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The Value of Comprehensive Credit Reports: Lessons from the U.S. Experience*

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1. Introduction

Credit bureau data on consumer borrowing and payment behavior has become the cornerstone of the underwriting decision for consumer loans in the United States. Armed with the most comprehensive consumer payment histories on the planet, creditors apply statistical scoring models to estimate an individual's repayment risk with remarkable accuracy. Reliance on risk scoring has fundamentally improved the efficiency of U.S. credit markets and has brought consumers lower prices and more equitable treatment. Perhaps most significantly, credit bureau data has made a wide range of credit products available to millions of households who would have been turned down as too risky just a generation ago.

The full benefits of comprehensive credit reporting have yet to be realized in most other countries. The credit-reporting environment varies widely around the globe. Limits on consumer payment histories may be government imposed (perhaps as a result of concerns about consumer privacy, but often due to lobbying for such restrictions by incumbent lenders wishing to limit competition), or may simply occur as a result of underdevelopment of the legal and technological infrastructure necessary to sustain a comprehensive credit-reporting market.

In many countries, consumer credit histories are fragmented by the type of lender originating the loan. This has often occurred when the evolution of the credit data repository was driven by industry affiliation. For example, in some Latin American countries (Argentina, Mexico, Brazil) banks historically participated in the exchange of information about their consumer loan experience. This exchange led to the construction of comprehensive credit histories on consumers but only with respect to loans held by commercial banks. Non-bank creditors are often barred from using the data built on bank experience and have found it useful to collaborate with each other to build their own credit profiles of customers. In each of these restricted-information scenarios, the data limitations create higher transaction costs for creditors wishing to enter the market, raise the costs of delivering credit and ultimately restrict the number of consumers who will receive loans and the amounts they borrow.

This paper will discuss what is known about the impact of credit reporting on the availability of credit to households and will describe a series of simulations that demonstrate how credit availability is hindered when credit histories are restricted. Section 2 reviews both the theoretical and empirical literature on the linkage between credit reporting/information sharing and the subsequent development of consumer loan markets and economic growth. Because credit reporting environments differ substantially around the globe, much can be learned via cross-border comparisons. The United States has the most complete credit files on the largest percentage of its adult population of any country. Consequently, the U.S. market provides a useful benchmark to which to compare lending markets in countries with more restrictive reporting environments. Section 3 of this paper describes the dimensions of U.S. consumer credit markets and briefly summarizes the privacy laws that govern the construction and distribution of credit histories upon which lending activity is based. An example from the U.S. credit card industry highlights how the availability of detailed credit histories has spurred entry and dramatic price competition in that market.

Section 4 considers a common restricted-information scenario in which creditors report only borrower delinquency or default. Historically, credit reporting in most countries began with the sharing of so-called “negative” information (delinquencies, chargeoffs, bankruptcies, etc.) on borrowers. Only gradually and recently has information about the ***successful*** handling of accounts (prior and current) been contributed to the data repository. For example, most Latin American countries are moving in the direction of sharing more “positive” data about consumers (i.e., accounts currently open and active, balances, credit limits). In these countries, (e.g., Brazil, Argentina, Chile) consumer credit files contain some positive information, although the majority of information in credit files is still negative. At the other end of the spectrum of countries who have credit reporting, Australia provides a stark example of a negative-only reporting environment. Since its passage in 1988, Australia’s Commonwealth Privacy Act has allowed only the reporting of "negative" information about borrowers, plus inquiries from potential creditors.

In Section 4 we examine the impact that the absence of positive credit information has on a lender’s ability to measure borrower risk. Because the Australian statute clearly and cleanly specifies what information is allowed in credit files, we have simulated the Australian environment using large samples of U.S. consumer credit files. The efficiency of scoring models built with U.S. data under U.S. reporting rules provides the benchmark. The simulation drops out the blocks of data banned under Australian law and determines the impact on risk measurement for the same group of consumers. Measurement efficiency is defined in terms of errors of commission (giving loans to consumers who will not repay) and omission (denying loans to good customers who would have repaid). The results of the simulation have implications for the performance of markets for financial services and consumer goods, small business credit and overall macroeconomic growth and stability. Although the results are derived from a simulation of the Australian environment they generally apply to any region, including Latin America, in which positive credit data is missing from many consumer files.

Section 5 applies the same methodology to consider other restricted-information scenarios that are common in Latin America. In particular, we simulate the impact on risk assessment of having past credit performance available only for retail accounts and, in a separate simulation, only for bank card accounts. Section 6 offers some concluding discussion and implications.

2. The Conceptual and Empirical Case for Comprehensive Reporting

A. The Problem of Adverse Selection Lending markets almost always display some degree of information asymmetry between borrowers and lenders. Borrowers typically have more accurate information than lenders about their willingness and ability to repay a loan. Since the expected gains from the loan contract are a function of both the pricing and the probability of repayment, lenders invest resources to try and determine a borrower’s likelihood of repayment. For the same reason, borrowers may also have incentive to signal their true riskiness (if it is low) or disguise it (if it is high). The actions of borrowers and lenders as they try to reduce the information asymmetry has significant consequences for the operation of credit markets and give rise to a variety of institutions intended to minimize the associated costs.

A large theoretical and empirical literature about the consequences of such information asymmetry has developed over the past 25 years. For purposes of this paper, Stiglitz and Weiss (1981) provide the conceptual launching point for explaining the evolution of credit bureaus. This seminal paper focuses on lending markets without information sharing and theoretically describes the adverse selection problem which reduces the gains to both borrowers and lenders. Simply put, ***when lenders can't distinguish good borrowers from bad borrowers all borrowers are charged an average interest rate that reflects their pooled experience.*** But, this rate is higher than good borrowers warrant and causes some good borrowers to drop out of the market, thereby shrinking the customer base and further raising the average rate charged to remaining borrowers.

The adverse selection argument embodies the intuition about why better information makes lending markets work more efficiently. ***Better information allows lenders to more accurately measure borrower risk and set loan terms accordingly.*** Low risk borrowers are offered more attractive prices, which stimulates the quantity of loans demanded, and fewer higher risk borrowers are rationed out of the market because lenders can offer them an appropriate price to accommodate them, rather than turn them away.

B. Why Would Lenders Share Information? The next step in explaining the evolution of credit bureaus was provided by Pagano and Japelli (1993). Their theoretical development explains the factors encouraging voluntary information sharing among lenders, as well as those conditions that deter voluntary information sharing. Where Stiglitz and Weiss showed how adverse selection can impair markets, Pagano and Japelli show how information sharing can reduce the problem and increase the volume of lending. Their theoretical model generates the following implications. Incentives for lenders to share information about borrowers (about payment experience, current obligations and exposure) are positively related to the mobility and heterogeneity of borrowers, to the size of the credit market, and to advances in information technology. Working in the opposite direction (discouraging the sharing of information about borrowers) is the fear of competition from additional entrants.

The intuition is straightforward. Mobility and heterogeneity of borrowers reduce the feasibility of a lender relying solely on its own experience to guide its portfolio management. Thus, these factors increase the demand for information about a borrower's experience with other lenders. The need for information to supplement a lender's own experience grows with the size of market. In addition, any declines in the cost of sharing information (perhaps through technological improvements) boost the net gains from sharing.

The case for information sharing among lenders having been established, the next conceptual step was to rationalize the existence of a credit bureau. Padilla and Pagano (1997) develop a theoretical rationale for credit bureaus as an integral third-party participant in credit markets. The authors explain the conditions under which lenders agree to share information about borrowers via a third party which can penalize those institutions who do not report accurately. The paper is directly relevant to credit relationships between firms and their lenders, but also has implications for the sharing of information in consumer lending markets. As noted in Pagano and Japelli (1993), information sharing has direct benefits to lenders by reducing the impact of adverse selection (average rates tend to ration out low-risk borrowers leaving only the high-risk borrowers remaining), and moral hazard (borrower has incentive to default unless there are consequences in future applications for credit). However, information sharing stimulates competition for good borrowers over time, which erodes the informational rents enjoyed by incumbent lenders (who have already identified and service the good customers, the very ones which competitors would like to identify and recruit).

In this paper the authors discuss an additional problem that can arise out of the informational asymmetry between borrowers and lenders. As noted above, as a lender establishes relationships with customers it becomes able to distinguish good borrowers from bad borrowers. At that point, the lender has an incentive to either hold back information about the good borrowers or purposely spread false information about them in order to discourage competitors from making overtures. Borrowers know this, and so have less incentive to perform well under the loan contract, because such efforts will not be rewarded with lower interest rates in the future (and may be exploited with higher rates and/or spread of misinformation). This tendency to underperform is reversed if borrowers perceive some gain to signaling they are good borrowers. Consequently, a lender's commitment to share accurate information with other lenders, coupled with an enforcement mechanism that ensures that accuracy, can actually benefit all parties. The third-party credit bureau fills the role of both clearinghouse and enforcer. As a consequence, Padilla and Pagano show that if they share information, interest rates and default rates are lower, on average, and interest rates decrease over the course of the relationship with each client and his bank. In addition, the volume of lending may increase as information sharing expands the customer base.

C. Limits on Information Sharing Is more information sharing always better? Interestingly, the theoretical models show that this may not be the case. For example, Vercammen (1995) sets forth a conceptual case for limiting the length of time that negative information could remain on an individual's credit history. In part it's the "clean slate" argument: truly high-risk borrowers over time reveal themselves consistently as such. The presence of their deep history convinces lenders they are high risk. Consequently, as their negative credit history dogs them, such borrowers have little incentive to perform better on loans. The possibility of establishing a clean slate would raise the cost to the borrower of handling the new line poorly. The flip side of this argument is the "one free bite" argument: truly low-risk borrowers over time reveal themselves as such. The presence of their deep and good payment history convinces lenders they are good and so reduces the incentive of such borrowers to pay as agreed on the next loan. Limiting the length of the credit history (forced obsolescence) or perhaps eliminating other pieces of information that allow low- risk borrowers to distinguish themselves *would keep both types of borrowers honest* by raising the reputational stakes associated with their performance on their next loan.[1]

[1] Empirical work conducted in the U.S. by Fair Isaac, Co. on behalf of the Associated Credit Bureaus (industry trade association) has demonstrated that "the presence of derogatory information continues to distinguish levels of credit risk in the studied populations even as the information ages. The implication of this finding is that information predictive of credit risk would be sacrificed by the accelerated deletion of aged references." Fair Isaac, 1990, p 3.

Padilla and Pagano (1999) provide yet another twist to the case for less-than-perfect information sharing. Building on the ideas in Vercammen, 1995, the authors develop a model which shows that information sharing among lenders can boost borrower incentives to perform well on loans, but only if the information shared is less than perfect. When lenders share information about past defaults, borrowers do not wish to damage their credit rating because a default will signal future lenders that the borrower is high-risk. Thus, information sharing has a positive disciplinary effect on borrower behavior. However, suppose an incumbent lender shared so much additional information about a borrower's characteristics that future lenders knew with certainty that a borrower was indeed low-risk. In the model, future lenders would compete for such borrowers and offer them better loan terms. Consequently, such borrowers would have no more incentive to perform well on the current loan than if no information was shared. Thus, the authors conclude that less sharing could be better, and that lenders will seek to fine-tune the amount of information disclosed to some level below "perfect" so as to maximize the disciplinary effect.

As we apply these theoretical concepts to actual lending markets, keep in mind the distinction between perfect and less-than-perfect information signals regarding a borrower's true risk. As we will see below, the presence of both positive and negative credit information about a borrower can improve a lender's assessment of repayment probability, but hardly constitutes a perfect picture of the borrower's true risk. In reality, positive information still does not equate to perfect information. There is plenty of empirical evidence to suggest that borrowers with no negative payment history still vary widely with respect to default probability and experience. So, while an interesting theoretical point, this is hardly a case for barring positive credit histories from credit reports.

D. Evidence on the Evolution of Credit Bureaus How well do the implications of these theoretical models explain the evolution of credit bureaus and the lending markets they support? Japelli and Pagano (1999) provide one of the very few attempts to test the predictions of the theoretical models regarding the impact of information sharing on lending activity. The authors compiled a unique dataset describing the nature and extent of information sharing arrangements in 43 countries. Consistent with the theoretical models, the authors found that the breadth and depth of credit markets was significantly related to information sharing. Specifically, total bank lending to the private sector is larger in countries that have a greater degree of information sharing, even after controlling for country size, growth rates and variables capturing the legal environment and protection of creditor rights. The authors also found that greater information sharing reduced defaults, though the relationship was somewhat weaker than the link to additional lending.

E. Predictive Power of Bureau-Based Risk Models The conceptual case that information sharing leads to more efficient lending markets hinges on the assertion that data about past payment behavior is useful for predicting future performance. Of course, the entire credit scoring industry stands as testimony to this premise. However, among the few published attempts to document the gains from utilizing increasingly detailed credit history data are two papers, Chandler and Parker (1989), and Chandler and Johnson (1992). In the earlier paper, the authors document the ability of U.S. credit bureau data to outperform application data in predicting risk. Their analysis was based on comparing credit bureau vs. application data in scoring three categories of credit card applications: bank card, retail store card and non-revolving charge card.

In their study, application information included variables such as the applicant's age, time at current/previous residence, time at current/previous job, housing status, occupation group, income, number of dependents, presence of telephone at residence, banking relationship, debt ratio, and credit references. Variable values were coded straight from the credit card application, without independent verification.

Credit bureau variables were grouped into three categories so that the authors could examine the impact of simple vs. detailed amounts of credit file data. The first category included only the number of inquiries from other creditors in the last six months (under U.S. law, these result from an application for credit), and the worst credit rating on the borrower's file. The next category in the progression from less to more detail included the number of inquiries in the last six months plus additional variables such as the number of new trade lines opened in the last six months, number of satisfactory credit ratings, number of 30, 60, and 90 day ratings, the number of public record items and the age of the oldest trade. The current Australian reporting environment falls somewhere between these first and second categories. Finally, the authors created a third category including all variables in the previous two categories plus more detail on the number of accounts by category of lender (bank revolving, bank nonrevolving, consumer finance company, captive auto finance company) and a variable capturing the percent of all revolving lines currently utilized.

Using models built to score bankcard applicants, the authors found that the application data without the credit bureau data yielded the lowest predictive power and did not fare well when compared with predictions based on any level of credit bureau data. The predictive power increased substantially at higher levels of credit bureau detail, with the most detailed model exhibiting predictive power 52% greater than the simple credit bureau treatment. In fact, a model incorporating the detailed credit bureau data plus application data actually performed worse than a model based on the detailed credit bureau data alone. Perhaps this is not surprising given that most application data on bankcard products is not verified because of the cost and consequent delay in the accept/reject decision. The bottom line: the more information available about a borrower's current and past credit profile, the greater was the ability of the scoring model to separate goods from bads.[2]

In models built to score the retail card applications, the combination of application plus detailed credit bureau information outperformed a model built just on application data as well as a model built just on detailed bureau data. Similar results were found for models built to score the non-revolving charge card accounts. The authors concluded that predictive power rises for every card product as the level of credit bureau detail increased. They also noted that if the credit bureau file was utilized by scoring only the two items in the first category the real predictive power of the bureau data could easily be overlooked.

[2] Other authors have noted that when variables that might be available to scoring models are artificially prohibited, the resulting models deliver relatively fuzzy risk predictions. Commenting on the consequence of the U.S. Equal Credit Opportunity Act (which prohibits lenders from using race, sex, religion, ethnic background and certain other personal characteristics in scoring models) Boyes, Hoffman and Low (1986) note that the resulting degradation in the lender's ability to separate goods from bads can prompt them to reallocate loanable funds away from consumer lending and toward other classes of products (for example, commercial loans).

Significantly for the simulations conducted below, the first category of bureau variables contains information allowed in Australian credit bureau files but the second and third categories incorporate "positive data" variables not allowed under current Australian law and often absent in other countries even when they are legally permitted. Because the detailed credit bureau history found in the U.S. files provided the greatest lift in the predictive power of the scoring models, this result suggests that lenders and consumers in restricted-reporting environments are missing significant benefits from their credit reporting system.

Section 3: Characteristics of a "Full Reporting" Environment: the U.S. Experience

A. Dimensions of the U.S. Market For Consumer Credit. By most any measure, the U.S. market for consumer and mortgage credit is vast. As of the end of 1998 mortgage credit owed by consumers totaled about $4.1 trillion, including both first and second mortgages and the increasingly popular home equity lines of credit. Non-mortgage consumer credit (including credit cards, auto loans and other personal installment loans) totaled an additional $1.33 trillion.

Whether or not these sums are large given the size of the population, perhaps the more impressive numbers relate to the growth in the proportion of the population using credit. For the past 35 years, federal policy in the U.S. has encouraged the credit industry to make credit and other financial services available to a broader segment of the U.S. population. The result of these public policies has been a dramatic increase in credit availability to all segments of the U.S. population, particularly to those toward the bottom of the socio-economic spectrum who need it the most. In 1956 about 55% of U.S. households had some type of mortgage or consumer installment (non-mortgage) debt. In contrast, by 1998 over 74% of all U.S. households held some type of debt. Put another way, 29.7 million households used consumer or mortgage credit in 1956, compared to 75 million households in 1998.[3]

By loan category, the increased availability and use of consumer credit is equally impressive. In 1956, about 20% of households (11 million) had an automobile loan. By 1998, this proportion had increased to 31% (32 million). A similar pattern is evident for mortgage credit. In 1956, 24% of U.S. households (13 million) had mortgage debt. By 1998, 43% of households (44 million) had home mortgage loans. In the case of both products, credit markets enable consumers to purchase and finance durable goods which provide a valuable stream of services to their owners over time. Over the past two generations, millions of Americans have gained access to credit to enable them to make such investments and raise their standard of living.

The same story has unfolded for credit card products, but even more dramatically given the shorter time frame. Figure 1 displays the percent of U.S. households which owned at least one general purpose credit card (e.g., Visa, MasterCard, Discover) at two points in time, 1983 and 1995. It reveals that every income grouping of households enjoyed substantially improved access to the versatile "bank card" product even within the relatively short span of a dozen years. By 1995, over 25 million more households had access to bank credit cards than was the case in the early 1980s.

[3] These statistics derive from Federal Reserve Board Surveys of Consumer Finances, various years, 1956 through 1998. For an overview of the most recent (1998) survey see Kennickell, Starr-McCluer and Surette, 2000.

B. Credit Bureau Information as a Catalyst for Growth At the heart of the lending decision is information about an applicant's creditworthiness. In this regard, perhaps no industry has been more dramatically affected by the enhanced power of the computer than the consumer credit industry. In the United States, computerized credit files have made it possible to store and instantaneously retrieve many years of payment history for over 200 million adult residents. Over 2 million credit reports are sold by the three major national credit bureaus every day. Ready access to such personal credit data which can be used to evaluate creditworthiness has fueled the explosion in consumer credit products since the mid-1970s.

Broader access to credit products is widely recognized as the consequence of four simultaneous and interdependent factors:

- Legal rules which permit the collection and distribution of personal credit data to those with an authorized purpose for requesting the information

- Dramatic reductions in data processing costs and equally dramatic improvements in the speed of data retrieval

- The development of statistical scoring techniques for predicting borrower risk

- The repeal of legislated interest rate ceilings which had limited the ability of creditors to price their loan products according to risk.

The bank credit card market provides a useful illustration of how and why these combined forces worked to broaden access to credit card products. When bankcards (Visa and MasterCard and their forerunners) were launched in the 1960s they typically were priced at only one margin, a finance charge, that was imposed on balances that revolved from month to month. By the late 1970s, card issuers recognized that many customers never revolved a balance. These non-revolving cardholders were utilizing a package of valuable (and costly) services without being charged for them. Revolvers who paid finance charges subsidized non-revolvers. The advent of annual fees by the early 1980s gave issuers a method of collecting revenue from the convenience users and reduced the pressure on finance charges to cover all the costs of the card operation. Annual fees were a somewhat clumsy tool for boosting revenues, since they were applied across the board to all customers. Still, they helped issuers to hold down the interest rate on the card and remain competitive in attracting and keeping cardholders who typically revolved. Through the 1980s, other fees (late payment, cash advance, overlimit) were added to cardholder agreements, each fee aimed at a class of customer who imposed extra costs on the issuer by utilizing specific features of the card. In each case the purpose of adding an extra fee was to reduce the subsidization of one group of users by other cardholders, which occurs whenever extra costs associated with unpriced services are packed into a higher interest rate.

During the period 1985-1991, a wave of new entrants into the bankcard market put greater downward pressure on card interest rates and annual fees. Credit bureau data was critical to this explosion in competition both as a way to identify potential customers and to offer them attractive but profitable pricing. New entrants used credit bureau data to identify and target low-risk borrowers for their low-rate cards. Existing issuers saw customer attrition escalate, particularly in the lowest risk categories. Competition forced incumbent issuers to make a choice: either leave the interest rate unchanged and risk defection of their best customers to the new, low-rate entrants, or cut interest rates and fees as a defensive measure.

In late 1991, American Express became the first major issuer to unveil a tiered pricing structure to slow customer defections. For cardholders with at least $1,000 in charge volume during the previous 12 months and no delinquency the interest rate was lowered to 12.5% on revolving balances. Cardholders with smaller charge volume and no delinquency paid 14.5%. All other cardholders paid a higher rate. The new rate structure was intended to prevent defection of low-risk, active cardholders to competitors without compromising the higher finance charges imposed on slow-payers. A short time later, Citibank announced a similar pricing structure for its cardholders who had been paying a 19.8% interest rate. Citibank officials estimated that by the end of 1992, nearly ten million Citibank cardholders had benefited from the new tiered rate structure.[4]

The highly publicized tiered-rate programs for these two major issuers ignited an unprecedented wave of price competition for the bank card product that continues today. Figure 2 illustrates the rapid decline in bank card rates between 1990 and 1992. The proportion of revolving balances being charged an interest rate greater than 18.0% plummeted from 70% to 44 percent in just 12 months.

Today, issuer portfolios are commonly divided into multiple categories, with different rates and features according to the payment history of the customer. Risk-based pricing, spurred by aggressive entry of new competitors, has eliminated the industry practice of packing the costs of handling delinquent accounts for a small number of customers into higher interest rates for all customers. Consequently, tiered pricing reduces the amount by which low-risk customers subsidize the costs of serving high-risk customers. For the card issuer, the economic success of this strategy hinges on two key factors: 1) the low-cost availability of a comprehensive credit history for cardholders, and 2) the legal ability to charge interest rates commensurate with borrower risk. The occurrence of both in the U.S. triggered the dramatic improvement in access to bank credit cards displayed in Figure 2.

In the U.S. the combination of technological advances and flexible public policy toward data collection have fostered an explosion in consumer credit availability. It is no coincidence that the expansion of credit during the past two decades corresponded to the advent of credit scoring, and its

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[4] For discussion of rate cuts by these and other major issuers see Sullivan, *Credit Card Management*, October, 1990; Hilder and Pae, *The Wall Street Journal*, May 3, 1991, Spiro, *Business Week*, December 16, 1991; Pae, *The Wall Street Journal*, February 4, 1992; "Citibank Leads an Exodus from Higher Rates," *Credit Card News*, May 1, 1992.

eventual widespread use by credit card issuers (late 1980s), automobile lenders in launching risk-based pricing (led by companies such as GMAC in 1989-1990) and mortgage lenders in the early to mid-1990s. By 1998, credit scoring models were being developed and applied to guide small business lending. Personal loans, credit cards and debit card products are available to the vast majority of the adult population. Moreover the time between application for credit and the decision to make the loan has fallen precipitously: approval for many auto loans is available in less than 30 minutes. Some retailers advertise "instant credit" available at the point of sale, and can deliver approval for a new account in less than 2 minutes.

At the same time, across all categories of loans, the dramatic increases in the proportion of the population using credit have come without equally dramatic increases in defaults. The percent of accounts which are delinquent at any point in time varies between 2 and 5 percent nationwide, depending upon the product.[5] Looking at the market from the standpoint of the borrower reveals a similar story: the percent of borrowers nationwide who were delinquent 30 days or more on any account as of September, 1999 was 2.8% for mortgage holders, 6.9% for installment borrowers, and 4.9% of credit card borrowers.[6] The credit reporting environment in the U.S. is the foundation for this remarkable combination of widespread availability and low default rates.

C. The Balance Between Privacy Rights and Creditors' Need For Payment History

Although quite sensitive to the threat of invasion of privacy, U.S. policy toward the collection of personal information also recognizes that consumers necessarily must reveal some information about past behavior in order to obtain credit. When a consumer applies for credit, he/she voluntarily trades away **some** privacy in exchange for goods or services. Loss of some privacy is the price of participating and enjoying the benefits of an information-intensive economy.

In the context of a single loan transaction, a consumer faces a straightforward task of weighing the gains vs. the costs of revealing some personal information. Presumably, for some types of transactions, the potential benefits aren't worth revealing personal financial information and the customer refuses to continue. For other transactions, such as applying for a loan, the customer gives up much information but places even greater value on obtaining the loan, and so willingly sacrifices some privacy. However, since personal information about consumers can be stored and subsequently transferred, the consumer loses some control over its use subsequent to the transaction. Thus, a key element of U.S. regulatory policy regarding the use of credit bureau data is to preserve the consumer's right to authorize release of the information.

To balance the consumer's value of privacy against business's need for information and its inevitable storage for re-use, the U.S. Fair Credit Reporting Act (FCRA) stipulates the following:

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[5]Source: American Bankers Association, *Consumer Credit Delinquency Bulletin*, Third quarter, 1999.

[6]Source: *Monthly Statements*, a monthly newsletter on consumer borrowing and payment trends, edited by Gregory Elliehausen, Credit Research Center, Georgetown University, and published by Trans Union, LLC, December, 1999.

1. Consumer reporting agencies (credit bureaus) may assemble credit reports but must limit their content to ***factual information pertaining to past credit experience*** (no subjective, investigative reports). Under the FCRA, credit bureaus in the U.S. maintain four categories of personal data in credit files:

- Personal identification information (e.g., name, address, social security number)
- Open trade lines (credit card accounts, auto loans and leases, first and second mortgage accounts, personal loans, etc.) with data such as outstanding balance, credit limit, date account opened, date of last activity, and payment history
- "Public record" items related to the use of credit, including bankruptcies, accounts referred to collection agencies, legal collection judgments and liens
- Inquiries on the credit file, including date and identity of inquirer, for at least the previous two years.

2. Consumer reporting agencies may release credit files only for ***permissible purposes.*** Permissible purposes for release of credit files were defined in the Act to be those in conjunction with a variety of voluntary, consumer initiated transactions. These include credit transactions, insurance and employment applications. Since the consumer must initiate the transaction, nobody is in a position to learn the consumer's detailed credit profile unless it is relevant to a transaction the consumer is trying to arrange.

To assist the enforcement of the permissible purposes clause, the FCRA requires credit bureaus to keep a log of all requests for a consumer's credit report (inquiries) for at least 2 years, and to disclose the names and addresses of recipients of reports upon request from the consumer. Disclosure to the consumer also aids in ensuring that the information included in the file is correct.

Derogatory information (e.g., delinquencies and chargeoffs) can be kept on the file a maximum of 7 years, with the exception of personal bankruptcy records which can stay on the file up to ten years. With these provisions, the FCRA allows but limits the centralized storage and use of data about an individual's creditworthiness. Limiting the release of stored data ensures that personal data will only be revealed to those with whom the consumer intends to make a transaction, ***so that the consumer's sacrifice of some privacy reflects conscious consent to the tradeoff.***

Recall that Section 2 reviewed the theoretical arguments and empirical evidence that, by reducing the adverse selection problem, information sharing via credit bureaus promotes the growth of consumer lending and lowers the cost of providing credit. Section 3 has focused on the linkage between the availability of comprehensive credit files and dramatic growth in access to consumer credit products in the United States. Next we turn to the question of how access to consumer credit products would be impaired if some information about a consumer's past payment history was unavailable. The following section simulates risk scoring under Australian vs. U.S. reporting rules to ***demonstrate that more information is better in terms of a scoring model's ability to distinguish goods from bads, and consequently accept more loans for any target default rate.*** Specifically, we compare the performance of a risk-scoring model built under the "negative-only" Australian credit reporting rules with the performance of a model built using the greater detail available in U.S. credit reports. The simulation will highlight the cost of artificial restrictions on credit bureau information collection.

Section 4. The Impact of Restricting Credit Files to Include Only Negative Information: The U.S. vs. Australian Environments

Borrowers in Australia have a credit file only if they have sought credit in the last five years. Information older than five years must be deleted. Credit files contain data on the borrower's name, address (current and previous), date of birth, driver's license number, employer, applications for credit during the past five years showing date the credit was sought, type of credit sought, credit provider to whom application was made, an indication of whether it was a joint or individual application, and whether any account was past due. Creditors can't report date of account openings, highest balance, current balance, credit limit or similar pieces of "positive" information. The law allows creditors to report the existence of an account with a given borrower, but Australian industry officials indicate that this option is seldom used because the law also requires creditors to remove such a listing within 45 days of the account being repaid or closed. In any case, no information about account activity can be reported, except for delinquency status.

As indicated in Section 2, the U.S. and Australian reporting environments differ sharply in that U.S. credit files contain balance and payment status information on all of a borrower's accounts, not just those which have fallen delinquent. This section describes simulations that compare the two reporting environments to determine how a credit scoring model may be impaired by having access to only negative (derogatory) information, but not positive information about the successful handling of accounts. Certainly, a negative-only environment gives creditors a profile of applicants that is less complete than if a complete inventory of account and balance information were available. Whether or not this makes a difference in predicting future payment behavior is an empirical question which the simulations are designed to resolve.

A. Methodology

The simulations in the remainder of this paper each examine the effectiveness of generic bureau scoring models for assessing borrower risk under various assumptions about how much information is available in credit bureau files. The scoring models are generic because they are not specific to a particular creditor's portfolio (and customer characteristics). Instead, they are built on the consumer's experience across all creditors who report to the bureau. The models are bureau-based in the sense that they utilize only the information available in consumer credit reports (no application information or customer demographics).

Generic scoring models have been utilized commercially by creditors in the U.S. since 1987 to predict bankruptcies, chargeoffs and serious delinquencies. Their application has assisted thousands of creditors in virtually every dimension of the credit granting decision, including new-applicant evaluation, target product solicitations, the setting of credit limits, purchase authorization, credit card re-issue and renewals, and appropriate collections activity.

Each of the following simulations builds a risk scoring model utilizing the full complement of both positive and negative information present in U.S. credit files. Then, variables which were available for the construction of the full model but would not be present in the simulated environments were dropped from the set of potential variables and the model was re-built on the remaining variables. This method allowed for the construction of the best possible model from among the available variables in each environment. After applying the respective models to a random sample of borrowers we compared the predictive power.

The risk scoring models were built using U.S. credit report data provided by Experian, one of the three major U.S. credit bureaus and a large multinational provider of credit report data and analytical services for risk management. All credit files are anonymous, i.e., have been stripped of unique personal identifying information. The simulations were conducted with samples drawn from a database containing a random sample of 10 million individual credit files. For the "positive-plus-negative" vs. "negative-only" simulation described in this section, we examined consumers who opened new accounts from any source in May, 1997 and observed their performance on those new accounts over the next two years. Specifically, the models were built to estimate the probability that a new account opened in May, 1997 would become 90 or more days delinquent within 24 months, i.e, by the end of April, 1999.

B. Data and Variable Construction

The precise composition of commercially available scorecards is proprietary and consequently not available for use in an academic simulation. Given access to all variables contained in the credit file and sufficient time and resources for modeling, academic researchers could eventually construct a scoring model that would closely approximate the performance of commercial models. However, since the resource requirements to replicate commercial models are typically beyond the scope of academic projects, we accept that our simulation models will not be as powerful as commercial models and adopt the following approach.

According to the website of a large U.S.-based provider of commercial credit scoring models (Fair Isaac, Co. based in San Rafael, California), the key determinants of a credit bureau delinquency model can be divided into the following four general categories. Our simulation models include credit bureau variables in each of these categories. For the simulations we have available the full set of bureau variables (500+) that were being marketed commercially by Experian in 1999. The models were built using subsets of variables, but include variables from each of the following categories. Inclusion of variables in our model building was guided to some degree by the Fair, Isaac website which hints at key variables used in commercial models and the direction of their influence on risk scores.

1) ***Outstanding Debt and Types of Credit in Use:*** Fair, Isaac advises consumers who seek to improve their credit score to keep balances low, including credit card balances. People who are heavily extended tend to be higher risks than those who use credit conservatively. They also advise individuals to apply for and open new credit accounts only as needed, as the amount of unused credit is an important factor in calculating credit scores. Table 1 lists the variables that have been introduced in the simulations to capture the extent and type of outstanding debt, with particular focus on revolving and bankcard debt as a proportion of total debt and relative to credit limits.

2) ***Length Of Credit History:*** Fair, Isaac advises that the longer someone has had credit established, the better is his or her credit score. For example, a borrower who has had credit for less than two years represents a relatively higher risk than someone who has had credit for five years or more. Table 1 lists the variables that have been introduced to capture the extent of experience in the credit markets.

3) ***New Applications For Credit (Inquiries):*** Fair, Isaac advises individuals to apply for new credit sparingly if they seek a better credit score. In particular, they suggest that one minimize the number of times creditors are given permission to check one's credit record. Such credit checks are called "inquiries." Table 1 lists the variables that have been introduced to capture the extent of inquiries.

4) ***Late Payments, Delinquencies, Bankruptcies:*** Fair, Isaac advises individuals who seek to improve their credit score to always pay their accounts before the due date. Simply put, the fewer late payments, the better the score. Further, Fair, Isaac indicates that if there are late payments, those that are most recent are more indicative of future default than those that occurred in the past. Naturally, having no late payments is best. Table 1 lists the variables that have been introduced to capture the extent and timing of detrimental events in the payment history of an individual.

Table 1

Variables Used in the Different Credit Scoring Models

Type of Variable: Outstanding Debt and Types of Credit	Variable Used in Full Model	Variable Used in Negative-only Model	Variable Exists for Bankcard-only Model	Variable Exists for Retail-only Model
Total number of open, paid, or closed trades	✔		✔	✔
No open, paid, or closed trades	✔		✔	✔
Number of trades open with a balance greater than or equal to zero	✔		✔	✔
No trades open with a balance greater than or equal to zero	✔		✔	✔
Number of trades opened in last 6 months	✔		✔	✔
No trades opened in last 6 months	✔		✔	✔
Number of trades opened in last 12 months	✔		✔	✔
No trades opened in last 12 months	✔		✔	✔
Proportion of open trades that is revolving	✔			✔
Proportion of open trades that is finance installment	✔			
Proportion of open trades that is real estate/property	✔			
Zero balance on open trades	✔		✔	✔
Average balance across all open trades	✔		✔	✔
Average balance across open revolving trades	✔			✔
Proportion of debt that is revolving	✔			✔
Proportion of debt that is finance installment	✔			
Proportion of debt that is real estate/property	✔			
Bankcard balance/limit ratio on all open trades reported in last 6 months	✔		✔	
Bankcard balance/limit ratio on all open trades opened in last 12 months	✔		✔	

Type of Variable: Length of Credit History	**Variable Used in Full Model**	**Variable Used in Negative-only Model**	**Variable Exists for Bankcard -only Model**	**Variable Exists for Retail-only Model**
Age, in months, oldest trade	✔		✔	✔
Age, in months, of most recently opened trade	✔		✔	✔
Age, in months, of most recently opened trade = 9999	✔		✔	✔
Average age, in months, of all trades	✔		✔	
Ratio of number of open trades reported, last 12 months to age of oldest trade	✔			

Type of Variable: New Applications For Credit (Inquiries)	**Variable Used in Full Model**	**Variable Used in Negative-only Model**	**Variable Exists for Bankcard -only Model**	**Variable Exists for Retail-only Model**
Total number of inquiries made for credit purposes	✔	✔		✔
No inquires made for credit purposes	✔	✔		✔
Total number of bankcard inquiries made for credit purposes	✔	✔	✔	
No bankcard inquires made for credit purposes	✔	✔	✔	
Months since most recent inquiry for credit purposes was made	✔	✔		
Months since most recent bankcard inquiry for credit purposes was made	✔	✔	✔	
Total number of inquiries for credit purposes made, last 6 months	✔	✔	✔	✔
Proportion of inquires to open trades, last 6 months	✔		✔	✔
Total number of inquiries for credit purposes made, last 12 months	✔	✔	✔	✔
Proportion of inquires to open trades, last 12 months	✔		✔	✔

Type of Variable: Late Payments, Delinquencies, and Bankruptcies	**Variable Used in Full Model**	**Variable Used in Negative -only Model**	**Variable Exists for Bankcard -only Model**	**Variable Exists for Retail-only Model**
Proportion of all trades never delinquent/ derogatory	✔		✔	✔
Proportion of all trades that have never been delinquent, last 12 months	✔			
Positive number of trades ever 60+ days delinquent or derogatory	✔	✔	✔	✔
Number of trades ever 60+ days delinquent or derogatory	✔	✔	✔	✔
Proportion of trades ever 60+ days delinquent or derogatory	✔		✔	✔
Positive number of trades ever derogatory, including collection, charge-off, etc.	✔	✔	✔	✔
Number of trades ever derogatory	✔	✔	✔	✔
Proportion of trades ever derogatory	✔		✔	✔
Positive number of bankruptcy tradelines ever	✔	✔	✔	✔
Total number of bankruptcy tradelines ever (only available for all)	✔	✔		
Proportion of trades ever bankruptcy tradelines	✔			
Months since most recent tradeline bankruptcy	✔	✔	✔	✔
Worst status ever (including current) on a trade	✔	✔		✔
Worst ever status on trades reported, last 12 months	✔	✔		✔
Worst present status on an open trade	✔	✔		✔
Worst status ever (including current) on a bankcard trade	✔	✔	✔	
Worst ever status on bankcard trades reported, last 12 months	✔	✔	✔	
Worst present status on an open bankcard trade	✔	✔	✔	
Months since most recent 30-180 day delinquency on any trade	✔	✔		
Not ever delinquent or derogatory on any trade	✔	✔		
Months since most recent 90+ delinquency or derogatory, any trade	✔	✔		
Not ever 90+ days delinquency or derogatory item on any trade	✔	✔		

C. The Value of Positive Information

In Australia, only derogatory information and inquiry information can be used in determining a credit score. No variables are permitted on the number of open lines, age of lines, balances or credit limits.[7] We use this definition of "negative-only" to simulate the effect of adopting such a system. The "full-model" uses all the variables listed in Table 1 above. The "negative-only" model uses only those variables in Table 1 that are indicated in the "negative-only" column. The dependent variable is constructed as equal to one if a new account becomes 90 or more days delinquent within two years, and equal to zero otherwise. In each case a probit model was used to estimate the probability of delinquency for a random sample of 312,484 new accounts opened at the start of the observation period.

There are a variety of ways to evaluate the effect of using only negative information and to present the results once we have calculated individual credit scores for the full-model and for the restricted model. For each model, we first rank individuals according to their "credit score". We can then pick a specific "approval rate", say 60%, and compare the default rates for the full model to that of the restricted model. For purposes of our simulations, the term "default" refers to the borrower becoming 90 days or more past due on the new account. Alternatively, for a given target default rate we can determine the reduction in the number of individuals who would be offered credit if only the restricted model was available. Tables 2 and 3 present the results of such comparisons for both the random sample that was used to estimate the credit scoring models and for a "hold-out" sample of equal size.

At a targeted approval rate of 60%, the negative-only model produces a 3.35% default rate among accepted applicants, as compared to a 1.9% default rate for the full model. Put another way, Table 2 reveals that at the given 60% approval rate, the default rate using the negative only model is 76.3% higher than if the full model were used. Next, consider the implications of the two models for extending credit to deserving borrowers. Suppose the economics of a lender's operation dictate an optimal default rate of 4%. Table 3 reveals that the full model approves 83.2% of consumers for a loan, while the negative-only model approves only 73.7% of consumers, an 11.4% reduction in loans made. In other words, at a default rate of 4%, for every 100,000 applicants, use of the negative-only model would result in 11,000 fewer consumer loans.

Note that the results reported in Tables 2 and 3 suggest that an environment which restricts lenders to using the negative-only model produces non-trivial changes in either the likelihood a loan is repaid (and thus, the cost of a loan) or the availability of credit. These results highlight the distinct tradeoff between 1) limiting the collection and use of personal credit histories and 2) making credit available to consumers at reasonable prices.

[7] Note that this does not imply that Australian creditors do not utilize such information. They can always request this information from the borrower on the credit application but must incur the costs and delays associated with verifying the information. Thus, while the information available to the underwriting decision could, in principle, be as detailed as in the U.S. model, in practice the costs of ferreting out the complete borrower profile independently of the credit bureau are likely prohibitive.

Table 2

Effects on Default Rates of Adopting Negative-only Credit Scoring Model for Various Approval Rates

Target Approval Rate	***Default Rates Estimating Sample***			***Default Rate Hold-out Sample***		
	Full Model	*Negative-only Model*	*Percent Increase in Default Rate on Loan with Negative-only Model*	*Full Model*	*Negative-only Model*	*Percent Increase in Default Rate on Loan with Negative-only Model*
40%	1.08%	2.92%	170.4%	1.15%	2.91%	153.0%
60%	1.90%	3.35%	76.3%	1.95%	3.36%	72.3%
75%	3.04%	4.07%	33.9%	3.09%	4.10%	32.7%
100%	9.31%	9.31%	0.0%	9.38%	9.38%	0.0%

Table 3

Effects on Credit Availability of Adopting a Negative-only Credit Scoring Model for Various Default Rates

Target Default Rate	***Percent of Consumers Who Obtain a Loan Estimating Sample***			***Percent of Consumers Who Obtain a Loan Hold-out Sample***		
	Full Model	*Negative-only Model*	*Percent Decrease in Consumers Who Obtain a Loan with Negative-only Model*	*Full Model*	*Negative-only Model*	*Percent Decrease in Consumers Who Obtain a Loan with Negative-only Model*
3%	74.8%	39.8%	46.8%	74.3%	39.0%	47.5%
4%	83.2%	73.7%	11.4%	82.9%	73.7%	11.1%
5%	88.9%	84.6%	4.8%	88.9%	84.2%	5.3%
6%	93.1%	90.8%	2.5%	92.8%	90.6%	2.4%
7%	95.5%	95.0%	0.5%	95.6%	94.6%	1.0%
Mean	100.0%	100.0%	0.0%	100.0%	100.0%	0.0%

Table 4 displays yet another method for assessing the effectiveness of the two models. Suppose we define a Type 1 error as rejecting a borrower who would actually repay. Alternatively, define a Type 2 error as accepting a borrower who will become seriously delinquent. Table 4 displays the percentage increase in Type 1 and Type 2 errors for both the full and restricted models assuming various target loan approval rates. Both types of errors increase in the restricted, negative-only environment.[8] [9]

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[8] These results were confirmed in separate simulations conducted by an Experian analytical team using methods typical of commercial scorecard development. There are two primary differences between the methods we employed and those underlying commercially available generic bureau scorecards. For a variety of reasons, commercial scorecards are typically constrained to the 15-20 most predictive variables, rather than the longer list we employed in developing our full-information model. Also, generic bureau scorecards marketed to date have generally been customer-based rather than loan-based models. That is, the observation unit for the generic bureau scorecard is a customer, not a loan, and the dependent variable describes whether a customer who opens one or more new accounts at the beginning of the observation period becomes seriously delinquent (90+ day) by the end of the period in at least one of the new accounts. Despite the differences in procedures, the Experian estimates were quite close to our own.

[9] We should note here that the choice of “bad” definition for the model, though widely used in the credit industry, nevertheless limits the model’s capacity to make even finer distinctions with respect to borrower risk. For example, a borrower who opens a new account, goes to 90 days delinquent after one year, and then brings the account current for the successive months in the observation period is defined as “bad”. Yet, from a profitability standpoint, this borrower may be a more valuable customer than one who is seriously delinquent at the end of the observation period. The argument that two borrowers who experience serious delinquency could differ with respect to profitability is essentially the same argument that supports the addition of positive information to a scorecard that formerly contained only negative payment history. Two borrowers who lack blemishes on the credit histories are not necessarily equally desirable customers from a creditor’s viewpoint. Admittedly, these are fine distinctions, when applied to borrowers with serious delinquencies on their files. However, scorecard builders seeking to fine tune their models and orient them more toward profitability have begun utilizing more complex definitions of the dependent variable.

Table 4

Effects on Type I, and Type II Errors of Adopting Negative-only Credit Scoring Model for Various Approval Rates

Type I Errors	***Percent of Good Credit Risks Who Do Not Receive a Loan*** ***Estimating Sample***			***Percent of Good Credit Risks Who Do Not Receive a Loan*** ***Hold-out Sample***		
Target Approval Rate	*Full Model*	*Negative-only Model*	*Percent Increase in Type I Error on Loan with Negative-only Model*	*Full Model*	*Negative-only Model*	*Percent Increase in Type I Error on Loan with Negative-only Model*
40%	56.1%	57.0%	1.6%	56.1%	56.9%	1.4%
60%	34.8%	35.8%	2.9%	34.7%	35.8%	3.2%
75%	19.5%	20.5%	5.1%	19.5%	20.4%	4.6%
100%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
Type II Errors	***Percent of Bad Risks Who Receive a Loan*** ***Estimating Sample***			***Percent of Bad Risks Who Receive a Loan*** ***Hold-out Sample***		
Target Approval Rate	*Full Model*	*Negative-only Model*	*Percent Increase in Type II Error on Loan with Negative-only Model*	*Full Model*	*Negative-only Model*	*Percent Increase in Type II Error on Loan with Negative-only Model*
40%	4.7%	12.6%	168.1%	4.9%	12.5%	155.1%
60%	12.3%	21.7%	76.4%	12.5%	21.6%	72.8%
75%	24.6%	32.9%	33.7%	24.8%	32.9%	32.7%
100%	100.0%	100.0%	0.0%	100.0%	100.0%	0.0%

Section 5: Bureau Data Restricted by Type of Lender

Credit reporting in Latin American countries has historically been driven by commercial banking consortiums. Positive data is more likely to appear for accounts reported and shared within the bank consortium, but is typically not available to institutions outside the consortium. Information on loans not held by consortium members has tended to be negative, when it appears at all. In some countries (e.g., Mexico) retailers and finance companies have attempted to form their own reporting consortiums to improve the quality and scope of data available on consumers to whom they would like to lend. As the consumer finance industry grows, an increasing portion of consumer credit oustandings will likely be held outside the domestic commercial banking system. For example, in the U.S. at the end of December, 1999, approximately 40-45% of non-mortgage credit outstanding ($560- $640 billion) was originated by non-banking financial institutions including finance companies, credit unions and retailers. A reporting system that provides a credit profile on a consumer's credit experience with either the bank or the non-bank sector, but not both, leaves a substantial gap in the overall profile for a given borrower.

In the absence of efforts to expand the scope of credit reporting, the size of the lender's blind spot in Latin America appears poised to increase as foreign financial institutions recognize the lucrative business opportunities in lending to Latin American consumers. Growth in retail lending is well underway. Until very recently, bank credit cards were held by a relatively small portion of well-to-do Latin American consumers, but Latin American charge card volume reported by Visa and MasterCard reached $106.2 billion in 1997, an 81% jump. U.S. companies, especially FleetBoston, Citigroup, and Wells Fargo are moving aggressively to expand their consumer finance operations in Brazil, Chile and Argentina. U.S. finance companies including Associates First Capital, GE Capital, GMAC and Ford Motor Credit have also been actively courting consumers. Analysts have attributed much of the foreign interest in lending to Latin American consumers to advances in the credit reporting systems in these countries which has, in turn, supported the application of credit scoring.[10] Mexico is also experiencing a rapid influx of U.S. capital since its economy has grown in excess of 3% each of the last four years while the domestic banking sector has scaled back lending to the private sector since 1995.[11]

We should emphasize again that, unlike Australia, there is some positive information reported about Latin American consumers. However, it tends to be sector-specific, i.e. bank-loan experience or retail loan experience. In the following simulations, we examine the impact on risk scoring models of having information about a consumer's credit history available only on certain types of loans.

The first restricted-sector simulation approaches the issue from a retail creditor's viewpoint as though the retailer could access credit histories only from a retailer consortium. Thus, in making a loan decision a retailer would be able to draw on its own experience with a customer (if any) as well as the experience of other retailers in the consortium with the same customer. Relative to the full-information model described in Section 4, we examine how well a scoring model built only on retail

[10] "FleetBoston, Citi Plan Push in Latin Consumer Banking," *American Banker*, March 20, 2000, p 4.
[11] "Credit Programs from GM, Others Help Fuel Growth in Mexican Economy," *The Wall Street Journal*, December 13, 1999.

loan experience performs. That is, we simulate the situation in which a retailer has access to both positive and negative information about a consumer, but only on existing and prior retail loans.

Specifically, the simulation used a probit model to estimate the probability of serious delinquency (90+ days) within two years among a random sample of 67,130 new retail accounts opened in May, 1997. The full-information model employed all the variables in the "full model" column of Table 1. The restricted, retail-information-only model used only those variables indicated in the "retail-only" column of Table 1. Note that all of the variables contained in the retail model were recalculated to apply only to the retail experience. For example, "total number of open trades" would indicate only the number of open retail trades. Some variables are lost altogether in the restricted model because they involve calculations of the proportion of overall debt or delinquency represented by a given type of account. Such a variable would not be available if a retailer could draw only on retail experience but not the experience of other financial institutions.

Tables 5 and 6 display the results of the retail-only simulations. As in the previous discussion of the negative-only simulation, suppose we use the estimated models (full and restricted) to estimate credit scores for each individual in the sample and rank them according to their scores. Table 5 reveals that at a target approval rate of 60%, the default rate in the full model would be 1.18% while the default rate using the restricted model would jump to 1.9%, a 61% increase. Alternatively, for a given target default rate of 3%, Table 6 reveals that the full model approves 83.4% of customers while the restricted model approves only 75.4% of customers, a decline of 9.6%. Put another way, among the pool of borrowers that could be served within the creditor's target default rate, for every 100,000 applicants, 9,600 deserving borrowers would not receive loans if only the restricted, retail-only model were available. Tables 5 and 6 show these results are validated with a hold-out sample of equal size.

We conducted another restricted-sector simulation assuming only bank credit card experience was available to a bankcard issuer. Specifically, the simulation used a probit model to estimate the probability of serious delinquency (90+ days) within two years among a random sample of 110,633 new bank credit card accounts opened in May, 1997. The full-information model employed all the variables in the "full model" column of Table 1. The restricted, bankcard-only model used only those variables indicated in the "bankcard only" column of Table 1. Note that all of the variables contained in the restricted bankcard model were recalculated to reflect only bankcard experience. For example, "total number of open trades" would indicate only the number of open bankcard trades.

Tables 7 and 8 display the simulation results. The most notable difference from the previous simulations is that the degradation in model performance is smaller when a bankcard issuer is constrained to use only bankcard data. This is an interesting result that suggests, among other things, that much of the predictive power in the full model derives from how customers acquire and handle their bank credit cards. Given the deep penetration of the bankcard product in the U.S. market, relative to the rest of the world, this result may be unique to the U.S.

Table 5

Effects on Retail Loan Default Rates of a Retail-only Credit Scoring Model for Various Retail Loan Approval Rates

	Default Rates ***Estimating Sample***			***Default Rate*** ***Hold-out Sample***		
Target Approval Rate	*Full Model*	*Retail-only Model*	*Percent Increase in Default Rate on Loan with Retail-only Model*	*Full Model*	*Retail-only Model*	*Percent Increase in Default Rate on Loan with Retail-only Model*
40%	0.53%	1.10%	107.5%	0.55%	1.10%	100.0%
60%	1.18%	1.90%	61.0%	1.10%	1.66%	50.9%
75%	2.13%	2.97%	39.4%	2.01%	2.72%	35.3%
100%	6.03%	6.03%	0.0%	5.87%	5.87%	0.0%

Table 6

Effects on Credit Availability of a Retail-only Credit Scoring Model for Various Retail Loan Default Rates

	Percent of Consumers Who Obtain a Loan ***Estimating Sample***			***Percent of Consumers Who Obtain a Loan*** ***Hold-out Sample***		
Target Default Rate	*Full Model*	*Retail-only Model*	*Percent Decrease in Consumers Who Obtain a Loan with Retail-only Model*	*Full Model*	*Retail-only Model*	*Percent Decrease in Consumers Who Obtain a Loan with Retail-only Model*
3%	83.4%	75.4%	9.6%	84.6%	78.1%	7.7%
4%	90.6%	80.6%	11.0%	92.1%	90.7%	1.5%
5%	96.3%	94.1%	2.3%	97.3%	95.8%	1.5%
Mean	100.0%	100.0%	0.0%	100.0%	100.0%	0.0%

Table 7

Effects on Bankcard Loan Default Rates of a Bankcard-only Credit Scoring Model for Various Bankcard Approval Rates

	Default Rates ***Estimating Sample***			***Default Rates*** ***Hold-out Sample***		
Target Approval Rate	*Full Model*	*Bankcard-only Model*	*Percent Increase in Default Rate on Loan with Bankcard-only Model*	*Full Model*	*Bankcard-only Model*	*Percent Increase in Default Rate on Loan with Bankcard-only Model*
40%	0.61%	0.82%	34.4%	0.61%	0.74%	21.3%
60%	1.07%	1.27%	18.7%	1.11%	1.24%	11.7%
75%	1.69%	1.95%	15.4%	1.81%	2.01%	11.0%
100%	5.34%	5.34%	0.0%	5.48%	5.48%	0.0%

Table 8

Effects on Credit Availability of a Bankcard-only Credit Scoring Model for Various Bankcard Loan Default Rates

	Percent of Consumers Who Obtain a Loan ***Estimating Sample***			***Percent of Consumers Who Obtain a Loan*** ***Hold-out Sample***		
Target Default Rate	*Full Model*	*Bankcard-only Model*	*Percent Decrease in Consumers Who Obtain a Loan with Bankcard-only Model*	*Full Model*	*Bankcard-only Model*	*Percent Decrease in Consumers Who Obtain a Loan with Bankcard-only Model*
2%	79.6%	75.6%	5.0%	77.8%	74.6%	4.1%
3%	89.3%	85.6%	4.1%	88.3%	85.3%	3.4%
4%	95.8%	93.4%	2.5%	95.0%	93.4%	1.7%
Mean	100.0%	100.0%	0.0%	100.0%	100.0%	0.0%

Section 6: Discussion and Implications

Based on the results of a burgeoning literature on the impact of information sharing, and also on the results of our simulations which compared the efficiency of scoring models built under comprehensive vs. restricted reporting environments, the following implications emerge:

1. Given the prevailing laws governing the reporting of personal credit histories, consumer credit will be less available in countries (e.g., Australia) where credit reporting is confined primarily to negative (delinquent) information, relative to the United States. It will also be less available in countries dominated by sector-specific reporting bureaus that exclude consumer borrowing experience with certain types of institutions and/or prohibit access of other institutions to the full bureau files. The effect will be especially noticeable for those consumers who are financially more vulnerable (higher risk categories) such as consumers who are young, have short time on the job or at their residence, and lower incomes.

2. As the amount of credit made available per capita increases in countries that lack comprehensive credit reporting, the pricing gradient will be steeper as compared to the United States. Consumer credit in restricted-reporting countries likely will be more costly in terms of finance charge as well as other features of the loan offer function, including down payment, convenience of access, credit limits and fees.

3. Less accessible consumer credit will likely impair the growth of consumer spending and growth in consumer durable industries in countries that lack comprehensive reporting.

4. Restrictions on the storage of past credit history will increase the value to developing other, alternative measures of the likelihood of repayment. Countries that have balked at more comprehensive credit reporting because of concerns over personal privacy should bear in mind that some of these alternative measures may be more invasive and less objective than the payment history itself.

5. The effects of more restrictive rules for reporting credit histories may be moderated by regulatory regimens that provide for harsher collection remedies or limits on access to personal bankruptcy, so as to minimize the reduction in credit availability that would otherwise take place. These, too, may be less desirable from a social standpoint than facilitating the reporting of more complete credit histories.

A quarter century of experience within a comprehensive reporting environment in the United States has produced an impressive list of benefits. Detailed information about a borrower's past payment history, including accounts handled responsibly, as well as a current profile of the borrower's obligations and available credit lines have proved to be an important tool for assessing risk. The resulting benefits include:

- Dramatic penetration of lending into lower socio-economic groups, making a variety of consumer loans available across the income spectrum.
- Reduction in loan losses that would have accompanied such market penetration in the past.

- Ongoing account monitoring and use of behavioral scoring by creditors to adjust credit lines and take early preventive action if a consumer is showing signals of overextension. Preventive measures include contacting customers to offer budgetary counseling or concessions on terms to prevent bankruptcy or chargeoff.
- Encouraged entry of new competitors, including non-bank financial institutions, which has stimulated vigorous price competition and more convenient products
- Made feasible the securitization of consumer loan receivables (e.g., mortgages, auto loans, credit cards) which has lowered the cost of providing credit and brought hundreds of billions of additional dollars into consumer lending markets.
- Lowered the prices for other financial products as customers have been freed from their binding relationships with banks and other depository institutions. In the past the customer's own bank was frequently the lowest cost source for a loan because other creditors lacked the information needed to measure risk. Consequently, banks have been forced to become more competitive for customers at all margins.
- Made consumers (and workers) more mobile by reducing the cost of severing established relationships and seeking better opportunities.

This last point may well be the most significant in the long run. Much has been made of the so-called New Economy in the U.S., the remarkable growth in U.S. productivity that's brought the unlikely coincidence of the tightest labor market in 30 years, strong growth in personal incomes (5% at the end of 1999, after 8.5 years of expansion), and extraordinarily low inflation. Economists are increasingly conceding that data sharing (especially about consumers) and free-flowing information has been a key to U.S. economic flexibility and consequent resiliency. It contributes to our mobility as a society, so that structural shifts within the economy cause temporary disruptions but without crippling long-term effects. As suggested in a recent speech by New York Federal Reserve Bank President William McDonough, the portability of information makes us more open to change. There is less risk associated with severing old relationships and starting new ones, because objective information is available that helps us to establish and build trust more quickly. At the same time, access to personal credit information is protected under U.S. disclosure rules so that the consumer retains some control over the release. It is this commitment to making personal credit information available but only with the consumer's permission that has been the engine behind the stunning growth in U.S. financial services markets in recent years.

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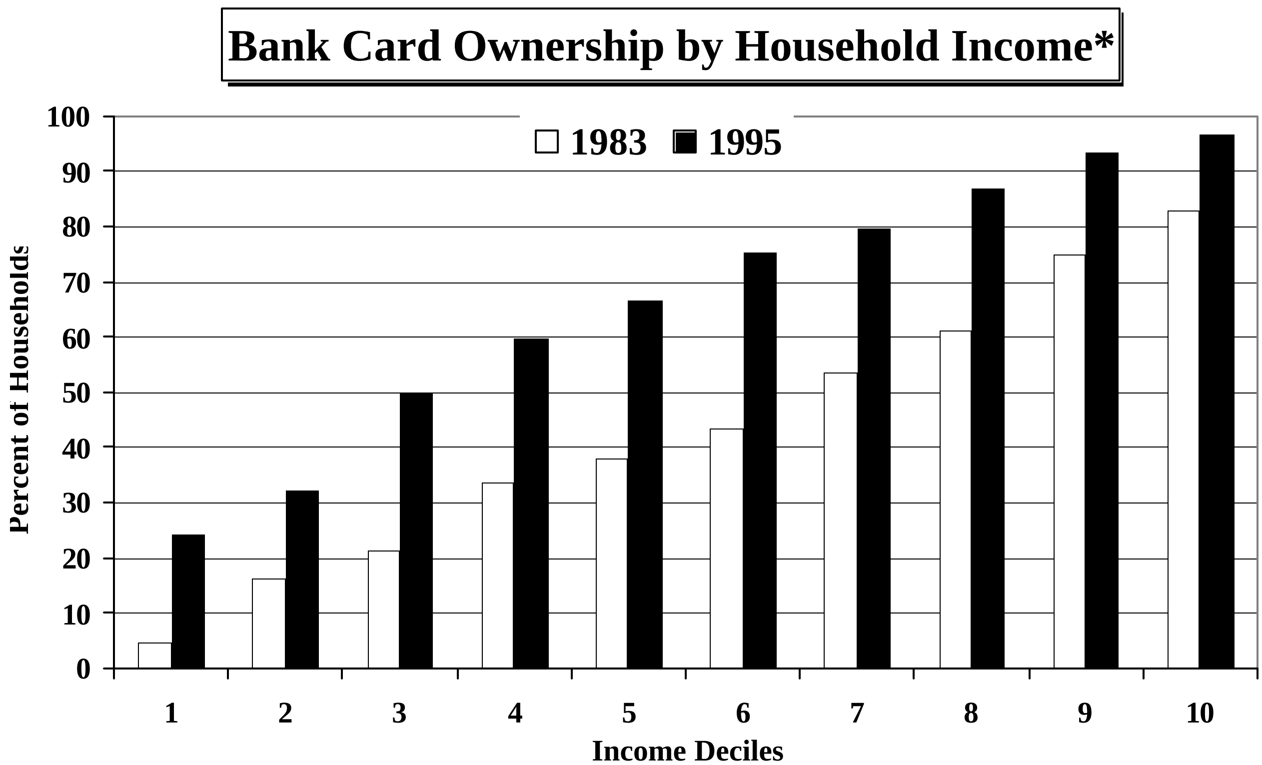
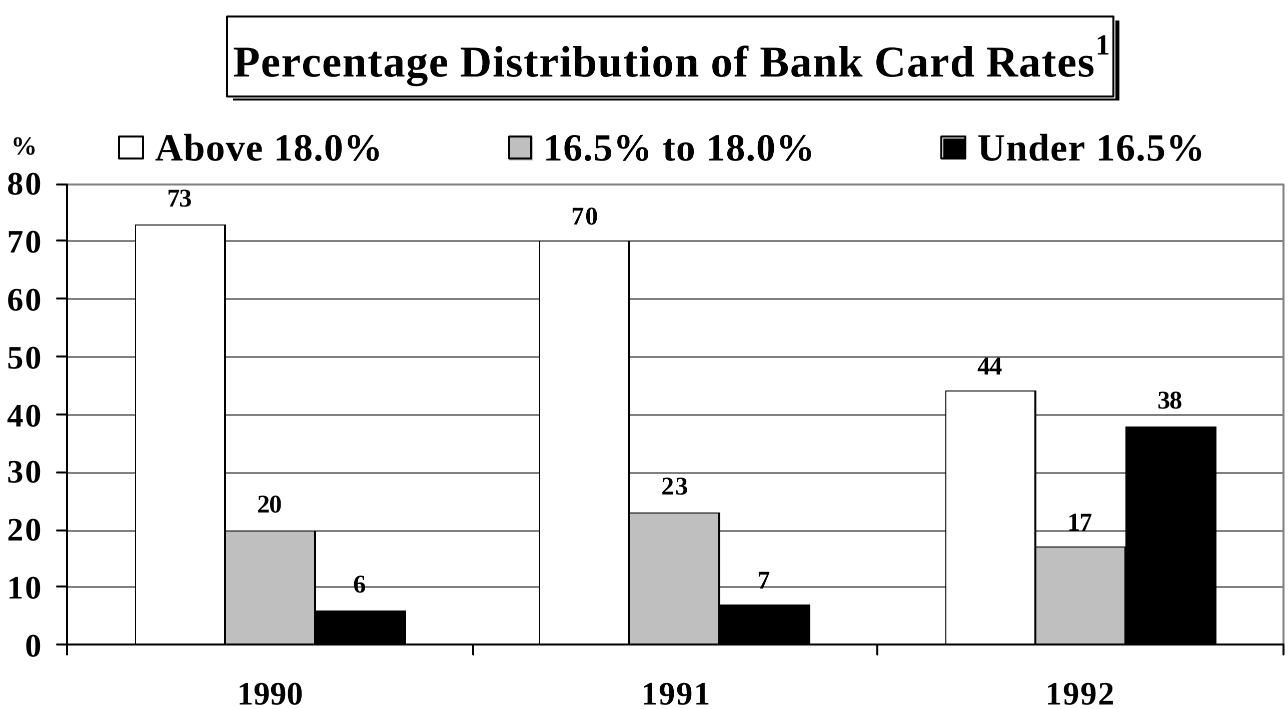
FIGURE 1



*Percent of households with at least one bank card.
Source: Federal Reserve Board.

FIGURE 2



Proportion of outstanding bank card balances.
Data derived from survey of 100 top issuers representing 93% of U.S. bank card receivables.
Source: *CardTrak*, RAM Research.