system. Mandating the reporting of energy utility, telecommunications, or other alternative data will result in a radical and disruptive paradigm change to the world's most successful credit reporting regime. The decision of any energy or telecommunications providers to become a "full file reporter" must ultimately be driven by a combination of each firm's self-interest (in reducing account delinquencies)[34] and by the understanding that doing so helps to promote access to mainstream credit markets for previously underserved groups.

Interestingly, for years, energy utility and telecommunications firms have been major consumers of credit reports from the big three national credit bureaus. Most of these firms, however, either report only negative information (delinquencies, defaults, and collections), or do not report at all. Such an imbalance in using payment history information, but not contributing to it, is particularly costly to those consumers who have no traditional payment histories, given that they will be building no positive payment histories by using the utility or telecommunications services, and they will likely be charged a relatively high deposit because they have no payment history. For some uses of consumer credit files, such as for marketing and prescreening lists, there is a principle of reciprocity, where companies wishing to use the information must have contributed to it. But these benefits may hold little value to entities, such as utilities, that provide services typically considered necessities and often face little or no competition.

Nonetheless, as the value of consumer payment data from nontraditional sources becomes more evident, efficient market responses may emerge by data aggregators and credit bureaus to bring the nontraditional data online. As potential furnishers of nontraditional data realize how providing payment data not only helps their bottom line, but also their customers, they will likely become more interested in supplying payment data. However, these market responses can happen when statutory prohibitions are removed or amended, and more important, when regulatory and legislative uncertainties surrounding the transfer of such data are cleared up.

Without sufficient credit history, it is impossible to begin the process of asset building and wealth creation.

REPORTING ENHANCES DEVELOPMENT OF COMMUNITIES

The sociodemographic analysis of the thin-file and unscoreable population confirmed beliefs about the characteristics of this group. It is composed largely of members of ethnic minorities, many of whom are economically disadvantaged and are recent immigrants. Many of these individuals reside in "domestic emerging markets"—urban markets and poorer, industrial and rural areas. For those living in such areas, the ability to improve one's life often depends on access to credit. Without sufficient credit history, it is impossible to purchase a car for traveling to work, to secure a student loan for the college of choice, to secure a home mortgage loan or a small business loan to begin the process of asset building and wealth creation.

A recent study analyzed credit scores, credit use, and delinquency patterns for low- to moderate-income individuals (LMIs) for 50 metropolitan areas.[35] Key findings from this analysis of more than 14 million partial credit files during a one-year period indicate high variance across metropolitan areas in credit use, score distribution, and credit management. Most relevant for this study was the finding that the portion of borrowers with extremely weak credit scores (scores lower than 75 percent of the total population) was considerably higher in urban markets than the national average. For low- to moderate-income persons in urban areas, nearly 41 percent have credit scores in the bottom quarter for the nation. Given the concentration of LMI households in most urban areas, and the prevalence of automated underwriting among mainstream lenders, this translates to a substantial barrier to accessing affordable capital to build assets in these urban markets.

The results from this study offer great promise for community development in domestic emerging markets, especially in urban areas. Not only are the credit scores of a majority of thin-file and unscoreable Americans improved by using alternative data, but credit access for LMI borrowers is dramatically improved. Thin-file borrowers with one or more alternative trade lines in their credit files accessed capital at four times the rate of thin-file borrowers without any alternative trade lines. In short, preliminary evidence strongly suggests that using alternative data in consumer credit reports makes a difference in credit access and fairness in lending. Enhanced access to affordable, mainstream credit—albeit just one part of the solution—can greatly assist with the economic development of urban markets.

Given the size of this population, and its risk profile when alternative data are considered, in an environment of pervasive alternative data reporting everything changes. First, if—and this is a big if—alternative data are reported in sufficient quantity in the near term (currently, a small but growing minority of energy utility and telecommunications firms fully report customer payment data to one or more credit bureaus), then credit bureaus, analytics firms, and lenders will have the data necessary to build new alternative scoring models or optimize existing scoring models. In short, lenders will have the tools to process the newly available information to make credit decisions. Empowered with new tools and information, lenders can profitably expand into previously overlooked markets—markets that may even become competitive.

Perhaps most important, millions of credit-worthy borrowers in urban areas who previously had to rely on check-cashing, payday lenders, or other predatory lenders can gain access to affordable mainstream credit. The miracle of instant credit can palpably affect the lives and life chances of millions, making possible the dream of homeownership and the ability to secure a secure a small business loan to launch a new enterprise, two avenues for asset-building. In an environment of pervasive alternative data reporting, the landscape of consumer banking in urban areas should fundamentally change to the benefit of those who live there. This, in turn, can have deep and systematic affects on community development and asset-building, resulting in improved opportunity and quality of life. ■

VIII. FUTURE RESEARCH DIRECTIONS

Evidence presented in this study supports the use of alternative data as one means to help bridge the credit information gap for millions of thin-file and unscoreable Americans. Although alternative data can be held out as a promising potential solution to the problem of too little credit information, it is not an easy solution.

First, there is a chicken-and-egg quality to alternative data. That is, consumer reporting agencies are not actively exhorting energy utility and telecommunications firms to fully report data because their major clients—large financial institutions—are not demanding alternative data and alternative scoring models. Lenders are not demanding alternative data and alternative scoring models because so little alternative data is fully reported. By one estimate, just under 5 percent of all credit files have one or more alternative trade lines, and alternative data composes less than 1 percent of all trade lines in a major credit bureau's database.

There does appear to be interest in using alternative payment data in the market. One example is Payment Reporting Builds Credit (PRBC), which uses self-reported (but verified) alternative payment information, thus sidestepping legal and regulatory barriers and accessing payment information not in standard credit reports. However, the advantage of this model (self-reported data) also likely limits its impact in bringing useful alternative data online.[36] Fair Isaac's Expansion Score and First American's Anthem model are scoring models specifically designed to use alternative payment data. These two models rely on data from niche aggregators, and remain somewhat of a black box. However, that a small number of important lenders are beginning to use them in credit decision suggests that a demand for alternative scoring models exists. Demand will likely grow as more alternative data come online. For instance, while the reporting of utility and telecommunications payments is far from pervasive, the TransUnion database nonetheless had more than 8 million consumer files with at least one alternative payment reported for at least a year as of March 2005, making this study possible.

It is clear, however, that much more needs to be done to jump-start a cycle of alternative data use and reporting, leading to its broad use. Data furnishers—in this case utility and telecommunications companies—must be convinced that reporting data to CRAs, and assuming Fair Credit Reporting Act data furnisher obligations, is in their best interest. Anecdotal evidence suggests that fully reporting customer data to credit bureaus, and consistently communicating the benefits of reporting to customers, can lead to a dramatic reduction in delinquencies and charge-offs. At a 2005 Brookings Urban Markets Initiative roundtable on alternative data and credit scoring, WE Energies and Verizon stated that fully reporting customer data, directly or in part, led to a substantial reduction in delinquencies.[37] Similarly, Nicor Gas reported a 20 percent reduction in delinquencies one year after it began fully reporting customer data to TransUnion.[38]

A systematic survey of energy utility and telecommunications firms on their experience reporting data to consumer reporting agencies could identify hurdles to reporting. From a policy perspective, the results of such a survey and analysis could serve as the basis for a national outreach program to expedite an environment in which alternative data are pervasively reported. Such an outcome could go a long way toward helping untold millions of thin-file and unscoreable Americans build assets and create wealth in a sustainable fashion. ■

Data furnishers—in this case utility and telecommunications companies—must be convinced that reporting data to credit reporting agencies, assuming Fair Credit Reporting Act guidelines, is in their best interest.

APPENDIX A. SAMPLE CHARACTERISTICS

This appendix compares the characteristics of the analysis file with the characteristics of the validation sample. Table A1 compares the demographic characteristics of the consumers in each sample. Table A2 compares their credit profiles excluding their utility and telecommunications trades. Table A3 presents the distribution of the samples by state. In presenting the statistics on the analysis file, consumers with utility trades are distinguished from those with telecommunications trades. Although there is a small overlap between the two groups, they are essentially separate groups and have been treated as such throughout this report.

DEMOGRAPHIC DIFFERENCES

Table A1 compares the samples based on the race, gender, age and income of the consumer. In general, the three population groups look remarkably similar. While consumers with telecommunications trades tend to have somewhat lower incomes and a higher proportion of males compared to validation sample, their other characteristics are about the same. Likewise, consumers with utility trades tend to have a higher proportion of males, a lower proportion of Hispanics and a higher proportion of blacks than the population at large (as measured by the validation sample), but again, these differences are not pronounced.

CREDIT DIFFERENCES

Table A2 compares the characteristics of the samples on the basis of credit profiles of consumers. In making these comparisons, we removed the utility and telecommunications trade lines from the credit reports of consumers contained in the analysis file. Removing these trade lines enabled us to compare the different samples on an "apples to apples" basis, and assess the extent to our analysis file is representative of the broader population of consumers in terms of their underlying credit profiles.

Again, the three population groups look fairly similar, although some different differences can be observed. In general, consumers with either a utility or telecommunications trades have somewhat stronger credit profiles than the general population as measured by their total number of trades (excluding utilities and telecommunications) as well as their credit scores. Although the differences are relatively modest for consumers with telecommunications trades, they are more pronounced for consumers with a reported utility. This pattern is not surprising given that the latter primarily reflect household heads or individuals living on their own.

Appendix Table A1. Distribution of Samples by Demographic Characteristics

	Consumers with Utility Trades (%)	Consumers with Telecommunications Trades (%)	Validation Sample (%)
Race			
Asian	3.6%	1.7%	4.2%
Black	8.5	5.8	6.3
Hispanic	8.9	11.7	12.1
Other	11.9	10.2	9.5
White	67.1	70.6	68.0
Total	100.0	100.0	100.0
Gender			
F	40.8	46.8	50.4
M	59.2	53.2	49.6
Total	100.0	100.0	100.0
Age			
18–25	1.7	2.3	2.6
26–35	15.5	16.8	14.3
36–45	23.4	24.4	21.3
46–55	24.5	24.1	25.3
56–65	16.1	15.3	17.2
66+	18.8	17.1	19.1
Total	100.0	100.0	100.0
Income			
<$20,000	17.8	25.3	18.6
$20,000–$29,999	9.0	11.5	10.1
$30,000–$49,999	18.9	20.3	20.0
$50,000–$99,999	36.5	30.7	34.0
$100,000+	17.8	12.3	17.3
Total	100.0	100.0	100.0
Sample Size	7,519,020	590,795	3,985,525

GEOGRAPHIC DIFFERENCES

Table A3 presents the distribution of the three population groups by state. As expected, the samples are not representative in terms of their geographic location. Consumers with utility trades are concentrated in Illinois (44 percent), Pennsylvania (16 percent) and Wisconsin (24 percent.) The telecommunications sample is also primarily in Pennsylvania (69 percent) and Texas (13 percent).

Appendix Table A2. Distribution of Samples by Credit Profiles of Consumer: Excluding All Utility and Telecommunications Trades

	Consumers with Utility Trades (%)	Consumers with Telecommunications Trades (%)	Validation Sample (%)
% Distribution by No. of Traditional Trades			
0	9.6	14.0	13.1
1	4.0	4.9	13.9
2	3.4	4.1	5.5
3	3.2	3.7	3.9
4	3.1	3.5	3.4
5	3.1	3.3	3.2
6	3.1	3.2	3.0
7+	70.5	63.3	53.9
All Consumers	100	100	100
% Distribution by VantageScore[a]			
851+	27.3	21.9	20.6
801–850	10.6	8.0	9.4
741–800	10.1	7.7	11.2
681–740	10.9	8.6	12.3
621–680	9.7	9.4	9.4
561–620	10.1	12.9	9.0
501–560	8.7	14.6	6.7
No Score	12.6	16.9	21.4
All Consumers	100	100	100
Sample Size	7,519,020	590,795	3,985,522

a The score was obtained by removing the utility and telecommunications trades from the consumer's credit files

Appendix Table A3. Distribution of Samples by State

State	Consumers with Utility Trades (%)	Consumers with Telecommunications Trades (%)	Validation Sample (%)
Alabama	0.1	0.1	1.6
Alaska	0.0	0.0	0.2
Arizona	2.4	0.2	2.0
Arkansas	0.1	1.4	1.0
California	0.7	0.8	12.7
Colorado	0.2	0.2	1.7
Connecticut	3.6	0.1	1.1
Delaware	0.0	0.1	0.3
DC	0.0	0.0	0.2
Florida	1.0	1.2	6.6
Georgia	0.3	0.4	2.9
Hawaii	0.0	0.0	0.4
Idaho	0.0	0.0	0.4
Illinois	44.6	0.3	3.3
Indiana	0.4	0.9	2.1
Iowa	0.6	0.0	1.0
Kansas	0.1	1.5	1.0
Kentucky	0.1	0.1	1.4
Louisiana	0.1	0.1	1.6
Maine	0.0	0.0	0.5
Maryland	0.2	0.4	1.9
Massachusetts	0.1	0.2	2.0
Michigan	0.7	2.7	3.5
Minnesota	0.8	0.1	1.7
Mississippi	0.1	0.1	1.0
Missouri	0.2	1.9	2.0
Montana	0.0	0.0	0.3
Nebraska	0.0	0.0	0.6
Nevada	0.2	0.1	0.9
New Hampshire	0.0	0.0	0.4
New Jersey	0.2	0.7	2.9
New Mexico	0.1	0.1	0.6
New York	0.3	0.7	6.3
North Carolina	0.3	0.3	3.0
North Dakota	0.0	0.0	0.2
Ohio	0.4	1.3	3.9
Oklahoma	0.1	0.5	1.3
Oregon	0.1	0.1	1.3
Pennsylvania	15.9	68.7	3.7
Rhode Island	0.0	0.0	0.3
South Carolina	1.1	0.1	1.4
South Dakota	0.0	0.0	0.2
Tennessee	0.2	0.1	2.0
Texas	0.6	12.6	8.2
Utah	0.0	0.0	0.8
Vermont	0.0	0.0	0.2
Virginia	0.2	0.3	2.5
Washington	0.2	0.1	2.3
West Virginia	0.1	0.0	0.6
Wisconsin	23.5	1.3	1.3
Wyoming	0.0	0.0	0.2
No Data	0.0	0.0	0.2
Sample Size	7,519,020	590,795	3,985,522

APPENDIX B. DETAILED MODEL RESULTS

Appendix Table B1. Serious Delinquencies by Target Acceptance Rates: VantageScore, Excluding Unscoreables

	Consumers with Utility Trades		Consumers with Telecom Trades	
Acceptance Rate	Including Utilities (#1) (%)	Excluding Utilities (#2) (%)	Including Telecom (#1) (%)	Excluding Telecom (#2) (%)
30	0.9	1.0	0.9	1.1
40	1.1	1.3	1.3	1.5
50	1.5	1.7	2.2	2.4
60	2.4	2.7	4.4	4.7
70	4.2	4.5	9.1	9.1
80	7.8	8.1	14.7	14.5
90	12.9	13.1	18.9	18.8

Source: PERC

Appendix Table B2. Acceptance Rates by Targeted Delinquency Rates: VantageScore, Excluding Unscoreables

	Consumers with Utility Trades		Consumers with Telecom Trades	
Acceptance Rate	Including Utilities (#1) (%)	Excluding Utilities (#2) (%)	Including Telecom (#1) (%)	Excluding Telecom (#2) (%)
2	56.6	53.9	48.3	46.4
3	64.4	62.7	54.8	53.7
4	69.5	68.1	58.8	57.8
5	72.9	72.0	61.8	61.0
6	75.9	75.0	64.2	63.7
7	78.3	77.5	66.3	65.8

Source: PERC

Appendix Table B3. Serious Delinquencies by Target Acceptance Rates: TransRisk New Account Model

	Consumers with Utility Trades		Consumers with Telecom Trades	
Acceptance Rate (%)	All Trade (%)	Excluding Utility Trades (%)	All Trades (%)	Excluding Telecom Trades (%)
All				
30	0.9	1.1	1.2	1.3
40	1.2	1.5	1.8	2.1
50	1.9	2.3	3.8	4.6
60	3.5	4.1	7.9	10.1
70	5.9	7.9	10.8	15.9
80	9.5	13.2	14.8	20.5
90	13.7	17.6	17.9	21.9
Excluding Unscoreables				
30	0.9	1.0	1.0	1.1
40	1.1	1.3	1.3	1.5
50	1.5	1.8	2.2	2.5
60	2.4	2.7	4.9	5.0
70	4.4	4.7	9.7	9.7
80	8.2	8.4	14.8	14.7
90	13.1	13.2	19.3	19.0

Source: PERC

Appendix Table B4. Acceptance Rates by Targeted Delinquency Rates: TransRisk New Account Model

	Consumers with Utility Trades		Consumers with Telecom Trades	
Delinquency Rate	All Trade	Excluding Utility Trades	All Trades	Excluding Telecom Trades
All				
2	50.7	47.2	41.2	38.8
3	57.3	55.0	45.9	44.7
4	62.5	59.7	50.6	48.4
5	66.4	62.9	53.5	50.8
6	70.6	65.8	56.0	53.0
7	73.3	68.1	58.1	54.8
Excluding Unscoreables				
2	56.8	53.2	48.5	45.7
3	64.0	61.9	54.1	52.7
4	68.5	67.2	57.7	57.1
5	71.6	70.8	60.1	59.9
6	74.5	74.0	62.6	62.5
7	77.0	76.5	64.6	64.7

Source: PERC

Appendix Table B5. Bankruptcies by Target Acceptance Rates: TransRisk Bankruptcy Model				
	Consumers with Utility Trades		Consumers with Telecom Trades	
Acceptance Rate (%)	All Trades (%)	Excluding Utility Trades (%)	All Trades (%)	Excluding Telecom Trades (%)
30	0.07	0.06	0.07	0.07
40	0.07	0.06	0.07	0.11
50	0.08	0.09	0.14	0.25
60	0.12	0.19	0.25	0.52
70	0.21	0.38	0.41	0.83
80	0.38	0.74	0.60	1.44
90	0.69	1.28	1.02	1.76
	Excluding Unscoreables			
30	0.06	0.06	0.06	0.07
40	0.06	0.06	0.06	0.07
50	0.07	0.07	0.12	0.13
60	0.11	0.11	0.28	0.27
70	0.21	0.22	0.52	0.50
80	0.41	0.41	0.75	0.75
90	0.70	0.74	1.17	1.18

Source: PERC

Appendix Table B6. Acceptance Rates by Targeted Bankruptcy Rates: TransRisk Bankruptcy Model				
	Consumers with Utility Trades		Consumers with Telecom Trades	
Bankruptcy Rate (%)	All Trade (%)	Excluding Utility Trades (%)	All Trades (%)	Excluding Telecom Trades (%)
0.25	72.7	63.9	60.6	50.0
0.50	85.0	74.3	74.4	59.1
0.75	90.9	80.0	84.5	67.6
1.00	96.3	84.4	88.7	73.1
	Excluding Unscoreables			
0.25	72.1	71.9	58.3	58.9
0.50	83.7	83.5	68.8	69.7
0.75	90.3	90.0	79.5	79.7
1.00	94.8	94.9	86.0	86.2

Source: PERC

Appendix Table B7. Bankruptcy Rates by Target Acceptance Rates: Bankruptcy Model II

	Consumers with Utility Trades		Consumers with Telecom Trades	
Acceptance Rate (%)	All Trades (%)	Excluding Utility Trades (%)	All Trades (%)	Excluding Telecoms Trades (%)
30	0.03	0.03	0.04	0.05
40	0.06	0.06	0.07	0.12
50	0.08	0.11	0.12	0.25
60	0.14	0.21	0.22	0.47
70	0.23	0.39	0.37	0.76
80	0.40	0.69	0.56	1.23
90	0.70	1.29	0.90	1.76
Excluding Unscoreables				
30	0.03	0.03	0.03	0.03
40	0.04	0.04	0.06	0.06
50	0.07	0.07	0.14	0.15
60	0.13	0.13	0.28	0.27
70	0.23	0.24	0.45	0.46
80	0.39	0.40	0.67	0.68
90	0.64	0.66	1.00	1.03

Source: PERC

Appendix Table B8. Acceptance Rates by Targeted Bankruptcy Rates: Bankruptcy Model II

	Consumers with Utility Trades		Consumers with Telecom Trades	
Bankruptcy Rate (%)	All Trades (%)	Excluding Utility Trades (%)	All Trades (%)	Excluding Telecoms Trades (%)
0.25	71	62	62	50
0.50	84	74	77	61
0.75	91	81	86	70
1.00	95	86	92	76
Excluding Unscoreables				
0.25	72	71	58	59
0.50	85	84	73	72
0.75	93	92	83	82
1.00	97	97	90	89

Source: PERC

Appendix Table B9. Impact on Acceptance Rates by Demographic Group (TransRisk New Account): (Assumes 3% Serious Delinquency Rate)

	Consumers with Utility Trades		Consumers with Telecom Trades	
	Including Utilities (#1)	Excluding Utilities (#2)	Including Telecoms (#1)	Excluding Telecoms (#2)
All Consumers	1.04	1.00	1.03	1.00
Race				
Asian	1.05	1.00	1.02	1.00
Black	1.06	1.00	1.02	1.00
Hispanic	1.08	1.00	1.03	1.00
Other	1.04	1.00	1.03	1.00
White	1.04	1.00	1.03	1.00
Gender				
F	1.04	1.00	1.03	1.00
M	1.04	1.00	1.03	1.00
Age				
18–25	1.08	1.00	1.04	1.00
26–35	1.03	1.00	1.02	1.00
36–45	1.03	1.00	1.02	1.00
46–55	1.03	1.00	1.02	1.00
56–65	1.03	1.00	1.02	1.00
66+	1.05	1.00	1.04	1.00
Income				
<$20,000	1.09	1.00	1.07	1.00
$20,000–$29,999	1.06	1.00	1.05	1.00
$30,000–$49,999	1.05	1.00	1.03	1.00
$50,000–$99,999	1.03	1.00	1.02	1.00
$100,000+	1.02	1.00	1.01	1.00

Source: January 31, 2005 Credit Files for Analysis sample

Appendix Table B10. Impact on Acceptance Rates by Demographic Group (TransRisk Bankruptcy): (Assumes 0.25% Bankruptcy Rate)

	Consumers with Utility Trades		Consumers with Telecom Trades	
	Including Utilities (#1)	Excluding Utilities (#2)	Including Telecoms (#1)	Excluding Telecoms (#2)
All Consumers	1.14	1.00	1.21	1.00
Race				
Asian	1.19	1.00	1.17	1.00
Black	1.39	1.00	2.67	1.00
Hispanic	1.43	1.00	1.70	1.00
Other	1.12	1.00	1.18	1.00
White	1.10	1.00	1.16	1.00
Gender				
F	1.09	1.00	1.18	1.00
M	1.08	1.00	1.11	1.00
Age				
18–25	1.17	1.00	1.36	1.00
26–35	1.07	1.00	1.13	1.00
36–45	1.06	1.00	1.09	1.00
46–55	1.06	1.00	1.08	1.00
56–65	1.06	1.00	1.07	1.00
66+	1.12	1.00	1.12	1.00
Income				
<$20,000	1.32	1.00	1.51	1.00
$20,000–$29,999	1.16	1.00	1.24	1.00
$30,000–$49,999	1.09	1.00	1.13	1.00
$50,000–$99,999	1.05	1.00	1.06	1.00
$100,000+	1.02	1.00	1.03	1.00

Appendix Table B11. Impact on Acceptance Rates by Demographic Group (Bankruptcy Model II): (Assumes 0.25% Bankruptcy Rate)

	Consumers with Utility Trades		Consumers with Telecom Trades	
	Including Utilities (#1)	Excluding Utilities (#2)	Including Telecoms (#1)	Excluding Telecoms (#2)
All Consumers	1.14	1.00	1.25	1.00
Race				
Asian	1.18	1.00	1.21	1.00
Black	1.32	1.00	2.40	1.00
Hispanic	1.36	1.00	1.69	1.00
Other	1.13	1.00	1.21	1.00
White	1.10	1.00	1.19	1.00
Gender				
F	1.10	1.00	1.24	1.00
M	1.09	1.00	1.14	1.00
Age				
18–25	1.19	1.00	1.58	1.00
26–35	1.08	1.00	1.19	1.00
36–45	1.06	1.00	1.12	1.00
46–55	1.07	1.00	1.10	1.00
56–65	1.07	1.00	1.09	1.00
66+	1.13	1.00	1.14	1.00
Income				
<$20,000	1.29	1.00	1.54	1.00
$20,000–$29,999	1.16	1.00	1.27	1.00
$30,000–$49,999	1.10	1.00	1.17	1.00
$50,000–$99,999	1.06	1.00	1.07	1.00
$100,000+	1.03	1.00	1.04	1.00

Source: PERC

ENDNOTES

1. See Michael Turner, et al., *The Fair Credit Reporting Act: Access, Efficiency and Opportunity.* (Washington, DC: The National Chamber Foundation, June 2003), available at **http://www.infopolicy.org/pdf/fcra_report.pdf**

2. Such changes in the actual value of the scores are short-run effects of bringing new data online. Because the scores represent some probability of default, and the new data would change this probability for each score (consumers would be resorted), the scores would need to be rescaled so that a score of 700 before the addition of the new data meant the same thing as a score of 700 with the new data. To gauge the longer-term effects of bringing new data online, one should focus on the results that show that the addition of the new data helps to better sort consumers by risk. We find that better sorting leads to increased access to credit, particularly among low-income consumers, ethnic minorities, the young, and the old.

3. Pari Sabety and Virginia Carlson, "Using Information to Drive Change: New Ways of Moving Markets" (Washington: Brookings Institution, 2003).

4. Dana Nottingham opening keynote speech at the 2006 UMI Forum

5. Michael A. Turner, "Giving Underserved Consumers Better Access to the Credit System: The Promise of Non-traditional Data." Information Policy Institute. New York City. July 2005.

6. Credit providers and commercial scoring firms have also developed scoring models for thin-file borrowers. For example, Fair Isaacs & Co. (FICO) recently introduced a FICO Expansion Score using nontraditional credit data. According to Fair Isaacs, the score "can effectively predict risk for the growing number of U.S. consumers that fail to receive a traditional FICO score due to non-existent or 'thin' credit histories." Although FICO does not reveal the underlying drivers of its score, nontraditional credit data generally capture the consumer's performance on obligations such as rent-to-own agreements. For more information, see **www.fairisaac.com/fairisaac/solutions/FICO+Expansion+Score/Expansion+Score+Overview**.

7. *Giving Underserved Better Access to the Credit System: The Promise of Non-Traditional Data.* (New York: Information Policy Institute, July 2005)

8. This statistic is based on the credit records of approximately 4 million randomly selected consumers in the validation sample. See Appendix A. Since some consumers are not included in credit bureau files (e.g., they have no established credit and have never been reported by a collection agency), 13 percent is most likely a lower bound estimate.

9. TransUnion and financial institutions providing the scores did not conduct the demographic analysis, and do not have this sort of sociodemographic data in their credit files.

10. None of the models in this study has been optimized specifically for utility or telecommunications data, something that will undoubtedly occur as the reporting of such data increases. The models instead treat these trades as general trades.

11. Our approach was similar to one employed in an earlier Information Policy Institute study, which examined the impact of deleting certain types of derogatory data from consumers' credit files. See "The Fair Credit Reporting Act: Access, Efficiency, and Opportunity" (Washington: Information Policy Institute, June 2003).

12. TransRisk Bankruptcy model.

13. The mortgage screening model is based entirely on data found in the consumer's credit report and contains no information on the characteristics of the mortgage itself (e.g., loan-to-value ratio). It is used as an initial screen to process loans, as opposed to credit decision tool.

14. Although most scoring models use a 24-month performance period, we used a 12 month period to capture a larger number of consumers with an established telecommunications or utility trade at the beginning of the performance period (March 31, 2005.) The number of providers reporting such trades has increased significantly in the past two years, and we wanted to capture as many consumers as possible. Even so, because many wireless companies began reporting in mid- to late 2005, our sample will exclude many individuals who now have a reported utility or telecommunications trade.

15. Giving Underserved Better Access to the Credit System: The Promise of Nontraditional Data (New York: Information Policy Institute, July 2005), available online **www.infopolicy.org/pdf/nontrad.pdf**

16. The nonoptimized models do, generally, a better job separating the good risks from the bad risks with the inclusion of the alternative data. Therefore, we take this performance as the floor of what we should expect from models reoptimized for this data.

17. Some consumers have more than one reported utility or telecommunications trade. Although they are treated as a single category in Table 1, multiple utility or telecommunications accounts are reflected in the consumer's total number of trades.

18. Total number of trades includes both the number of alternative trades and traditional trades.

19. In order to be selected for our sample, a consumer had to have at least one fully reported utility or telecommunications trade. Thus, by definition, their current credit profiles (Columns 1 and 3 in Table 2) will include at least one reported trade line.

20. Ideally, any control sample would be restricted to consumers with an established, but unreported telecommunications or utility trade. However, it was impossible to determine the extent to which consumers in the validation sample have such accounts. If one assumes that consumers who have such accounts have stronger credit profiles than those who do not, our comparisons may overestimate the marginal impact of reporting utility and telecommunications trades.

21. See Michael Turner et al, The Fair Credit Reporting Act: Access, Efficiency & Opportunity Part II. (New York: The Information Policy Institute, September 2002), available at **www.infopolicy.org/pdf/institute_fcra_ptII.pdf**

22. The performance measure used to assess the accuracy of a given model was geared to the specific purpose of that model, although we limited the performance period to 12 months to capture as many consumers as possible in our analysis file. For example, the new account model is designed to predict the probability that a consumer will experience a 90-day delinquency on a new account over a two-year period. In assessing the impact on the model, we based our analysis on the occurrence of at least 90-day delinquency on a new account between April 1, 2005, and March 31, 2006. Likewise, our assessment of two bankruptcy models was based on the number of consumers who experienced a bankruptcy within the observation period. Thus, while our performance period differs, the performance measure used to assess the impact of the utility and the telecommunications trades on a given model was the same as that used to construct the model.

23. In general, increases of more than 10 percentage points in a model's K-S statistic are considered significant by model developers.

24. These calculations are based on subsamples consisting of individuals who had scores with and without the alternative data (utility or telecommunications trades). These subsamples, therefore, consisted of individuals with at least one traditional trade.

25. These sample sizes correspond to the VantageScore model since scoreablity differs across models.

26. These sample sizes correspond to the VantageScore model since scoreablity differs across models.

27. The lender also has screening models designed for refinancing, as well as for thin-file consumers and CRA loans. The results observed for these models are similar to those described in the text.

28. The p-values were less than .001.

29. Because the dependent variable is dichotomous, we also ran a logit regression and found that the goodness-of-fit of the models (Nagelkerke R-Squared) rose by 40 percent and 17 percent, respectively, with the addition of the alternative utilities and telecommunications data.

30. Results when the calculations are limited to consumers who can be scored with or without their utility and telecommunications trades are presented in Appendix B. In general, the marginal impact of the utility and telecommunications trades is considerably smaller when this restriction is imposed.

31. For a given acceptance rate, the rate of serious delinquencies that is observed for consumers with utility trades is lower than it is for consumers with telecommunications trades. This pattern is consistent with our earlier finding that consumers in the utility sample generally have stronger credit profiles than consumers with telecommunications trades.

32. The socio-demographic data appended to the indivdual credit files were generated by Acxiom from a combination of data sources including, self-reported sources, estimates from some of the individual's characteristics, extrapolation from census data, and public record information.

33. See appendix B for results for additional results based on other score models.

34. TransUnion, "TransUnion Case Study: How reporting helped Nicor Gas reduce bad debt." (Chicago, Il: TransUnion, 2002)

35. Matthew Fellowes, "Where is the Asset Building Opportunity?: A Profile of Credit Utilization and Management in 50 Metros." Presented at CFED Asset Building Conference, Phoneix, AZ. Sept. 2006.

36. Its impact is limited by the number of people who utilize its service and by the fact that individuals can choose which payment information they would like to include. It is likely that consumers will want to only include the payment histories which paint them in the best light, thus biasing the picture of themselves they present to users of the information.

37. For a complete transcript of the event, see **www.brookings.edu/metro/umi/events/20051215_paid.htm**

38. TransUnion, "TransUnion Case Study: How Reporting Helped Nicor Gas Reduce Bad Debt" (Chicago: TransUnion, 2002).

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