

The Democratization of Credit and the Rise in Consumer Bankruptcies*

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Abstract

Financial innovations are a common explanation for the rise in credit card debt and bankruptcies. To evaluate this story, we develop a simple model that incorporates two key frictions: asymmetric information about borrowers' risk of default and a fixed cost of developing each contract lenders offer. Innovations that ameliorate asymmetric information or reduce this fixed cost have large extensive margin effects via the entry of new lending contracts targeted at riskier borrowers. This results in more defaults and borrowing, and increased dispersion of interest rates. Using the Survey of Consumer Finances and Federal Reserve Board interest rate data, we find evidence supporting these predictions. Specifically, the dispersion of credit card interest rates nearly tripled while the "new" cardholders of the late 1980s and 1990s had riskier observable characteristics than existing cardholders. Our calculation suggest these new cardholders accounted for over 25% of the rise in bank credit card debt and delinquencies between 1989 and 1998.

Keywords: Credit Cards, Endogenous Financial Contracts, Bankruptcy.

JEL Classifications: E21, E49, G18, K35

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1 Introduction

Financial innovations are frequently cited as a key factor in the dramatic increase in households' access to credit cards between 1980 and 2000. By making intensive use of improved information technology, lenders were able to price risk more accurately and to offer loans more closely tailored to the risk characteristics of different groups (Mann 2006; Baird 2007). The expansion in credit card borrowing, in turn, is thought to be a key force driving the surge in consumer bankruptcy filings and unsecured borrowing (see Figure 1) over the past thirty years (White 2007).

Surprisingly little theoretical work, however, has explored the implications of financial innovations for unsecured consumer loans. We help fill this gap by developing an incomplete markets model of bankruptcy to analyze the qualitative implications of improved credit technology. To guide us in assessing the model's predictions, we document that many key innovations in the U.S. credit card industry occurred during the mid-1980s to the mid-1990s. This leads us to compare the model's predictions to cross-sectional data on the evolution of credit card debt and interest rates during these years.

Our model incorporates two frictions that are key in shaping credit contracts: asymmetric information about borrowers' default risk, and a fixed cost of creating a credit contract. While asymmetric information is a common element of credit models, fixed costs of contract design have been largely ignored by the academic literature.¹ This is surprising, as texts targeted at practitioners document significant fixed costs. According to Lawrence and Solomon (2002), a prominent consumer credit handbook, developing a consumer lending product involves selecting the target market, designing the terms and conditions of the product and scorecards to assess applicants, testing the product, forecasting profitability, and preparing formal documentation. Even after the initial launch, there are ongoing overhead costs, such as regular reviews of the product design and scorecards as well as maintenance of customer databases, that vary little with the number of customers. Finally, it is worth noting that fixed costs are consistent with the observation that consumer credit contracts are differentiated but rarely individual-specific.

We incorporate these frictions into a two-period model that builds on the classic contribution of Jaffee and Russell (1976). The economy is populated by a continuum of two-period lived risk-neutral borrowers. Borrowers differ in their probabilities of re-

¹Notable exceptions to this are Allard, Cresta, and Rochet (1997) and Newhouse (1996), who show that fixed costs can support pooling equilibria in insurance markets with a finite number of risk types.

ceiving a high endowment realization in the second period. To offer a lending contract, which specifies an interest rate, a borrowing limit and a set of eligible borrowers, an intermediary incurs a fixed cost. When designing loan contracts, lenders face an asymmetric information problem, as they observe a noisy signal of a borrower's true default risk, while borrowers know their type. There is free entry into the credit market, and the number and terms of lending contracts are determined endogenously. To address well known issues related to existence of competitive equilibrium with adverse selection, the timing of the lending game builds on Hellwig (1987). This leads prospective lenders to internalize how their entry decisions impact other lenders' entry and exit decisions.

The equilibrium features a finite set of loan contracts, each "targeting" a specific pool of risk types. The finiteness of contracts follows from the assumption that a fixed cost is incurred per contract, so that some "pooling" is necessary to spread the fixed cost across multiple types of borrowers. Working against larger pools is that these require a broader range of risk types, leading to wider gaps between the average default rate and the default risk of the least risky pool members. With free entry of intermediaries, these forces lead to a finite set of contracts for any (strictly positive) fixed cost.

We use this framework to analyze the qualitative implications of three channels through which financial innovations may have impacted credit card lending since the mid-1980s: (i) reductions in the fixed cost of creating contracts; (ii) increased accuracy of lenders' predictions of borrowers' default risk; and (iii) a reduced cost of lenders' funds. As we discuss in Section 2, the first two channels capture the idea that improvements in information technology reduced the cost of designing loan contracts, and allowed lenders to price borrowers' risk more accurately. The third channel is motivated by the increased use of securitization (which reduced lenders' costs of funds) and by lower costs of servicing consumer loans following improvements in information technology.

All three channels significantly impact the extensive margin of who has access to risky loans. The measure of households offered risky loans depends on both the number of risky contracts and the size of each pool. Intuitively, financial innovation makes the lending technology more productive, which leads to it being used more intensively to sort borrowers into smaller pools. Holding the number of contracts fixed, this reduces the number of households with risky borrowing. However, improved lending technology makes the marginal contract more attractive to borrowers by lowering the break-even interest rate. Thus, sufficiently large financial innovations lead to the entry of new contracts, targeted at riskier types than those served by existing contracts. In

the model, the new contract margin dominates the local effect of smaller pools, so new contracts increase the number of borrowers.

Aggregate borrowing and defaults are driven by the extensive margin, with more borrowers leading to more borrowing and defaults. Changes in the size and number of contracts induced by financial innovations result in more disperse interest rates, as rates for low risk borrowers decline while high risk borrowers gain access to high rate loans. Smaller pools lower the average gap between a household's default risk and interest rate, leading to improved risk-based pricing. This effect is especially pronounced when the accuracy of the lending technology improves, as fewer high risk borrowers are misclassified as low risk.

While all three channels are driven by a common information-intensive innovation in lending technology, a natural question is whether they differ in predictions. One dimension along which improved risk assessment differs from the other channels is the average default rate of borrowers. On the one hand, whenever the number of contracts increases, households with riskier observable characteristics gain access to risky loans. However, an increase in signal accuracy also reduces the number of misclassified high risk types offered loans targeted at low risk borrowers, which lowers defaults. In our numerical example, these effects roughly offset, so that improved risk assessment leaves the average default rate of *borrowers* essentially unchanged. Another dimension along which the three channels differ is in their impact on overhead costs. While a decline in the fixed costs leads to a decline in the overhead costs of borrowing, this is not so for the other channels. An increase in signal accuracy and a fall in the cost of funds leads to an *increase* of overhead costs (even as a percentage of total loans), as more types of contracts are offered, each with its own fixed cost.

To evaluate the empirical relevance of our model, we examine changes in the distribution of credit card debt and interest rates, primarily using data from the Survey of Consumer Finances from 1983 to 2004. We find the model predictions line up surprisingly well with trends in the credit card market. Using credit card interest rates as a proxy for product variety, we find that the number of different contracts tripled between 1983 and 2001. Even more strikingly, the empirical density of credit card interest rates has become much "flatter". While nearly 55% of households in 1983 reported the same rate (18%), by the late 1990s no rate was shared by more than 10% of households. This has been accompanied by more accurate pricing of risk, as the relationship between observable risk factors and interest rates has tightened since the early 1980s.

Consistent with the model's predictions, the jump in the fraction of households with a bank credit card from 43% in 1983, to 56% in 1989 and 68% in 1998, entailed the extension of cards to borrowers with riskier characteristics. Since the SCF is a repeated cross-section, we build on Johnson (2007) and use a probit regression of bank card ownership on household characteristics in 1989 to identify "new" and "existing" cardholders in 1998. The "new" cardholders have riskier characteristics, being less likely to be married, less educated, and have lower income and net worth – and higher interest rates and delinquency rates. Building on this exercise, we conclude that the new cardholders account for roughly a quarter of the increase in credit card debt from 1989 to 1998. We conduct a similar exercise to quantify the contribution of the new cardholders to the rise in delinquencies (a proxy for increased bankruptcy risk). We find that between a quarter and a third of the rise can be attributed to the extensive margin of new cardholders.

Our empirical results on the quantitative importance of the extensive margin of new cardholders for the rise in credit card debt and bankruptcy may surprise some. A widespread view among economists is that the rise in bankruptcy was due primarily to either an *intensive margin* of low risk borrowers taking on more debt (e.g. Narajabad (2012), Sanchez (2012)) or a fall in the *stigma* of bankruptcy (Gross and Souleles 2002). Interestingly, our empirical exercise yields results for *existing* cardholders similar to those of Gross and Souleles (2002) who found that the default probability, controlling for risk measures, of a sample of credit card borrowers jumped between June 1995 and June 1997. Thus, our empirical findings suggest that the rise in bankruptcy over the 1990s can be accounted for largely by the extensive margin and lower "stigma".

The model provides novel insights into competition in the credit card market. In an influential paper, Ausubel (1991) argued that the fact that declines in the risk-free rate during the 1980s did not lower average credit card rates was "... paradoxical within the paradigm of perfect competition." However, this episode is consistent with our competitive framework. A decline in the risk-free rate makes borrowing more attractive, encouraging entry of new loan contracts that target riskier borrowers. This pushes up the average risk premium, increasing the average borrowing rate. Thus, unlike in the standard competitive lending model, the effect of a lower risk-free rate on the average borrowing rate is ambiguous. Our extensive margin channel is related also to recent work by Dick and Lehnert (2010). They find that increased competition, due to interstate bank deregulation (possibly aided by the adoption of information technology), contributed to the rise in bankruptcies. Our model provides a theoretical mechanism

for their empirical findings. By lowering barriers to interstate banking, deregulation expands market size, effectively lowering the fixed cost of contracts. In our framework, this leads to the extension of credit to riskier borrowers, resulting in more bankruptcies.

Our framework also offers new insights into the debate over the welfare implications of financial innovations. In our environment, financial innovations increase average (*ex ante*) welfare but are not Pareto improving, as changes in the size of contracts result in some households being shifted to higher interest rate contracts. Moreover, the competitive allocation in general is not efficient, as it features more contracts and less cross-subsidization than would be chosen by a social planner who weights all households equally. This results in the financial sector consuming more resources than is optimal.

This paper is related to the incomplete market framework of consumer bankruptcy of Chatterjee et al. (2007) and Livshits, MacGee, and Tertilt (2007).² Livshits, MacGee, and Tertilt (2010) and Athreya (2004) quantitatively evaluate alternative explanations for the rise in bankruptcies and borrowing. Both papers conclude that changes in consumer lending technology, rather than increased idiosyncratic risk (e.g., increased earnings volatility), are the main factors driving the rise in bankruptcies.³ Unlike this paper, they abstract from how financial innovations change the pricing of borrowers' default risk, and model financial innovation as a fall in the "stigma" of bankruptcy and a decline in lenders' cost of funds. Hintermaier and Koeniger (2009) find changes in the risk-free rate have little impact on unsecured borrowing and bankruptcies.

Closely related in spirit is complementary work by Narajabad (2012), Sanchez (2012), Athreya, Tam, and Young (2012), and Drozd and Nosal (2008). Narajabad (2012), Sanchez (2012) and Athreya, Tam, and Young (2012) examine improvements in lenders' ability to predict default risk. In these papers, more accurate or cheaper signals lead to relatively lower risk households borrowing more (i.e., an intensive margin shift), which increases their probability of defaulting. Drozd and Nosal (2008) examine a fall in the fixed cost incurred by the lender to solicit potential borrowers, which leads to lower interest rates and increased competition for borrowers. Our work differs from these papers in several key respects. First, we introduce a novel mechanism which operates through the extensive rather than intensive margin. Second, our tractable framework allows us to derive closed form solutions and thereby provides insights into the mechanism, while

² Chatterjee et al. (2008, 2010) formalize how credit histories support repayment of unsecured credit.

³ Moss and Johnson (1999) argue, based on an analysis of borrowing trends, that the main cause of the rise in bankruptcies is an increase in the share of unsecured credit held by lower income households.

the previous literature has focused on complex quantitative models. Third, we document several novel facts on the evolution of the credit card industry.

Also related to this paper is recent work on competitive markets with adverse selection. Adams, Einav, and Levin (2009), Einav, Jenkins, and Levin (2012) and Einav, Jenkins, and Levin (2009) find that subprime auto lenders face moral hazard and adverse selection problems when designing the pricing and contract structure of auto loans, and that there are significant returns to improved technology to evaluate loan applicants (credit scoring). Earlier work by Ausubel (1999) also found that adverse selection is present in the credit card market. Recent work by Dubey and Geanakoplos (2002), Guerrieri, Shimer, and Wright (2010) and Bisin and Gottardi (2006) considers existence and efficiency of competitive equilibria with adverse selection. Our paper differs both in its focus on financial innovations, and its incorporation of fixed costs of creating contracts.

The remainder of the paper is organized as follows. Section 2 documents innovations in the credit card industry since the 1980s, and Section 3 outlines the general model. In Section 4 we characterize the set of equilibrium contracts, while Section 5 examines the implications of financial innovations. Section 6 compares these predictions to data on U.S. credit card borrowing, and Section 7 analyzes the quantitative role of the extensive margin. Section 8 concludes. Additional details on the theory and empirical analysis is provided in a supplementary web appendix.

2 Credit Card Industry: Evolution and Driving Forces

We begin by summarizing key aspects of the credit card industry today and its recent evolution. This examination of current industry practice plays a key role in shaping our modeling decisions (described in Section 3), particularly in motivating the fixed costs of designing new credit card contracts. Subsection 2.2 outlines some of the key innovators who reshaped the credit industry over the 1980s and 1990s (summarized in Table reftimeline), while Subsection 2.3 documents the improvements in computing and information technology that made possible an information intensive approach to borrower risk assessment and contract design. The timing of these innovations leads us to focus on comparing the model predictions with data from the late 1980s and 1990s.

2.1 Credit Cards and Credit Scorecards

Credit card lenders today offer highly differentiated cards that vary in pricing (i.e., the interest rate, annual fees and late fees) and other dimensions (e.g., affinity cards). This entails a data-intensive strategy that designs contracts tailored to specific market segments (e.g., see Punch (1998)). In practice, this typically involves a numerically intensive evaluation of the relationship between borrowers' characteristics and credit risk (using proprietary data and data purchased from credit bureaus). Credit card companies also often undertake lengthy and costly experiments with alternative contract terms.⁴

Central to this data intensive approach to risk assessment is the use of specially developed credit *scorecards*.⁵ Each scorecard is a statistical model (estimated with historical data) mapping consumer characteristics into repayment and default probability for a specific product. Indeed, some large banks use 70 to 80 different scoring models in their credit card operations, with each scorecard adapted to a specific product or market segment (McCorkell 2002). This involves substantial costs; developing, implementing and managing a (single) customized scorecard can cost from \$40,000 to more than \$100,000 (see Mays (2004), p. 34).⁶ Custom scorecards are built in-house or developed by specialized external consultants (e.g., *Moody's Analytics and Risk Management Services* and *Capital Card Services Inc.*).⁷ While developing scorecards entails significant fixed costs, the resulting automated system reduces the cost of evaluating individual applicants.⁸

These scorecards are distinct from (and typically supplement) general-purpose credit scores, such as FICO.⁹ While many lenders use FICO scores as an input to their credit evaluations, it is typically only one piece of information used to evaluate an individual's credit risk, and is combined with a custom score based on borrower characteristics (with the score often conditioned on the specific product terms). This reflects the limitation of

⁴Experiments involve offering contract terms to random samples from a target population and tracking borrowing and repayment behaviour (often over 18 to 24 months). Based on these data, lenders adjust the terms and acceptance criteria (see Ausubel (1999) and Agarwal, Chomsisengphet, and Liu (2010)).

⁵One indication of the wide use of scorecards are the numerous handbooks providing practitioners detailed guides on their development (e.g., Lawrence and Solomon (2002), Mays (2004), and Siddiqi (2006)).

⁶Customized scorecards are updated every few years to account for changes in the applicant population and macroeconomic conditions. As a result, scorecard development requires recurring fixed costs.

⁷Siddiqi (2006) discusses a company that outsourced scorecard development and purchased ten different cards at an average cost of \$27,000 each.

⁸Citing the Federal Reserve Board (2007): "Credit-scoring systems generally involve significant fixed costs to develop, but their 'operating' cost is extremely low – that is, it costs a lender little more to apply the system to a few million cases than it does to a few hundred."

⁹While FICO scores (introduced by Fair Isaac and Company) are the best known example, Mays (2004) lists over 70 different generic credit scores.

general-purpose scores, which are designed to predict default probabilities rather than expected recovery rates or expected profitability of different borrowers for a specific contract. As a result, a customized score can improve the accuracy of credit risk assessment for borrowers offered a specific product. The estimation of scorecards often uses both lender specific information (e.g., from experiments or client histories) and information purchased from credit bureaus, such as generic credit scores, borrowers' repayment behaviour, and borrowers' debt portfolio.¹⁰

2.2 Evolution of the Credit Card Industry

While the idea of systematically using historical data on loan performance to shape loan underwriting standards dates back to Durand (1941), until recently consumer loan officers still relied primarily upon "the 4Cs" (i.e., Character, Capacity, Capital, Collateral) (Smith 1964). This began to change in the late 1960s, as the emergence of credit cards and advances in computing brought the development of application credit scoring models. Pioneered by Fair Isaac, these models provided lenders with generic estimates of the likelihood of serious delinquency in the upcoming year (Thomas 2009).

By the 1980s, advancements in information technology paved the way for a revolution in how consumer loans are assessed, monitored and administered (Barron and Staten 2003; Berger 2003; Evans and Schmalensee 2005). With lower costs of computation and data storage, behavioural credit scoring systems that incorporated payment and purchase information and information from credit bureaus, were developed, triggering the widespread adoption of credit scoring (McCorkell 2002; Engen 2000; Asher 1994; Thomas 2009).¹¹ These innovations are asserted to have played a key role in the growth of the credit card industry (Evans and Schmalensee 2005; Johnson 1992).¹²

The 1980s saw new entrants such as MBNA, First Deposit and Capital One build on these advances to design credit card contracts for targeted segments of the population. Shortly after its founding in 1981 as the first *monoline* credit card issuer (i.e., lender

¹⁰U.S. credit bureaus report borrowers' payment history, debt and public judgments (Hunt 2006). More than two million credit reports are sold daily by U.S. credit bureaus (Riestra 2002)

¹¹Fair Isaac and Company started building credit scoring systems in the late 1950s. Their first behaviour scoring system was introduced in 1975, first credit bureau score in 1981 and first general-purpose FICO score in 1989. See <http://www.fico.com/en/Company/Pages/history.aspx>.

¹²Credit scoring improved lenders' ability to assess risk and lowered operating costs. Both are significant for credit cards which provide risky unsecured loans and face operating costs of nearly 60% of total operations costs, compared to less than 20% of mortgage lending (Canner and Luekett 1992).

specializing in credit cards), MNBA embarked on a strategy of data-based screening of targets and underwriting standards for different credit card products (Cate and Staten 2003). In 1984, First Deposit Corporation¹³ adopted a business model of developing analytic methods of targeting card offers to mispriced demographic groups (i.e., groups with relatively low default probabilities for that product).¹⁴ Structured experimentation was pioneered by Rich Fairbank and Nigel Morris in 1988. Initially working with a regional bank (Signet), they used experiments which involved sending out offers for various products (i.e., credit cards with different terms) to consumers to design differentiated credit products for individual market segments (Clemons and Thatcher 1998). This “test and learn” strategy was so successful that in 1994, Signet spun off their group as a monoline lender, Capital One, which became one of the largest U.S. credit card issuers. Capital One initiated the dynamic re-pricing customer accounts, a practice that required intensive ongoing analysis of customer data (Clemons and Thatcher 2008).

This strategy of using quantitative methods and borrower data to design credit products targeted at different groups of borrowers was adopted by other large banks and new monoline lenders throughout the late 1980s and early 1990s.¹⁵ By the end of 1996, 42 large monoline lenders accounted for 77% of the total outstanding credit card balances of commercial banks (Federal Reserve Board 1997). The shifting landscape led to changes in the pricing strategy of credit card lenders, with companies such as AmEx introducing cards with different interest rates based on customers’ risk.¹⁶ This resulted in declines (increases) in interest rates for lower (higher) risk borrowers (Barron and Staten 2003).¹⁷ The 1990s also saw non-bank lenders such as Sears (Discover), GM, AT&T and GE enter the credit card market to take advantage of proprietary data on their customers.

While the changes in the credit card market are widely discussed, there is surpris-

¹³Ultimately, it became Provident Financial Corporation, a leading issuer of credit cards.

¹⁴Initially developed by Andrew Kahr, their first credit card product targeted low-risk “revolvers” by dropping the annual fee, upped the interest rate to 22%, lowering the minimum monthly payment, and offering new customers a cash-advance loan (at a high interest rate). Four years after opening, First Deposit had over 350,000 customers and \$1 billion in credit card receivables (Nocera (1994), pp 315-324).

¹⁵A proxy for this diffusion is the fraction of large banks using credit scoring in loan approval, which rose from 50% in 1988 to 85% in 2000 (American Bankers Association 2000). Similarly, the fraction of large banks using fully automated loan processing (for direct loans) increased from 12% in 1988 to nearly 29% in 2000 (American Bankers Association 2000). While larger banks often customize their own scorecards, smaller banks adopted this technology by purchasing scores from specialized providers (Berger 2003).

¹⁶In 1992, AmEx’s Optima card charged prime rate plus 8.25% from its new customers, prime plus 6.5% from its best customers, and prime plus 12.25% from chronic late-payers (Canner and Lueckett 1992).

¹⁷A similar finding holds for small business loans, where the adoption of credit scoring led to the extension of credit to “marginal applicants” at higher interest rates (Berger, Frame, and Miller 2005). For another example of the adoption of small business scoring models see Paravisini and Schoar (2013).

Table 1: Credit Card Evolution Timeline

Year	Innovation	Innovator	Strategy
1981	Monoline	MBNA	Specializes in offering credit cards nationally.
1984	Segmentation	First Deposit Corporation (later Provident)	Target liquidity-constrained borrowers with no-annual-fee cards with low minimum payments, but high rates
Late 1980s	Use of proprietary information	Non-bank entrants (Sears, GM, and AT&T)	Use proprietary information on customers to design products and target mispriced segments
1988	Experimentation	Signet (later Capital One) R. Fairbank & N. Morris	Design randomized experiments with credit card terms to identify profitable segments
1992	Risk-based re-pricing	AmEx (Optima card)	Interest rates respond to borrower's payment behaviour

Sources: See text, Section 2.2.

ingly little quantitative documentation of the diffusion of new practices.¹⁸ To document the timing of the diffusion of new lending technologies, we collected data on references to credit scoring in various publications. Figure 2(a) plots normalized counts of the words “credit scoring” and “credit score” in trade journals, the business press and academic publications.¹⁹ The figure shows a dramatic rise in references to credit scoring in the professional press after 1987. Using *GoogleScholar* to count mentions in Business, Finance, and Economics publications, we find a similar trend (see Figure 2(b)). Together, these measures paint a clear picture: credit scoring was negligible in the 1970s, picked up in the 1980s and accelerated in the mid 1990s.

2.3 Underlying Factors

Thus far, we have documented key innovations in the credit card industry — the development of customized scorecards and greater use of detailed borrower data to price borrower risk. Why did these innovations take hold in the 1980s and '90s? Modern credit scoring is a data-intensive exercise that requires large data sets (of payment his-

¹⁸This is a common challenge: “A striking feature of this literature [...] is the *relative dearth of empirical studies* that [...] provide a quantitative analysis of financial innovation.” Frame and White (2004).

¹⁹More specifically, the figure displays the word count relative to the counts of the phrase “consumer credit.” This normalization is necessary as the total number of printed words increased over time. See Appendix B for details.

tories and borrower characteristics) and rapid computing to analyze them (Giannasca and Giordani 2013). Thus, technological improvements in IT that shrunk the costs of data storage and processing were an essential prerequisite for the development and widespread adoption of credit scoring (McCorkell 2002; Engen 2000; Asher 1994).

The dramatic decline in IT costs in the second half of the 20th century is illustrated by the IT price index constructed by Jorgenson (2001) (Figure 2(c)), and by data on the cost of computing from Nordhaus (2007) (Figure 2(d)). Coughlin, Waid, and Porter (2004) report that the cost per MB of storage fell by a factor of roughly 100 between 1965 and the early 1980s, before falling even faster over the next twenty years. Lower IT and data storage costs led to the digitization of consumer records in the 1970s, in turn reducing the cost of developing and using credit scoring tools to assess risk (Poon 2011).

Another key development in the credit industry related to how credit card companies finance their operations. Beginning in 1987, lenders began to securitize credit card receivables. Securitization increased rapidly, with over a quarter of bank credit card balances securitized by 1991, and nearly half by 2005 (Federal Reserve Board 2006). This facilitated the rapid growth of monolines, and helped lower financing costs for some credit card lenders (Furletti 2002; Getter 2008).

3 Model Environment

We analyze a two-period small open economy populated by a continuum of borrowers, who face a stochastic endowment in period 2. Markets are incomplete as only non-contingent contracts can be issued. However, borrowers can default on contracts by paying a bankruptcy cost. Financial intermediaries can access funds at an (exogenous) risk-free interest rate r .

To capture key features of the credit card market as described in Section 2, our environment incorporates two additional features. First, we assume that financial intermediaries incur a fixed cost to design each financial contract (characterized by a lending rate, a borrowing limit and eligibility requirement for borrowers). Second, we assume lenders observe a (potentially) noisy signal of borrowers' risk types. In Section 5 we vary the magnitude of these two frictions to capture the impact of improved information technology on the credit card industry.

3.1 People

Borrowers live for two periods and are risk-neutral, with preferences represented by:²⁰

$$c_1 + \beta E c_2.$$

Each household receives the same deterministic endowment of y_1 units of the consumption good in period 1. The second period endowment, y_2 , is stochastic taking one of two possible values: $y_2 \in \{y_h, y_l\}$, where $y_h > y_l$.²¹ Households differ in their probability ρ of receiving the high endowment y_h . We identify households with their type ρ , which is distributed uniformly on $[0, 1]$.²² While borrowers know their own type, lenders do not observe it. However, upon paying a fixed cost (discussed below), the lenders get a signal σ regarding a borrower's type. With probability α , this signal is accurate: $\sigma = \rho$. With probability $(1 - \alpha)$, the signal is an independent draw from the ρ distribution ($U[0, 1]$).

We assume $\beta < \bar{q} = \frac{1}{1+r}$, so that households want to borrow at the risk-free rate. Households' borrowing, however, is limited by their inability to commit to repayment.

3.2 Bankruptcy

There is limited commitment by borrowers who can choose to declare bankruptcy in period 2. The cost of bankruptcy to a borrower is the loss of fraction γ of the second-period endowment. Lenders do not recover any funds from defaulting borrowers.

²⁰Linearity of the utility function allows a clean characterization of the unique equilibrium. Using CRRA preferences would complicate the analysis, as different types within a contract interval could disagree about the optimal size of the loan (given the price). While introducing risk aversion would lose the analytical tractability, we believe the main mechanism is robust as fixed costs create an incentive to pool different types into contracts even with strictly concave utility functions.

²¹While the assumption of two possible income realizations affords us a great deal of tractability (in part by making it easy to rank individual risk types), the key mechanism we highlight carries over to richer environments. That is, as the costs of advancing loans fall, contracts become more "specialized," and lenders offer risky loans to new (and riskier) borrowers.

²²The characterization of equilibria is practically unchanged for an arbitrary support $[a, b] \subseteq [0, 1]$. Assuming the uniform distribution deliver very clean and elegant characterization of equilibrium allocation but is not essential for any of the key results.

3.3 Financial Market

Financial markets are competitive. Financial intermediaries can borrow at the exogenously given interest rate r and make loans to borrowers. Loans take the form of one period non-contingent bond contracts. However, the bankruptcy option introduces a partial contingency by allowing bankrupts to discharge their debts.

Financial intermediaries incur a fixed cost χ to offer each non-contingent lending contract to (an unlimited number of) households. Endowment-contingent contracts are ruled out (e.g., due to non-verifiability of the endowment realization). A contract is characterized by $(L, q, \underline{\sigma})$, where L is the face value of the loan, q is the per-unit price of the loan (so that qL is the amount advanced in period 1 in exchange for a promise to pay L in period 2), and $\underline{\sigma}$ is a cut-off for which household types qualify for the contract.

The fixed cost of offering a contract is the costs of developing a scorecard (discussed in Section 2.1), which allows the lender to assess borrowers' risk types. Thus, upon paying the fixed cost χ , a lender gets to observe a signal σ of a borrower's type, which is accurate (equal to ρ) with probability α . While each scorecard is specific to a contract (that is, it informs a lender whether a borrower's σ meets a specific threshold $\underline{\sigma}$), the signal σ is perfectly correlated across lenders (and is known to the borrower).²³

In equilibrium, the bond price incorporates the fixed cost of offering the contract (so that the equilibrium operating profit of each contract equals the fixed cost) and the default probability of borrowers. Since no risk evaluation is needed for the risk-free contract $(\gamma y_i, \bar{q}, 0)$, no fixed cost is required.²⁴ Households can accept only one loan, so intermediaries know the total amount borrowed.

3.4 Timing

The timing of events is critical for supporting pooling across unobservable types in equilibrium (see Hellwig (1987)). The key idea is that "cream-skimming" deviations are made unprofitable if pooling contracts can exit the market in response.

²³Consider, for example, a low-risk borrower who lives in a zip code with mostly high-risk consumers. If the zip code is an input used for scorecards, all lenders will misclassify this borrower into a high risk category (and the borrower is aware of that). This mechanism also applies to high-risk borrowers with low-risk characteristics (e.g., long tenure with their current employer or at their current address).

²⁴In an earlier version of the paper, we treated the risk-free contract symmetrically. This does not change the key model predictions, but complicates the exposition and computational algorithms.

- 1.a. Intermediaries pay fixed costs χ of entry and announce their contracts — the stage ends when no intermediary wants to enter given the contracts already announced.
- 1.b Households observe all contracts and choose which one(s) to apply for (realizing that some intermediaries may choose to exit the market).
- 1.c Intermediaries decide (using the scorecard) whether to advance loans to applicants or exit the market.
- 1.d Lenders who chose to stay in the market notify qualified applicants.
- 1.e Borrowers who received loan offers pick their preferred loan contract. Loans are advanced.
- 2.a Households realize their endowments and make default decisions.
- 2.b Non-defaulting households repay their loans.

3.5 Equilibrium

We study (pure strategy) Perfect Bayesian Equilibria of the extensive form game described in Subsection 3.4. In the complete information case, the object of interest become Subgame Perfect Equilibria, and we are able to characterize the complete set of equilibrium outcomes. In the asymmetric information case, we characterize “pooling” equilibria where all risky contracts have the same face value (i.e. equilibria that are similar to the full information equilibria) and then numerically verify existence and uniqueness. Details are given in Section 4.2.

In all cases, we emphasize equilibrium outcomes (the set of contracts offered and accepted in equilibrium) rather than the full set of equilibrium strategies. While the timing of the game facilitates existence of pooling equilibria, it also makes a complete description of equilibrium strategies quite involved. The key idea is that the timing allows us to support pooling in equilibrium by preventing “cream skimming” — offering a slightly distorted contract which only “good” types would find appealing, leaving the “bad” types with the incumbent contract. Allowing the incumbent to exit if such cream-skimming is attempted (at stage 1.c) thus preempts cream skimming, so long as the incumbent earns zero profit on the contract. For tractability, we simply describe the set of contracts offered in equilibrium.

An *equilibrium* (outcome) is a set of active contracts $\mathcal{K}^* = \{(q_k, L_k, \underline{\sigma}_k)_{k=1, \dots, N}\}$ and consumers' decision rules $\kappa(\rho, \sigma, \mathcal{K}) \in \mathcal{K}$ for each type (ρ, σ) such that

1. Given $\{(q_k, L_k, \underline{\sigma}_k)_{k \neq j}\}$ and consumers' decision rules, each (potential) bank j maximizes profits by making the following choice: to enter or not, and if it enters, it chooses contract $(q_j, L_j, \underline{\sigma}_j)$ and incurs fixed cost χ .
2. Given any \mathcal{K} , a consumer of type ρ with public signal σ chooses which contract to accept so as to maximize expected utility. Note that a consumer with public signal σ can choose a contract k only if $\sigma \geq \underline{\sigma}_k$.

4 Equilibrium Characterization

We begin by examining the environment with complete information regarding households' risk types ($\alpha = 1$). With full information, characterizing the equilibrium is relatively simple since the public signal always corresponds to the true type. This case is interesting for several reasons. First, this environment corresponds to a static version of recent papers (i.e. Livshits, MacGee, and Tertilt (2007) and Chatterjee et al. (2007)) which abstract from adverse selection. The key difference is that the fixed cost generates a form of "pooling", so households face actuarially unfair prices. Second, we can analyze technological progress in the form of lower fixed costs. Finally, abstracting from adverse selection helps illustrate the workings of the model. In Section 4.2 we show that including asymmetric information leads to remarkably similar equilibrium outcomes.

4.1 Perfectly Informative Signals

In the full information environment, the key friction is that each lending contract requires a fixed cost χ to create. Since each borrower type is infinitesimal relative to this fixed cost, lending contracts have to pool different types to recover the cost of creating the contract. This leads to a finite set of contracts being offered in equilibrium.

Contracts can vary along two dimensions: the face value L , which the household promises to repay in period 2, and the per-unit price q of the contract. Our first result is that all possible lending contracts are characterized by one of two face values. The face value of the risk-free contract equals the bankruptcy cost in the low income state, so that

households are always willing to repay. The risky contracts' face value is the maximum such that borrowers repay in the high income state. Contracts with lower face value are not offered in equilibrium since, if (risk-neutral) households are willing to borrow at a given price, they want to borrow as much as possible at that price. Formally:

Lemma 4.1. *There are at most two loan sizes offered in equilibrium: A risk-free contract with $L = \gamma y_l$ and risky contracts with $L = \gamma y_h$.*

Risky contracts differ in their bond prices and eligibility criteria. Since the eligibility decision is made after the fixed cost has been incurred, lenders are willing to accept any household who yields non-negative operating profits. Hence, a lender offering a risky loan at price q rejects all applicants with risk type below some cut-off ρ such that the expected return from the marginal borrower is zero: $\bar{q}\rho L - qL = 0$, where $\rho\bar{q}L$ is the expected present value of repayment and qL is the amount advanced to the borrower. This cut-off rule is summarized in the next Lemma:

Lemma 4.2. *Every lender offering a risky contract at price q rejects an applicant iff the expected profit from that applicant is negative. The marginal type accepted into the contract is $\rho = \frac{q}{\bar{q}}$.*

This implies that the riskiest household accepted by a risky contract makes no contribution to the overhead cost χ . We order the risky contracts by the riskiness of the clientele served by the contract, from the least to the most risky.

Lemma 4.3. *Finitely many risky contracts are offered in equilibrium. Contract n serves borrowers in the interval $[\underline{\sigma}_n, \underline{\sigma}_{n-1})$, where $\underline{\sigma}_0 = 1$, $\underline{\sigma}_n = 1 - n\sqrt{\frac{2\chi}{\gamma y_h \bar{q}}}$, at bond price $q_n = \bar{q}\underline{\sigma}_n$.*

Proof. If a contract yields strictly positive profit (net of χ), then a new entrant will enter, offering a better price that attracts the borrowers from the existing contract. Hence, each contract n earns zero profits in equilibrium, so that:

$$\chi = \int_{\underline{\sigma}_n}^{\underline{\sigma}_{n-1}} (\rho\bar{q} - q_n)Ld\rho = L \left(\frac{(\underline{\sigma}_{n-1})^2 - (\underline{\sigma}_n)^2}{2} \bar{q} - (\underline{\sigma}_{n-1} - \underline{\sigma}_n)q_n \right).$$

Using $q_n = \underline{\sigma}_n \bar{q}$ and $L = \gamma y_h$ from Lemmata 4.1 and 4.2, and solving for $\underline{\sigma}_n$, we obtain $\underline{\sigma}_n = \underline{\sigma}_{n-1} - \sqrt{\frac{2\chi}{\gamma y_h \bar{q}}}$. Using $\underline{\sigma}_0 = 1$ and iterating on $\underline{\sigma}_n$, gives $\underline{\sigma}_n = 1 - n\sqrt{\frac{2\chi}{\gamma y_h \bar{q}}}$. \square

Lemma 4.3 establishes that each contract serves an interval of borrower types of equal length,²⁵ and that the measure pooled in each contract increases in the fixed cost χ and

²⁵This result follows from the assumption of uniform distribution of types. With a non-uniform distribution, contracts would serve intervals of different lengths.

the risk-free interest rate, and decreases in the bankruptcy punishment γy_h . If the fixed cost is so large that $\sqrt{\frac{2\chi}{\gamma y_h \bar{q}}} > 1$, then no risky loans are offered.

The number of risky contracts offered in equilibrium is pinned down by the households' participation constraints. Given a choice between several risky contracts, households always prefer the contract with the highest q . Thus, a household's decision problem reduces to choosing between the best risky contract they are eligible for and the risk-free contract. The value to type ρ of contract (q, L) is

$$v_\rho(q, L) = qL + \beta [\rho(y_h - L) + (1 - \rho)(1 - \gamma)y_l],$$

and the value of the risk-free contract is

$$v_\rho(\bar{q}, \gamma y_l) = \bar{q}\gamma y_l + \beta [\rho y_h + (1 - \rho)y_l - \gamma y_l].$$

A household of type ρ accepts risky contract (q, L) only if $v_\rho(q, L) \geq v_\rho(\bar{q}, \gamma y_l)$, which reduces to

$$q \geq (\bar{q} - \beta) \frac{\gamma y_l}{L} + \beta \left(\rho + (1 - \rho) \frac{\gamma y_l}{L} \right) \quad (4.1)$$

Note that the right-hand side of equation (4.1) is increasing in ρ . Hence, if the participation constraint is satisfied for the highest type in the interval, $\underline{\sigma}_{n-1}$, it will be satisfied for any household with $\rho < \underline{\sigma}_{n-1}$. Solving for the equilibrium number of contracts, N , thus involves finding the first risky contract n for which this constraint binds for $\underline{\sigma}_{n-1}$.

Lemma 4.4. *The equilibrium number of contracts offered, N , is the largest integer smaller than:*

$$\frac{(y_h - y_l)[\bar{q} - \beta(1 + \sqrt{\frac{2\chi}{\gamma y_h \bar{q}}})]}{[\bar{q}y_h - \beta(y_h - y_l)]\sqrt{\frac{2\chi}{\gamma y_h \bar{q}}}}.$$

If the expression is negative, no risky contracts are offered.

Proof. We need to find the riskiest contract for which the household at the top of the interval participates: i.e. the largest n such that risk type $\underline{\sigma}_{n-1}$ prefers contract n to the risk-free contract. Substituting for contract n in the participation constraint (4.1) of $\underline{\sigma}_{n-1}$:

$$q_n \geq (\bar{q} - \beta) \frac{y_l}{y_h} + \beta \left[\underline{\sigma}_{n-1} + (1 - \underline{\sigma}_{n-1}) \frac{y_l}{y_h} \right]$$

Using $q_n = \underline{\sigma}_n \bar{q}$ and $\underline{\sigma}_n = 1 - n \sqrt{\frac{2\chi}{\gamma y_h \bar{q}}}$ from Lemma 4.3, and solving for n , this implies

$$n \leq \frac{(y_h - y_l) \left[\bar{q} - \beta \left(1 + \sqrt{\frac{2\chi}{\gamma y_h \bar{q}}} \right) \right]}{[\bar{q} y_h - \beta(y_h - y_l)] \sqrt{\frac{2\chi}{\gamma y_h \bar{q}}}}$$

□

The set of equilibrium contracts is fully characterized by the following theorem, which follows directly from Lemmata 4.1-4.4, and is illustrated in Figure 3(a).

Theorem 4.5. *If $(\bar{q} - \beta)[y_h - y_l] > \bar{q} y_h \sqrt{\frac{2\chi}{\gamma y_h \bar{q}}}$, then there exists $N \geq 1$ risky contracts characterized by: $L = \gamma y_h$, $\underline{\sigma}_n = 1 - n \sqrt{\frac{2\chi}{\gamma y_h \bar{q}}}$, and $q_n = \bar{q} \underline{\sigma}_n$. N is the largest integer smaller than $\frac{(y_h - y_l) \left[\bar{q} - \beta \left(1 + \sqrt{\frac{2\chi}{\gamma y_h \bar{q}}} \right) \right]}{[\bar{q} y_h - \beta(y_h - y_l)] \sqrt{\frac{2\chi}{\gamma y_h \bar{q}}}}$. One risk-free contract is offered at price \bar{q} to all households with $\rho < \underline{\sigma}_N$.*

4.2 Incomplete Information

We now characterize equilibria with asymmetric information. We focus on “pooling” equilibria which closely resemble the complete information equilibria of Section 4.1.²⁶ These “pooling” equilibria feature one risk-free contract with loan size $L = \gamma y_l$ and finitely many risky contracts with $L = \gamma y_h$, each targeted at a subset of households with sufficiently high public signal σ . While we are unable to provide a complete characterization of equilibria with asymmetric information for arbitrary parameter values, we are able to numerically verify that the “pooling” equilibrium is in fact the unique equilibrium for the parameter values we consider.

The main complication introduced by asymmetric information arises from mislabeled borrowers. The behaviour of borrowers with incorrectly high public signals ($\sigma > \rho$) is easy to characterize, since they always accept the contract offered to their public type. Customers with incorrectly low public signals, however, may prefer the risk-free contract over the risky contract for their public type. While this is not an issue in the best loan pool (as no customer is misclassified downwards), the composition of riskier pools

²⁶In contrast, a “separating” equilibrium would include smaller risky “separating” loans targeted at mislabeled borrowers who were misclassified into high-risk contracts. Note that our notion of “pooling” is not quite standard, as it allows mislabeled types to decline the risky “pooling” loan they are offered, and join the risk-free loan pool.

(and thus the pricing) may be affected by the “opt-out” of misclassified low risk types. For each risky contract, denote $\hat{\rho}_n$ the highest true type willing to accept that contract over a risk-free loan. Using the participation constraints, we have:

$$\hat{\rho}_n = \frac{q_n y_h - \bar{q} y_l}{\beta(y_h - y_l)}. \quad (4.2)$$

Since $\hat{\rho}_n$ is increasing in q_n , lower bond prices result in a higher opt-out rate. Households who decline risky loans (i.e., those with public signal $\sigma \in [\underline{\sigma}_n, \underline{\sigma}_{n-1})$ and true type $\rho > \hat{\rho}_n$) borrow via the risk free contract. Figure 3(b) illustrates the set of equilibrium contracts.

Despite this added complication, the structure of equilibrium loan contracts remain remarkably similar to the full information case. Strikingly, as the following lemma establishes, the intervals of public signals served by the risky contracts are of equal size.

Lemma 4.6. *In a “pooling” equilibrium, the interval of public types served by each risky contract is of size $\sqrt{\frac{2\chi}{\alpha\bar{q}\gamma y_h}}$.*

Proof. This result follows from the free entry and uniform type distribution assumptions. Consider an arbitrary risky contract. For any public type σ , let $E\pi(\sigma)$ denote expected profits. Note that the lowest public type accepted $\underline{\sigma}$, yields zero expected profits. Free entry implies the contract satisfies the zero profit condition, so total profits from the interval of public types between $\underline{\sigma}$ and $\underline{\sigma} + \theta$ must equal χ .

$$\int_0^\theta E\pi(\underline{\sigma} + \delta) d\delta = \chi \quad (4.3)$$

With probability α the signal is correct (so $\rho = \sigma$), while with probability $1 - \alpha$ the signal is incorrect, in which case types $\rho > \hat{\rho}$ choose to opt out. To determine the profit from type $\underline{\sigma} + \delta$, note that the fraction of households that do not opt out is $\alpha + (1 - \alpha)\hat{\rho}$. Hence:

$$\begin{aligned} E\pi(\underline{\sigma} + \delta) &= (\alpha + (1 - \alpha)\hat{\rho})E\pi(\underline{\sigma} + \delta | \rho < \hat{\rho}) \\ &= (\alpha + (1 - \alpha)\hat{\rho}) [\bar{q}E(\rho | \sigma = \underline{\sigma} + \delta, \rho < \hat{\rho})\gamma y_h - q_n\gamma y_h]. \end{aligned}$$

The additional repayment probability from public type $\underline{\sigma} + \delta$ over type $\underline{\sigma}$ is $\frac{\alpha\delta}{\alpha + (1 - \alpha)\hat{\rho}}$, which is simply the probability that the signal is correct times the difference in repayment rates corrected for the measure that accepts the contract ($\alpha + (1 - \alpha)\hat{\rho}$). Thus:

$$E\pi(\underline{\sigma} + \delta) = (\alpha + (1 - \alpha)\hat{\rho}) \left[\frac{\alpha\delta\bar{q}}{\alpha + (1 - \alpha)\hat{\rho}}\gamma y_h + \bar{q}(E(\rho | \sigma = \underline{\sigma}, \rho < \hat{\rho}))\gamma y_h - q_n\gamma y_h \right].$$

At the bottom cutoff, $\underline{\sigma} < \underline{\sigma} + \theta \leq \hat{\rho}$. Thus, the last two terms equal the expected profit from public signal $\underline{\sigma}$:

$$E\pi(\underline{\sigma} + \delta) = (\alpha + (1 - \alpha)\hat{\rho}) \left[\frac{\alpha\delta\bar{q}}{\alpha + (1 - \alpha)\hat{\rho}} \gamma y_h + E\pi(\underline{\sigma}) \right].$$

Since the expected profit for type $\underline{\sigma}$ is zero, this simplifies to $E\pi(\underline{\sigma} + \delta) = \alpha\delta\bar{q}\gamma y_h$. Plugging this into equation (4.3), we have $\int_0^\theta \alpha\bar{q}\gamma y_h \delta d\delta = \chi$. It follows that $\theta = \sqrt{\frac{2\chi}{\alpha\bar{q}\gamma y_h}}$. \square

The expression for the length of the interval (of public types) served closely resembles the complete information case in Lemma 4.3. The only difference is that less precise signals increase the interval length by the multiplicative factor $\sqrt{1/\alpha}$. This is intuitive, as the average profitability of a type decreases as the signal worsens, and thus larger pools are needed to cover the fixed cost. What is surprising is that the measure of public types targeted by each contract is the same, especially since the fraction who accept varies due to misclassified borrowers opting out. As the proof of Lemma 4.6 illustrates, this is driven by two effects that exactly offset each other: lower-ranked contracts have fewer borrowers accepting, but make up for it through higher profit per borrower. As a result, the profitability of a type $(\underline{\sigma} + \delta)$ is the same across contracts $(= \alpha\delta\bar{q}\gamma y_h)$.

As in the full information case, the number of risky contracts offered in equilibrium is pinned down by the household participation constraints. Type ρ is willing to accept risky contract (q, L) whenever $v_\rho(q, L) \geq v_\rho(\bar{q}, \gamma y_l)$. This also implies that if the n -th risky contract $(q_n, \gamma y_h, \underline{\sigma}_n)$ is offered, then $\hat{\rho}_n \geq \underline{\sigma}_{n-1}$. That is, no accurately labeled customer ever opts out of a risky contract in equilibrium. Combining Lemma 4.6 with the zero marginal profit condition, one can derive a relationship between the bond price and the cutoff public type for each contract. The next theorem summarizes this result.

Theorem 4.7. *Finitely many risky contracts are offered in a “pooling” equilibrium. The n -th contract $(q_n, \gamma y_h, \underline{\sigma}_n)$ serves borrowers with public signals in the interval $[\underline{\sigma}_n, \underline{\sigma}_{n-1})$, where $\underline{\sigma}_0 = 1$, and $\underline{\sigma}_n = 1 - n\sqrt{\frac{2\chi}{\alpha\bar{q}\gamma y_h}}$. The bond price q_n solves*

$$\bar{q}\underline{\sigma}_n\alpha = q_n (\alpha + (1 - \alpha)\hat{\rho}_n) - \bar{q}(1 - \alpha)\frac{(\hat{\rho}_n)^2}{2},$$

where $\hat{\rho}_n$ is given by equation (4.2). If the participation constraints of mislabeled borrowers do not bind ($\hat{\rho}_n = 1$), this simplifies to $q_n = \bar{q} (\alpha\underline{\sigma}_n + (1 - \alpha)\frac{1}{2})$.

To verify that this “pooling” allocation is an equilibrium, we need to rule out the

possibility of profitable entry of new (separating) contracts. Specifically, one needs to rule out “cream skimming” deviations targeted at borrowers whose public signals are lower than their true type. Such deviation contracts necessarily involve smaller loans offered at better terms, since public types that are misclassified downwards must prefer them to the risk-free contract and true types must prefer the risky contract they are eligible for. In the numerical examples, we computationally verify that such deviations are not profitable. The fixed cost plays an essential role, as it forces potential entrant to “skim” enough people to cover the fixed cost. See Appendix A for a detailed description of the possible deviation and verification procedure.

By numerically ruling out these deviations we also establish that “pooling” is the unique equilibrium. Given our timing assumptions, the existence of a “separating” equilibrium would rule out the “pooling” equilibrium, since “separating” is preferred by the best customers (highest ρ 's). Uniqueness within the class of “pooling” equilibria follows from the same argument given for the complete information case in Section 4.1.

5 Implications of Financial Innovations

In this section, we analyze the model implications for three channels through which financial innovations could impact consumer credit: (i) a decline in the fixed cost χ , (ii) a decrease in the cost of loanable funds \bar{q} , and (iii) an improvement in the accuracy of the public signal α . Given the stylized nature of our model, we focus on the qualitative predictions for borrowing, defaults, interest rates and the composition of borrowers. We find that all three channels affect the extensive margin of who has access to credit. “Large enough” innovations lead to more credit contracts, access to risky loans for higher risk households, more disperse interest rates, more borrowing, and defaults. Each of these channels have different implications for changes in the ratio of overhead cost to total loans and the average default rate of borrowers.

5.1 Decline in the Fixed Cost

It is widely agreed that lower information processing costs have facilitated the increased use of data intensive analysis to design credit scorecards for new credit products (McNab and Taylor 2008). In our model, this corresponds to lower fixed costs, χ . We use the

analytical results from Section 4.1, and an illustrative numerical example (see Figure 4), to explore how the model predictions vary with χ .²⁷ For simplicity, we focus on the full information case ($\alpha = 1$). Qualitatively similar results hold when $\alpha < 1$.

A decline in the fixed cost of creating a contract, χ , impacts the set of equilibrium contracts via both the measure served by each contract and the number of contracts (see Figure 4.A and B). Since each contract is of length $\sqrt{\frac{2\chi}{\gamma y_h \bar{q}}}$, holding the number of contracts fixed, a reduction in χ reduces the total measure of borrowers. However, a large enough decline in the fixed cost lowers the borrowing rates for (previously) marginal borrowers enough that they prefer the risky to the risk-free contract. This increase in the number of contracts introduces discontinuous jumps in the measure of risky borrowers. Globally (for sufficiently large changes in χ), the extensive margin of an increase in the number of contracts dominates, so the measure of risky borrowers increases. This follows from Theorem 4.5, as the measure of risky borrowers is bounded by:

$$1 - \underline{\sigma}_N = N \sqrt{\frac{2\chi}{\gamma y_h \bar{q}}} \in \left(\frac{(y_h - y_l)(\bar{q} - \beta) - \bar{q} y_h \sqrt{\frac{2\chi}{\gamma y_h \bar{q}}}}{\bar{q} y_h - \beta(y_h - y_l)}, \frac{(y_h - y_l)[\bar{q} - \beta(1 + \sqrt{\frac{2\chi}{\gamma y_h \bar{q}}})]}{\bar{q} y_h - \beta(y_h - y_l)} \right).$$

Note that the global effect follows from the fact that both the left and the right boundaries of the interval are decreasing in χ .

Since all risky loans have the same face value $L = \gamma y_h$, variations in χ affect credit aggregates primarily through the extensive margin of how many households are eligible. As a result, borrowing and defaults inherit the “saw-tooth” pattern of risky borrowers (see Figure 4.C, D and E). However, the fact that new contracts extend credit to riskier borrowers leads (globally) to defaults increasing faster than borrowing. The reason is that the amount borrowed, $q_n L$, for a new contract is lower than for existing contracts since the bond price is lower. Hence, the amount borrowed rises less quickly than does the measure of borrowers (compare Figure 4.C with 4.D). Conversely, the extension of credit to riskier borrowers causes total defaults ($\int_{\underline{\sigma}_N}^1 (1 - \rho) d\rho = 1/2 - \underline{\sigma}_N + \frac{\underline{\sigma}_N^2}{2}$) to increase faster, leading to higher default rates (see Figure 4.E).

The rise in defaults induced by lower χ is accompanied by a tighter relationship between individual risk and borrowing interest rates. The shrinking of each contract interval lowers the gap between the average default rate in each pool and each borrower’s default risk, leading to more accurate risk-based pricing. As the number of contracts

²⁷The example parameters are $\beta = 0.75, \gamma = 0.25, y_l = 0.6, y_h = 3, \bar{r} = 0.04$, with $\chi \in [0.0005, 0.00001]$.

increases, interest rates become more disperse and the average borrowing interest rate slightly increases. This reflects the extension of credit to riskier borrowers at high interest rates, while interest rates on existing contracts fall (see Figure 4.F).

There are two key points to take from Figure 4.G, which plots total overhead costs as a percentage of borrowing. First, overhead costs in the example are very small. Second, even though χ falls by a factor of 50, total overhead costs (as % of debt) fall only by a factor of 7. The smaller decline in overheads costs is due to the decrease in the measure served by each contract, so that each borrower has to pay a larger share of the overhead costs. This suggests that cost of operations of banks (or credit card issuers) may not be a good measure of technological progress in the banking sector.

The example also highlights a novel mechanism via which interstate bank deregulation could impact consumer credit markets. In our model, an increase in market size is analogous to a lower χ , since what matters is the ratio of the fixed cost to the measure of borrowers. Thus, the removal of geographic barriers to banking across geographic regions, which effectively increases the market size, acts similarly to a reduction in χ and results in the extension of credit to riskier borrowers. This insight is particularly interesting given recent work by Dick and Lehnert (2010), who find that interstate bank deregulation (which they suggest increased competition) was a contributing factor to the rise in consumer bankruptcies. Our example suggests that deregulation may have led to more bankruptcies not by increasing competition per se, but by facilitating increased market segmentation by lenders. This (for large enough changes) leads to the extension of credit to riskier borrowers, and thus more bankruptcies.²⁸

5.2 Decline in the Risk Free Rate

Another channel through which financial innovations may have affected consumer credit is by lowering lenders' cost of funds, either via securitization or lower costs of loan processing. To explore this channel, we vary the risk free interest rate in our model. For simplicity, we again assume that $\alpha = 1$, although similar results hold for $\alpha < 1$.

The effect of a decline in the risk free rate is similar to a decline in fixed costs. Once again, the measure of borrowers depends upon how many contracts are offered and the

²⁸Bank deregulation and improved information technology may explain the increased role of large credit card providers who offer cards nationally, whereas early cards were offered by regional banks.

measure served by each contract. The length of each contract is $\sqrt{\frac{2\chi}{\alpha y_h \gamma q}}$, so a lower risk-free interest rate leads to fewer borrowers per contract. Intuitively, the pass-through of lower lending costs to the bond price q_n makes the fixed cost smaller relative to the amount borrowed. Since the contract size depends on the trade-off between spreading the fixed cost across more households versus more cross-subsidization across borrowers, the effective reduction in the fixed cost induces smaller pools. Sufficiently large declines in the risk-free rate increase the bond price (q_{n+1}) of the marginal risky contract by enough that borrowers prefer it to the risk-free contract. Since the global effect of additional contracts dominates the local effect of smaller pools, sufficiently large declines in the cost of funds lead to more households with risky loans (see Figure 5.A and B).

As with χ , credit aggregates are affected primarily through the extensive margin. Since increasing the number of borrowers involves the extension of risky loans to riskier borrowers, globally default rates rise with borrowing (see Figure 5.D and E). The average borrowing interest rate reflects the interaction between the pass-through of lower cost of funds, the change in the composition of borrowers, and increased overhead costs. For each existing contract, the lending rate declines by less than the risk-free rate since with smaller pools the fixed cost is spread across fewer borrowers. Working in the opposite direction is the entry of new contracts with high interest rates, which increases the maximum interest rate (see Figure 5.F). As a result, the average interest rate on risky loans declines by less than 1 point in response to a 4 point decline in the risk-free rate.

This example offers interesting insights into the debate over competition in the U.S. credit card market. In an influential paper, Ausubel (1991) documented that the decline in risk-free interest rates in the 1980s did not result in lower average credit card rates. This led some to claim that the credit card industry was imperfectly competitive. In contrast, Evans and Schmalensee (2005) argued that measurement issues associated with fixed costs of lending and the expansion of credit to riskier households during the late 1980s implied that Ausubel's observation could be consistent with a competitive lending market. Our model formalizes this idea.²⁹ As Figure 5.F illustrates, a decline in the risk-free interest rate can leave the average interest rate largely unchanged, as cheaper credit pulls in riskier borrowers, which increases the risk-adjusted interest rate.

²⁹ Brito and Hartley (1995) formalize a closely related mechanism, but with an exogenously fixed number of contracts (risk categories), whereas in our model entry of new new contracts plays a key role.

5.3 Improvements in Signal Accuracy

The last channel we consider is an improvement in lenders' ability to assess borrowers' default risk. This is motivated by the improvement of credit evaluation technologies (see Section 2), which maps naturally into an increase in signal accuracy, α . We again use our numerical example to help illustrate the model predictions (see Figure 6).³⁰

Variations in signal accuracy (α) impact who is *offered* and who *accepts* risky loans. As in Sections 5.1 and 5.2, the measure offered a risky loan depends upon the number and "size" of each contract. From Theorem 4.7, the measure eligible for each contract ($\sqrt{\frac{2\chi}{\alpha\bar{q}\gamma y_h}}$) is decreasing in α (see Figure 6.B). Intuitively, higher α makes the credit technology more productive, which results in it being used more intensively to sort borrowers into smaller pools. Higher α also pushes up bond prices (q_n) by lowering the number of misclassified high risk types eligible for each contract. This results in fewer misclassified low risk households declining risky loans, narrowing the gap between the measure accepting versus offered risky loans (see Figure 6.C). A sufficiently large increase in α raises the bond price of the marginal risky contract enough that it is preferred to the risk-free contract, resulting in a new contract being offered (see Figure 6.A). Globally, the extensive margin of the number of contracts dominates, so the fraction of the population offered a risky contract increases with signal accuracy.

More borrowers leads to an increase in debt. Similar to a decline in the fixed cost of contracts, an increase in the number of contracts involves the extension of credit to higher risk (public) types, which increases defaults (Figure 6.E). However, the impact of higher α on the default rate of borrowers is more nuanced, as the extension of credit to riskier public types is partially offset by fewer misclassified high risk types. These offsetting effects can be seen in the expression for total defaults (Equation 5.1).

$$\text{Defaults} = \underbrace{\alpha \left(1 - \underline{\sigma}_N - \frac{1 - \underline{\sigma}_N^2}{2} \right)}_{\text{Correctly Classified}} + \underbrace{(1 - \alpha) \sum_{j=1}^N (\underline{\sigma}_{j-1} - \underline{\sigma}_j) \left(\hat{\rho}_j - \frac{(\hat{\rho}_j)^2}{2} \right)}_{\text{Misclassified}} \quad (5.1)$$

As α increases, the rise in the number of contracts (N) lowers $\underline{\sigma}_N$, which leads to more defaults by correctly classified borrowers. However, higher α also lowers the number of misclassified borrowers, who are riskier on average than the correctly classified. In our example, this results in the average default rate of borrowers varying little in response to

³⁰We vary the fraction of people with a correct signal from 0.75 to 0.9999, with $\chi = 0.0001$.

α , so that total defaults increase proportionally to the total number of (risky) borrowers.

Figure 6.F shows that interest rates fan out as α rises, with the minimum rate declining, while the highest rises. This again reflects the offsetting effects of improved risk assessment. By reducing the number of misclassified borrowers, default rates for existing contracts decline, which lowers the risk premium and thus the interest rate. The maximum interest rate, in contrast, rises (globally) since increases in α lead to new contracts targeted at riskier borrowers. Finally, since the average default rate for borrowers is relatively invariant to α , so is the average risk premium (and thus the average interest rate). Overall, higher α leads to a tighter relationship between (ex-post) individual default risk and (ex-ante) borrowing interest rates.

Total overhead costs (as a percentage of risky borrowing) increase with α (Figure 6.G), which reflects more intensive use of the lending technology induced by its increased accuracy. As a consequence, equating technological progress with reduced cost of lending can be misleading, since technological progress (in the form of an increase in α) may increase overhead costs.

5.4 Financial Innovations and Welfare

The welfare effects of the rise in consumer borrowing and bankruptcies, and financial innovations in general, have been the subject of much discussion (Tufano 2003; Athreya 2001). In our model, we find that financial innovations improve *ex-ante* welfare, as the gains from increased access to credit outweigh higher deadweight default costs and overhead lending costs. However, financial innovations are not Pareto improving, as some borrowers are disadvantaged *ex-post*.

The natural welfare measure in our model is the *ex-ante* utility of a borrower before their type (ρ, σ) is realized. As panel H of Figures 4, 5 and 6 show, all three financial innovations increase welfare. The impact of “large” innovations (which induce entry of additional contracts) is intuitive, as borrowers who switch from the risk-free to risky contracts benefit (otherwise they would not switch). The “local” welfare effects are less straightforward, as financial innovations both reduce access to risky borrowing (which lowers welfare) and lower risky borrowing rates (which increase welfare). Reduced access, however, has a small welfare effect, since the marginal borrowers (who lose access) are (relatively) risky types. As a result, their loss is largely offset by a lower average

default premium which reduces other borrowers' interest rates. Overall, this means that the direct effect of innovation on borrowing rates dominate.

While financial innovations increase *ex-ante* welfare, they are not Pareto improving as they generate both winners and losers *ex-post* (i.e., once people know their type (ρ, σ)). When the length of the contract intervals shrink, the worst borrowers in each contract (those near the bottom cut-off $\underline{\sigma}_n$) are pushed into a higher interest rate contract. Thus, these borrowers always lose (locally) from financial innovation. While this effect holds with and without asymmetric information, improved signal accuracy adds an additional channel via which innovation creates losers. As α increases, some borrowers who were previously misclassified with high public signal become correctly classified, and as a result face higher interest rates (or, no access to risky loans). Conversely, borrowers who were previously misclassified "down" benefit from better borrowing terms as do (on average) correctly classified risk types.

Although financial innovations are welfare improving, the competitive equilibrium allocation is not constrained efficient.³¹ Formally, we consider the problem of a social planner who maximizes the *ex-ante* utility of borrowers before types (ρ, σ) are realized, subject to the technological constraint that each (risky) lending contract offered incurs fixed cost χ .³² The constrained efficient allocation features fewer contracts, each serving more borrowers, than the competitive equilibrium. Rather than using the zero expected profit condition to pin down the eligibility set (Proposition 4.2), the planner extends the eligibility set of each contract to include borrowers who deliver negative expected profits while making the best type (within the contract eligibility set) indifferent between the risky contract and the risk-free contract (i.e. equation (4.1) binds). Since this allocation "wastes" fewer resources on fixed costs, average consumption is higher.

This inefficiency is not directly related to adverse selection, as the perfect information equilibrium is also inefficient.³³ Instead, this inefficiency is analogous to the *business stealing effect* of entry models with fixed costs where the competitive equilibrium suffers from excess entry (Mankiw and Whinston 1986). Borrowers would like to commit to

³¹This contrasts with the constrained efficiency result in Allen and Gale (1989). The key difference between their model and ours arises from the option to pool multiple borrowers to cover the fixed cost of issuing a loan (security). In our model, the inefficiency arises from the creation of too many (i.e. inefficiently small) pools, which does not occur in Allen and Gale (1989) as pooling is ruled out.

³²See the web appendix for the explicit representation and solution characterization.

³³Since borrowers are risk-neutral there are no direct welfare gains from increased *ex post* cross-subsidization across borrowers. Thus, the inefficiency differs from the standard mechanism in competitive equilibria with adverse selection due to inefficient risk-sharing, as in Prescott and Townsend (1984).

larger pools with greater cross-subsidization ex-ante (before their type is realized); but ex post some borrowers prefer the competitive contracts. This highlights the practical challenge of improving upon the competitive allocation, as any such policy would make some borrowers worse off and essentially requires a regulated monopolist lender.

6 Comparing the Model Predictions to the Data

In this section, we ask whether the empirical evidence is consistent with three key model predictions of the effect of financial innovation: (i) an increase in the “variety” (number) of credit contracts, (ii) increased access to borrowing for riskier borrowers, and (iii) an increase in risk-based pricing.³⁴ Motivated by the evidence in Section 2, we focus on developments in the credit card market between the mid-1980s and 2000. Subsection 6.1 documents a surge in the number of credit card products during this period. In subsection 6.2 we show that the rise in the fraction of households with access to credit involved the extension of cards to riskier borrowers. Finally, subsection 6.3 outlines evidence of an increase in risk-based pricing since the late 1980s. Our conclusion is that these key model predictions are broadly consistent with the timing of the changes in the credit card industry documented in Section 2.

6.1 Increased Variety in Consumer Credit Contracts

The three financial innovations we consider all predict an increase in the number of risky contracts. In our model, a rise in product variety manifests as an increase in the number of different interest rates offered and as a larger spread between the average and maximum rates. We find a similar trend in the data: the number of different credit card interest rates offered to consumers has increased, the distribution (across borrowers) has become more dispersed and the gap between the average and maximum rate has risen.

We use data from the Survey of Consumer Finances (SCF) on the interest rate paid on credit cards to count the number of different interest rates reported. The second and third columns of Table 2 show that the number of different interest rates reported nearly

³⁴The underlying model-implied changes result from an increase in α , a decrease in χ or lower cost of funds sufficiently large to increase the number of contracts offered.

tripled between 1983 and 2004.³⁵ This has been accompanied by increased dispersion across households as the coefficient of variation (CV) also nearly tripled.³⁶

Table 2: Credit Card Interest Rates, SCF

Year	# of Rates All Households	# of Rates (HH with $B > 0$)	CV All HH	CV (HH with $B > 0$)
1983	78	47	0.22	0.21
1995	142	118	0.30	0.32
1998	136	115	0.32	0.35
2001	222	155	0.37	0.40
2004	211	145	0.56	0.56

Source: Authors' calculations based on Survey of Consumer Finances.

Comparing the empirical density of interest rates demonstrates this point even more clearly. Figure 7 displays the fraction of households reporting different interest rates in the SCF for 1983 and 2001. It is striking that in 1983 more than 50% of households faced a rate of *exactly* 18%. The 2001 distribution (and other recent years) is notably “flatter” than that of 1983, with no rate reported by more than 12% of households.

We also find increased dispersion in borrowing interest rates from survey data collected from banks by the Board of Governors on credit card interest rates and 24-month consumer loans.³⁷ As can be seen from Figure 8(a), the CV for 24-month consumer loans was relatively constant throughout the 1970s, then started rising sharply in the mid-1980s. A similar increase also occurred in credit cards.³⁸ The rise in dispersion has been accompanied by an increased spread between the lowest and highest interest rates. Moreover, despite a decline in the the average (nominal) interest rate, the maximum rate charged by banks has actually increased (see Figure 8(b)).

³⁵This likely understates the increase in variety, as Furletti (2003) and Furletti and Ody (2006) argue credit card providers make increased use of features such as annual fees and purchase insurance to differentiate their products, while Narajabad (2012) documents increased dispersion in credit limits.

³⁶Since we are comparing trends in dispersion of a variable with a changing mean (due to lower risk-free rates), we report the coefficient of variation (CV) instead of the variance of interest rates.

³⁷We use data from the Quarterly Report of Interest Rates on Selected Direct Consumer Installment Loans (LIRS) and the Terms of Credit Card Plans (TCCP). See Appendix B for more details. Since each bank can report only one (the most common) interest rate this likely understates the increase in options.

³⁸While credit card interest rates is the better measure for our purposes, this series begins in 1990. However, since the two series move largely in parallel, we view the evidence from the 24-month consumer loans as indicative.

6.2 Increased Access to Risky Loans for Riskier Borrowers

The extensive margin plays a central role in the model as improvements in the lending technology generate an extension of (risky) loans to riskier borrowers. The increase in the number of households with a bank credit card is clear: the fraction of households with a bank credit card jumped from 43% in 1983 to 68% in 1998 (see Table 3). This supports the common narrative of a “democratization of credit” in the 1980s and 1990s.

Table 3: Percent of Households with Bank Credit Card, by Income Quintile

Quintile	1983	1989	1992	1995	1998	2001	2004
1	0.11	0.19	0.25	0.29	0.29	0.37	0.38
2	0.27	0.40	0.54	0.55	0.59	0.66	0.62
3	0.41	0.61	0.64	0.72	0.73	0.79	0.77
4	0.57	0.77	0.80	0.84	0.86	0.88	0.88
5	0.79	0.89	0.91	0.95	0.96	0.95	0.96
All	0.43	0.56	0.62	0.66	0.68	0.73	0.71
<i>N</i>	4103	3143	3906	4299	4305	4442	4519

Source: Survey of Consumer Finances, Bankcards only.

Were the new credit card holders of the 1980s and 1990s riskier than the typical credit card holder of the early 1980s? A direct - but rough - proxy for risk is household income. Table 3 shows that the rise in card ownership was largest in the middle and lower middle income quintiles, where bank card ownership rose by more than 30 percentage points between 1983 and 1995. This increase in access for lower income households has been accompanied by a significant increase in their share of total credit card debt outstanding. Figure 8(c) plots the cdf for the share of total credit card balances held by various percentiles of the earned income distribution in 1983 and 2004. The fraction of debt held by the bottom 30% (50%) of earners nearly doubled from 6.1% (16.8%) in 1983 to 11.2% (26.6%) in 2004. Given that the value of total credit card debt also increased, this implies that lower income households’ credit card debt increased significantly.³⁹

An alternative approach is to directly examine changes in the risk characteristics of bank credit card holders from 1989 to 1998 in the SCF.⁴⁰ Since the SCF is a repeated

³⁹The increased access of lower income households to credit card debt is well established, see e.g. Bird, Hagstrom, and Wild (1999), Fellowes and Mabanta (2007), Lyons (2003), Black and Morgan (1999), Kenickell, Starr-McCluer, and Surette (2000), and Durkin (2000).

⁴⁰We choose 1989 and 1998 for three reasons. First, since 1989 the SCF asks whether households were at

cross-section, not a panel, we require a procedure to identify “new” from “existing” cardholders. Here we follow Johnson (2007), and assume that of the 69.5% of households with a card in 1998, 57% (the fraction with a card in 1989, see Table 4) are “existing” and the other 12.5% “new.”⁴¹ To identify who is new, we run a probit regression of bank card ownership on households’ characteristics in 1989. Using the 1989 regression coefficients together with the 1998 data, we compute the likelihood of card ownership in 1998. We then order the 1998 bank cardholders and label those with the highest probabilities (up to 57%) “existing cardholders” and the remaining 12.5% as “new cardholders.”⁴²

Table 4 reports averages for several relevant household characteristics. The “new” bank cardholders are riskier along a number of observable dimensions: they are less likely to be married, have less education, lower income, and lower net worth.⁴³ These higher risk characteristics are reflected in both higher borrowing interest rates and delinquency rates for the “new” cardholders.

The new cardholders play a significant role in the rise in credit card borrowing. Despite their much lower average income, new cardholders accounted for roughly a quarter of the total rise of credit card debt. As a result, their contribution to the rise in credit card debt is proportionally larger than the rise in credit holders of roughly 20% (i.e. 12.5/57). The remainder of the rise was driven by the existing cardholders, whose average balance rose by roughly 60% (in 1998 dollars) from 1989 to 1998. Overall, this left average real balances of all cardholders up by nearly 50% from 1989.

least 60 days late on a bill payment, which we use as a proxy for households at higher risk of bankruptcy. Second, the largest rise in bankruptcy filings occurred during the 1990s, with the filing rate per adult doubling between 1989 and 1998. Finally, both years correspond to similar points in the business cycle (i.e. well into expansions and roughly 2 years before recessions) which controls for cyclical trends.

⁴¹We differ from Johnson (2007) in our focus on bank-issued cards (she includes other cards such as store and gasoline cards) and the explanatory variables in the probits. We focus on bank cards since bank cards issuers were heavy users (and innovators) of IT intensive contract design, and bank cards are more widely used for short term borrowing than gas and store cards which typically have low credit limits.

⁴²The ownership rates differ slightly from Table 3 since we focus on households under 65 with net worth less than 5 million. See the web appendix for further details.

⁴³These characteristics are associated with higher risks of bankruptcy, e.g. see Agarwal, Chomsisengphet, and Liu (2011). See Moorman and Garasky (2008) for a review of work linking serious delinquency to an increased probability of bankruptcy. Our conclusion that “new” credit card borrowers had riskier observable characteristics is consistent with Black and Morgan (1999) and Johnson (2007).

Table 4: Characteristics of Bank Card Holders, SCF

Characteristics	1989	1998	1998	1998
	All cardholders	All cardholders	“Existing”	“New”
Fraction HH	57.0	69.5	57.0	12.5
Income	68,343.1	64,824.9	73,041.1	27,277.6
Net Worth	26,4584.2	257,444.4	303,551.5	46,737.8
DSR*	0.20	0.22	0.22	0.21
Debt	61,599.7	71,584.3	82,521.2	21,603.0
CC Balance*	1,925.4	2,934.1	3,001.9	2,624.1
Own Home	75.4	74.0	80.1	44.9
Age (of HH head)	42.4	43.2	43.9	40.3
No HS Degree*	8.8	6.0	3.0	19.8
College Degree	44.3	45.8	51.8	18.4
Married	71.1	68.1	73.2	44.9
CC IR*	NA	14.4	14.1	15.5
Delinquent	2.7	5.6	3.8	13.6

*DSR = Debt Service Ratio, CC = credit card, IR = interest rate, HS = high school

Source: Authors’ calculations based on Survey of Consumer Finances. Values for 1989 are expressed in 1998 dollars using the CPI. Figures are averages using population weights for households, and rates are as a fraction of the sample: households under 65 with a net worth of less than 5 million.

6.3 Increased Risk Based Pricing

A third key prediction of the model is that more contracts should be accompanied by better risk-based pricing. To see whether credit card interest rates reflect household risk more accurately, we compare the SCF distribution of interest rates for households who report being sixty days late on at least one debt payment (delinquents) to non-delinquents. While the distributions for delinquents and non-delinquents are nearly identical in 1983 (Figure 7, Panel A), by 2001 the delinquent interest rate distribution has shifted to the right of non-delinquents (Figure 7, Panel B). This suggests that interest rates have become more closely related to borrowers’ default risk.

Several recent papers document similar findings. For example, Edelberg (2006) combines data from the PSID and the SCF, and finds that lenders have become better at identifying higher risk borrowers, and have made increased use of risk-based pricing. The timing coincides with the observation that in the late 1980s some credit card banks began to offer a wider variety of credit card plans “targeted at selected subsets of con-

sumers, and many charge[d] lower interest rates” (Canner and Luckett 1992).⁴⁴

7 The New Cardholders and the Rise in Bankruptcies

While the rise in credit card debt is often cited as a key cause of the surge in consumer bankruptcies (e.g. see White (2007) and Mann (2006)), the quantitative importance of the extension of cards to new (riskier) borrowers is not widely accepted. Instead, many economists argue that bankruptcies rose primarily due to an *intensive margin* channel of low risk borrowers taking on more debt (e.g., Narajabad (2012), Sanchez (2012)), or to a fall in the cost of bankruptcy (often labeled *stigma*, see Gross and Souleles (2002)).

To quantify the contribution of the “new” credit card borrowers to the rise in bankruptcy, we build on our decomposition of new versus existing borrowers in Section 6.2. For reasons discussed in Section 6.2, we focus on the 1989-1998 period and use 60-day delinquency as a proxy for an increased risk of bankruptcy.

As an initial estimate of the new cardholder contribution, we compare the delinquency rates for five groups of borrowers: all, all cardholders, existing cardholders, new cardholders, and households without a card (see Table 5). As in Section 6.2, we divide cardholders into “new” and “existing” cardholders based on the likelihood of households having a card in 1989. The (SCF sample) delinquency rate rose by 0.9 percentage points (from 6.4% to 7.3%) between 1989 and 1998, while the delinquency rate for borrowers without a bankcard was unchanged at 11.4%. This suggests the rise in delinquency was driven by cardholders. Existing cardholders account for roughly 70% of the rise in delinquency: they are 57% of the sample population (see Table 4) and their delinquency rate increased from 2.7 to 3.8 percent, which implies a 0.63 percentage point rise in the aggregate delinquency rate. The remaining (roughly) 30% is attributable to the new cardholders — a contribution of more than double their population share (12.5%). At 13.6% in 1998, the delinquency rate of new cardholders was 2.2 percentage points higher than that of households without a card, so that new cardholders contributed 0.275 (=2.2*0.125) to the 0.9 rise in the delinquency rate.

While suggestive, this calculation does not control for the expected delinquency of new cardholders if they had not held a bank card. To address this, we compute the predicted delinquency of cardholders. We estimate a probit of delinquency status on

⁴⁴Furletti and Ody (2006) report credit card issuers have also increased fees on riskier borrowers.

Table 5: Delinquency Rates, SCF

Group	1989	1995	1998
All	6.4	6.5	7.3
All cardholders	2.7	3.9	5.6
Existing	2.7	3.2	3.8
New		7.9	13.6
No Card	11.4	11.9	11.4

Source: Authors' calculations based on Survey of Consumer Finances. Rates are as a fraction of the (population weighted) sample: households under 65 with a net worth of less than \$5,000,000.

household demographics, income, assets and debt measures using the 1989 SCF. Using the coefficients from 1989, we compute the predicted delinquency rates for 1998 and the counterfactual delinquency rate of the new cardholders if they had not gained access to credit cards. The predicted rate for the new cardholders in 1998 is 12.4%, somewhat lower than their actual level of 13.6%. The counterfactual delinquency rate of these households if they had not held credit cards (with their debt level and debt service ratios correspondingly lower) is 10.7%. Accordingly, one can attribute a rise in the expected probability of delinquency of roughly 1.7 percentage points (12.4% - 10.7%) to the extension of cards. Since new cardholders comprise 12.5% of the population, this estimate implies that the extensive margin accounted for roughly a quarter ($=0.125 \cdot 1.7 / 0.9$) of the rise in delinquencies between 1989 and 1998.

In contrast to the conventional wisdom, our analysis thus finds the extension of credit cards to “new,” riskier borrowers to be quantitatively important, accounting for between a quarter and a third of the rise in defaults. To evaluate the role of increased debt (i.e., the intensive margin) and lower default costs (stigma) in accounting for the remaining 70%, we conduct a similar counterfactual for existing cardholders. Using the 1989 regression coefficients to predict 1998 delinquency risk, we find a negligible role for changes in demographics or debt, as the predicted delinquency level is 2.5% (slightly lower than in 1989). Interestingly, despite our use of a different data source, our analysis is consistent with Gross and Souleles (2002) who found that observed default probabilities in a sample of credit card accounts from June 1995 to June 1997 jumped, even controlling for household risk measures such as the credit score.

Our interest in underlying trends during the 1990s, combined with an attempt to

control for business cycle effects, led us to focus on 1989 and 1998. The importance of controlling for cyclical effects can be seen in Figure 1, as bankruptcies first peak and then decline after the 1991 recession.⁴⁵ A similar pattern holds for delinquencies, as the (population) delinquency rate in the SCF in 1995 was only slightly above 1989's (see Table 5). Do the predictions of our model for the extensive margin hold in 1995? At first glance, the answer appears to be no. Replicating our procedure to sort cardholders into new and existing groups, we find a much lower delinquency rate for new cardholders (at 7.9%) than in 1998. A closer look, however, suggests that cyclical factors (and relatively new accounts) are important. Using the coefficients from the 1989 delinquency regression, the predicted delinquency rate for the new cardholders is 13.7%, well above the actual level of 7.9%. In other words, the observable characteristics of the new cardholders in 1995 suggests that their delinquency rate was likely to rise – consistent with the subsequent rise in delinquency and bankruptcy (see Figure 1).⁴⁶

A potential concern is that 60-day delinquencies (our proxy for bankruptcies) may overstate the contribution of the extensive margin. Although delinquency is correlated with bankruptcy, the percentage rise in delinquencies is smaller than the rise in filings during the 1980s and 1990s. Livshits, MacGee, and Tertilt (2010) and White (2007) summarize empirical work finding that bankrupts in the late 1990s tended to have lower income relative to the median household than bankrupts in the early 1980s. Given that the new cardholders tended to have lower income than existing cardholders, the new cardholders may well have had an even larger role in accounting for the rise in bankruptcies than delinquencies.

8 Conclusion

Our findings support the view that financial innovations, based on improved information technology, in the credit card market were a critical factor in the rise in unsecured borrowing and bankruptcies during the 1980s and 1990s. The model analyzed in this paper predicts that financial innovations lead to more credit contracts, with each con-

⁴⁵Delinquency (bankruptcy) rates rise during recessions and then fall in the early years of an expansion before rising again (Fieldhouse, Livshits, and MacGee (2013)).

⁴⁶Although we examine bankcards, our results are broadly consistent with Johnson (2007) who finds that new cardholders also had high delinquency rates. However, our conclusions on the extensive margin differ from Black and Morgan (1999). This largely reflects their focus on the change in delinquency in the SCF between 1989 and 1995.

tract targeted at smaller groups, and to the extension of credit to riskier households. As a result, financial innovations lead to higher aggregate borrowing and defaults. We find that these predictions are remarkably consistent with changes in the aggregate and cross-sectional pattern of borrowing and defaults in the U.S. since the late 1980s.

Our stylized model provides three channels (i.e. increases in α , decreases in χ or \bar{q}) via which “sufficiently large” financial innovations could contribute to the rapid rise in bankruptcy and credit card borrowing during the 1980s and 1990s (see Figure 1). While we view all three channels as stemming from the same underlying force — improved information technology — they differ in their implications for overhead costs and default rates. Based on these varying implications and the empirical evidence, we conclude that it is unlikely that any single channel was the sole driving force.

The available data on aggregate overhead costs suggest that lower fixed costs are unlikely to have been the only factor at work. The model predicts that reductions in the fixed cost lower overhead costs as a percent of borrowing, while improvements in signal accuracy or reduced costs of funds lead to higher overhead costs. The closest empirical analog to overhead costs is the ratio of non-interest costs to total assets. Berger (2003) reports that non-interest costs of U.S. commercial banks rose from roughly 3% of total assets in the early 1980s to 3.5% by the mid 1990s. This is consistent with reduced funding costs or with more accurate risk assessment, but not with lower fixed costs.

Similarly, improvements in signal accuracy have ambiguous effects on bankruptcies per debtor. Such improvements may lower bankruptcies per borrower, as misclassification of high-risk borrowers into low-risk types is reduced, thus lowering the average bankruptcy risk of borrowers. Since bankruptcy and delinquency rates of credit card holders increased during the 1980s and 1990s, we find it unlikely that improvements in signal accuracy were the sole driving force. Finally, increased securitization does not appear to be the main driving force either. To get a large increase in bankruptcies through this channel, the cost of funds must decrease substantially. However, not all credit lenders adopted securitization of credit card receivables as a funding source, which suggests it did not have a large impact on funding costs. Summarizing, our interpretation is that the most likely scenario is that all channels were simultaneously at play. Quantifying the contribution of each channel is left for future work.

Finally, our analysis suggests that interpretations of the unsecured credit market using a “standard” competitive framework may be misleading. We find that even a small fixed cost of creating a lending contract can lead to significant deviations from the pre-

dictions of the standard competitive framework. Incorporating fixed costs into a quantitative model could be a promising avenue for future research.

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A Verifying Equilibrium under Incomplete Information

To verify that the allocation we have characterized is an equilibrium, we need to check that a potential entrant cannot make positive profits by cream-skimming misclassified borrowers (by offering them (q', L') — a smaller risky loan with a better interest rate).

The most profitable potential deviation makes the best customer indifferent between (q', L') and the risk-free contract.⁴⁷ Without loss of generality, $u_1(q', L') = u_1(\bar{q}, \gamma y_l)$, which implies

$$L' = \frac{\bar{q} - \beta}{q' - \beta} \gamma y_l. \quad (\text{A.1})$$

⁴⁷Keeping the loan size fixed, any lower price would imply losing the best and most numerous customers, while any higher price would be leaving too much surplus to borrowers.

Equation (A.1) establishes a simple relation between q' and L' . The search for the most profitable deviation then amounts to searching over all possible q' . A single smaller risky loan may attract borrowers from a number of bins, and we thus have to calculate (and sum over) the profits generated from each of the equilibrium bins $[\underline{\sigma}_n, \underline{\sigma}_{n-1})$, for $n = 2, \dots, N$. It is important to note that any contract that attracts misclassified borrowers necessarily disrupts the existing contract (into which these borrowers were misclassified). To see this, consider a contract (q', L') with $L' < \gamma y_h$ and $q' > q_n$, which attracts borrowers with $\rho' > \hat{\rho}_n$. Since ρ' prefers this contract to the risk-free contract, so will every borrower with $\rho < \rho'$, including $\hat{\rho}_n$. Since $\hat{\rho}_n$ is indifferent between the risk-free contract and $(q_n, \gamma y_h)$, she strictly prefers (q', L') to the existing contract $(q_n, \gamma y_h)$.

Thus, for a given q' , and existing bin $[\underline{\sigma}_n, \underline{\sigma}_{n-1})$ served by $(q_n, \gamma y_h)$, we have to consider two possible scenarios. First, the disruption to the existing contract may be small enough that the incumbent lender chooses not to exit the market. This happens when the incumbent's profit loss is smaller than χ . Second, if the profit loss from losing the best (misclassified) customers is larger than χ , the incumbent lender will exit. Anticipating this scenario, the entrant offers a replacement contract $(q'_n, \gamma y_h)$ to (correctly labeled) customers with $\sigma \in [\underline{\sigma}_n, \underline{\sigma}_{n-1})$ in order to prevent them from applying for the (q', L') contract, which would make it unprofitable. If the entrant is unable to offer such a replacement contract, the entrant will avoid dealing with the bin $[\underline{\sigma}_n, \underline{\sigma}_{n-1})$ by setting the eligibility requirement of the (q', L') contract to $\underline{\sigma} = \underline{\sigma}_{n-1}$.

We provide the details of the numerical implementation in a separate web appendix.

B Data Appendix

Tables 2, 3, 4 and 5 Figures 7 and 8(c) are based on data from the Survey of Consumer Finances. More details are in the web appendix.

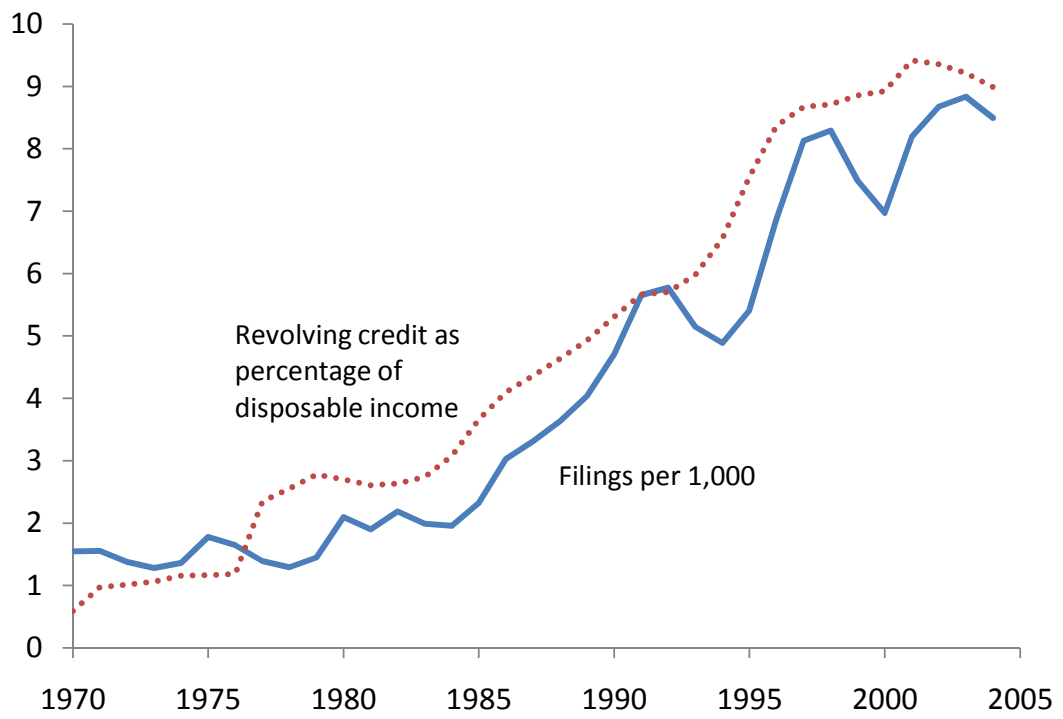
The Survey of Consumer Finances questions on the credit card interest rate of respondents for 1995 - 2004 were for the card with the largest balance, while the 1983 survey asked for the average annualized interest on the bank or store card used most often if the full amount was not paid. When counting the number of different interest rates in Table 2, we drop imputed values. The sample size increases, but by much less than the reported number of different interest rates (see the web appendix for the sample size by

year). In Figure 8(c), earned income is Wages + Salaries + Professional Practice, Business, Limited Partnership, Farm + Unemployment or Worker's Compensation.

Figures 8(a) and 8(b) are based on surveys of banks administered by the Board of Governors. The 24-months consumer loans series is available since February 1972 from the *Quarterly Report of Interest Rates on Selected Direct Consumer Installment Loans* (LIRS) (item LIRS7808). The survey asks for the most common (annual percentage) rate charged on "other loans for consumer goods and personal expenditures (24-month)." It includes loans for goods other than automobiles or mobile homes whether or not the loan is secured. Home improvement loans and loans secured primarily by real estate are excluded. The sample declines from 296 banks in 1972 to 100 in 2007. The credit card interest rate data series is TCCP6258 (including only nationally available plans), from the bi-annual (since 1990) *Terms of Credit Card Plans* (TCCP). The annual response rates range from 200 to 400.

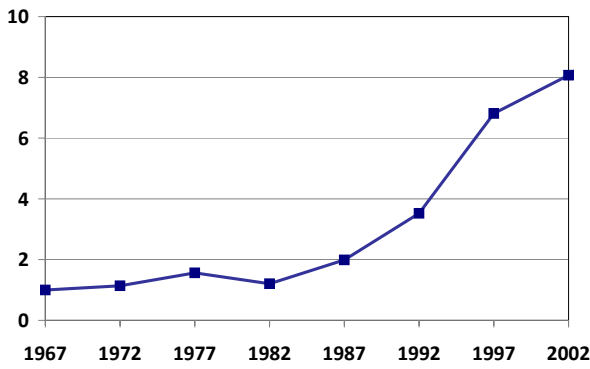
Figure 2(a) Credit Scoring Keyword Count (trade and scholarly publications): We accessed the database "ProQuest" on June 22, 2013, chose the search subject area "Business" and used the "Advanced Search" option, selecting only "Trade Journals" and "Scholarly Journals." We searched using the date range 01/01/1965 to 06/22/2013 (the last ten years were not plotted to be consistent with other Figures). We searched for articles containing at least one of the following phrases: "credit score", "credit scores", or "credit scoring." Hits were counted for every five-year period and plotted for the middle year of that period. To control for the increase in the total numbers of words over time, we searched for "consumer credit" and "consumer credits in the same way, and then divided the counts for the first search with those of the second. We further normalized the resulting data series so that the count for the first data point (1965-1969), is one.

Figure 2(b) Normalized Credit Scoring Keyword Count (Google Scholar): The underlying data was collected on January 27, 2012. We accessed "Google Scholar" using advanced search and checking the option "Business, Administration, Finance, and Economics." The search was conducted for the keyword "credit scoring." We searched using the data range 01/01/1965 to 31/12/2004. Hits were counted for every five-year period and plotted for the middle year of that period. To normalize the data series, we searched for "consumer credit." For each year, we divided the counts for the "credit scoring" search by those of the "consumer credit" search. Unfortunately, Google has since revised the advanced search options, and removed the options we used.

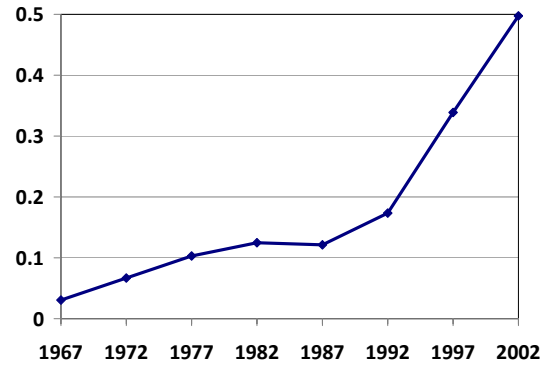


Source: Livshits, MacGee, and Tertilt (2010)

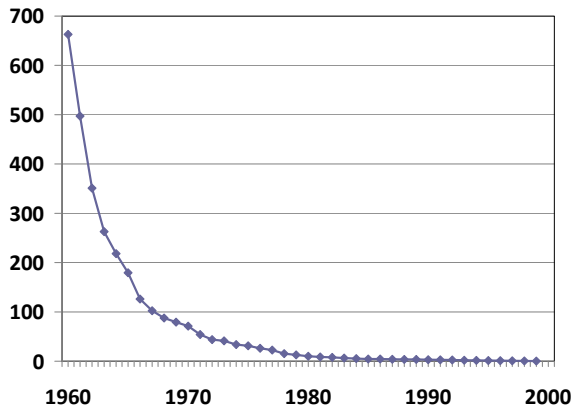
Figure 1: Aggregate Facts



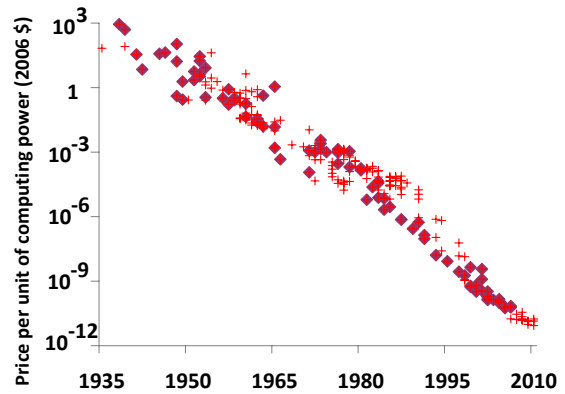
(a) Credit Scoring Keyword Count (trade and scholarly publications, normalized)



(b) Credit Scoring Keyword Count (Google Scholar, normalized)

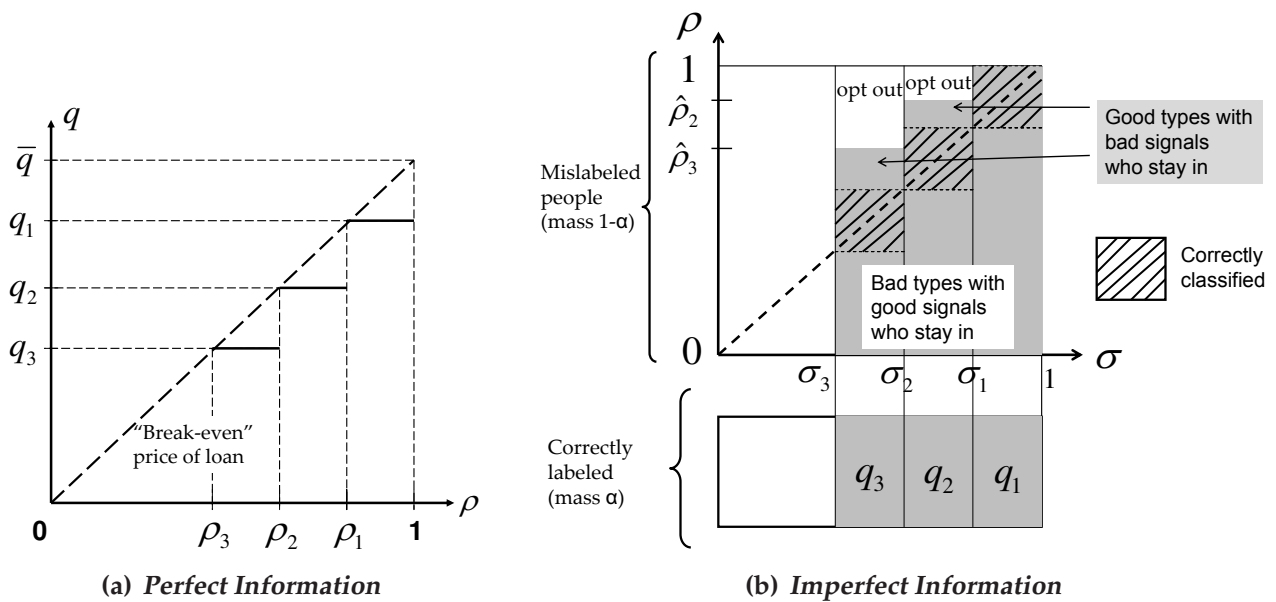


(c) Computer Price Index, Jorgenson 2001



(d) Cost of Computation per Second, Nordhaus 2007

Figure 2: Changes in Computing Technology and Credit Scoring



(a) Perfect Information

(b) Imperfect Information

Figure 3: Illustration of Equilibrium Contracts

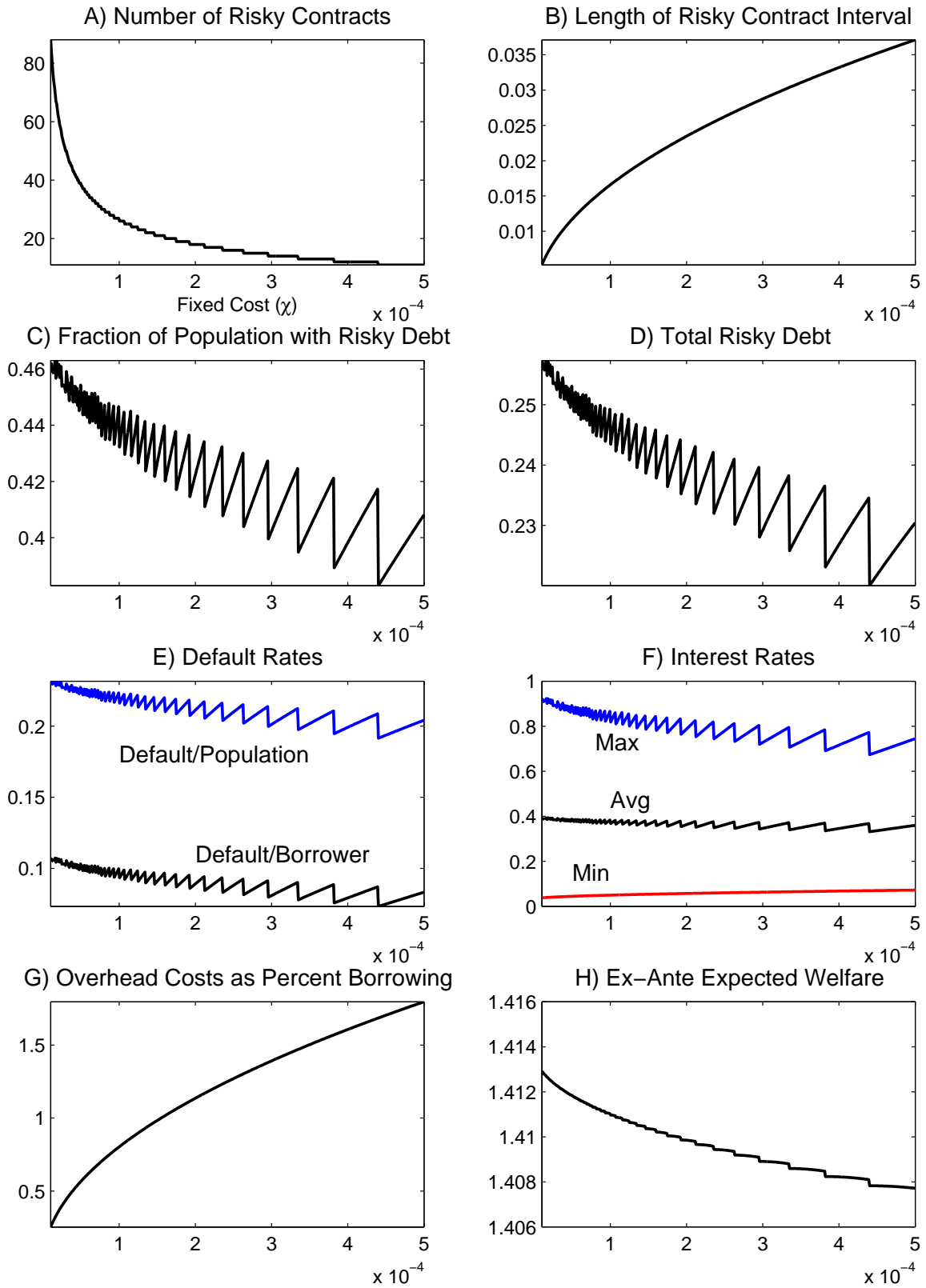


Figure 4: Varying the Fixed Cost

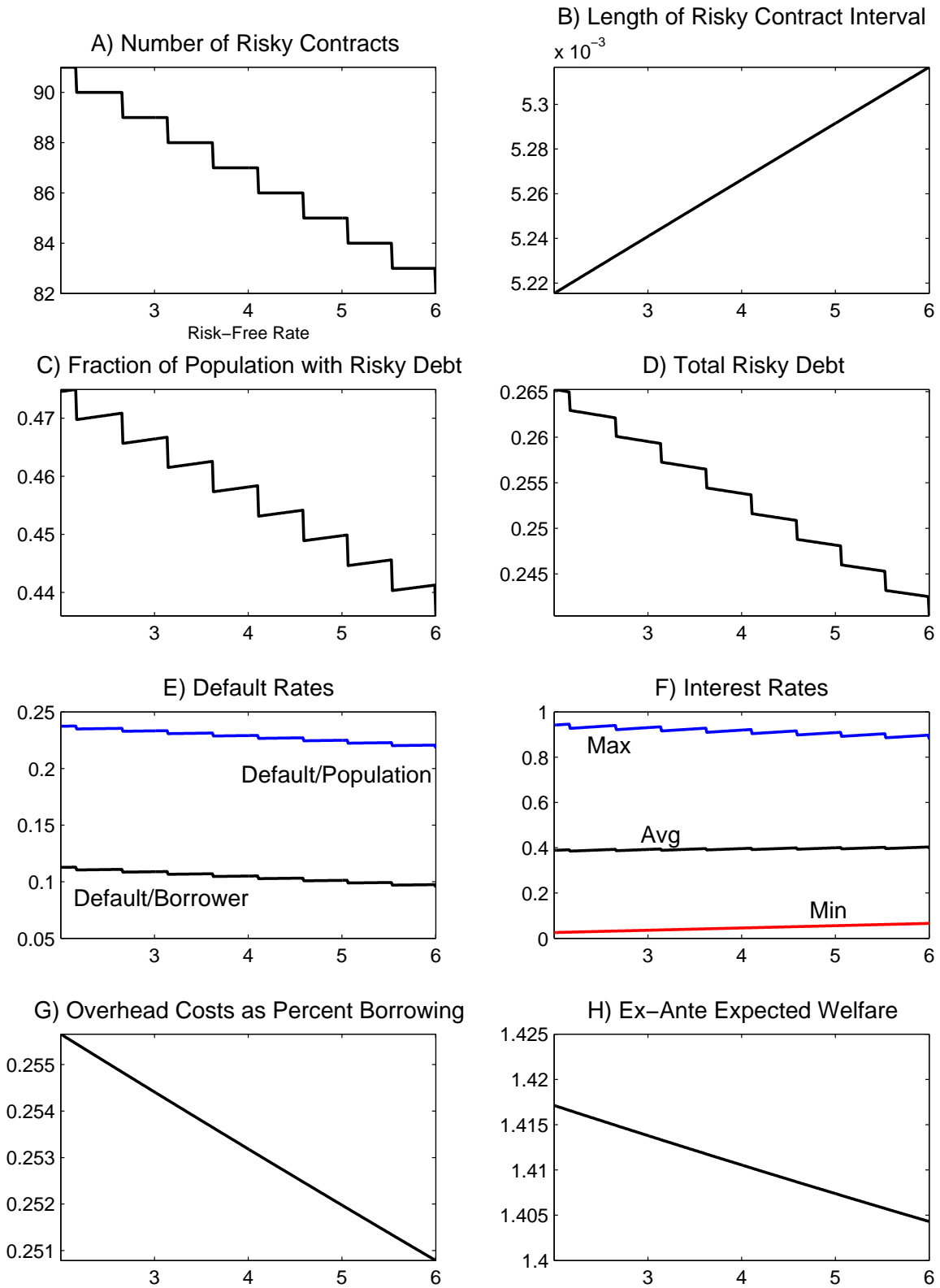


Figure 5: Varying the Interest Rate

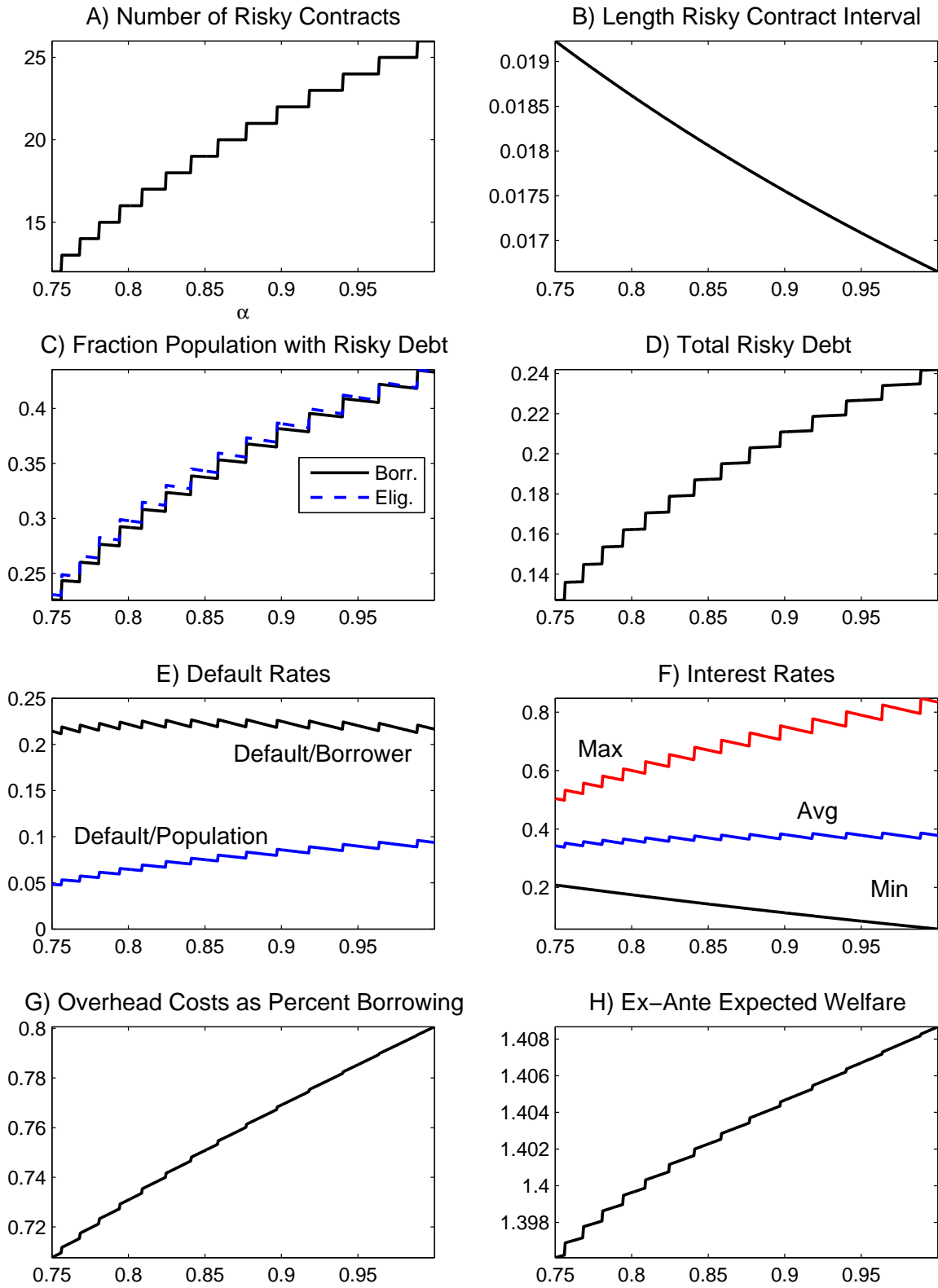
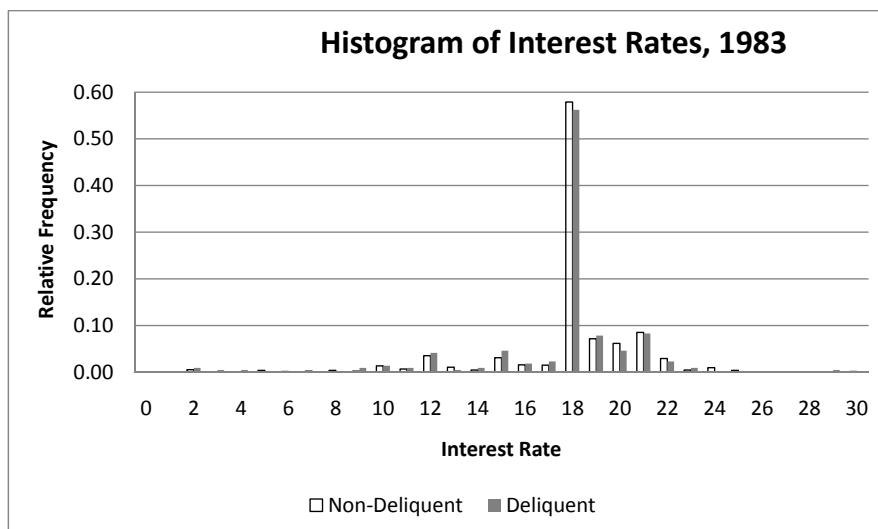
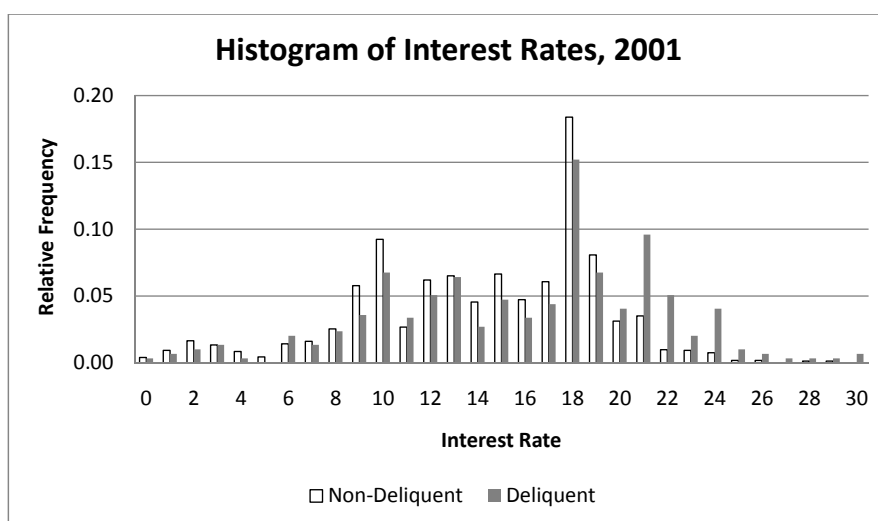


Figure 6: Varying the signal accuracy

PANEL A

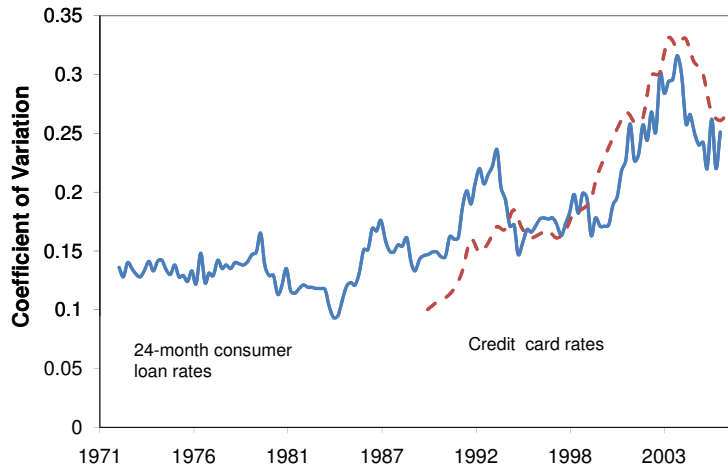


PANEL B

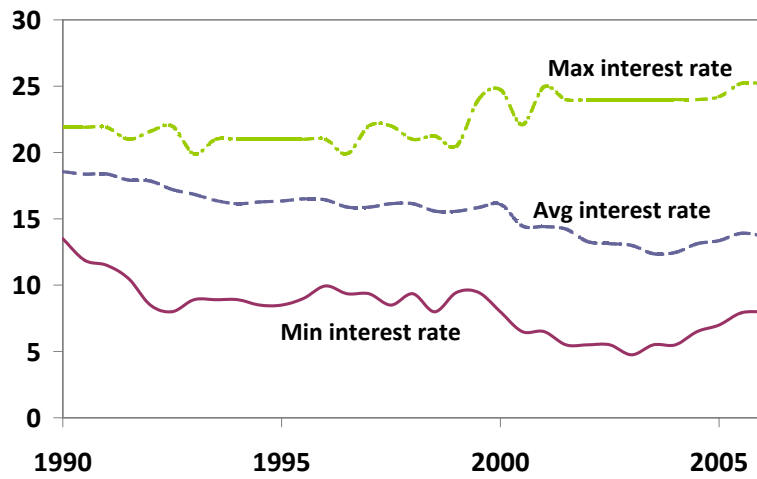


Source: Authors' calculations based on SCF. Each bin spans one percentage point, and aggregates different interest rates within this range.

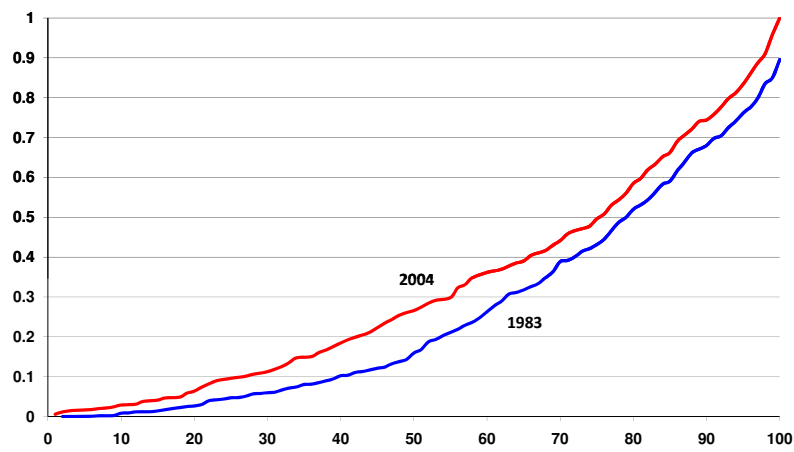
Figure 7: Histogram of Interest Rates for Delinquents vs. Non-delinquents



(a) CV Consumer Interest Rates



(b) Average, Min and Max Interest Rate Across Banks



(c) CDF Credit Card Borrowing vs Earned Income

Figure 8: Contract Variety, based on data from SCE, TCCP and LIRS