NBER WORKING PAPER SERIES

COSTLY CONTRACTS AND CONSUMER CREDIT

Igor Livshits
James MacGee
Michèle Tertilt

Working Paper 17448
http://www.nber.org/papers/w17448

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
September 2011

We thank Kartik Athreya and Richard Rogerson as well as seminar participants at Alberta, Arizona State, British Columbia, Brock, Carleton, NYU, Pennsylvania State, Rochester, Simon Fraser, UCSD, UCSB, USC, Windsor, Federal Reserve Bank of Richmond, Federal Reserve Bank of Cleveland, Stanford and Philadelphia Fed Bag Lunches, the 2007 Canadian Economic Association and Society for Economic Dynamics, and the 2008 American Economic Association Annual meetings for helpful comments. We are especially grateful to Karen Pence for her assistance with the Board of Governors interest rate data. We thank the Economic Policy Research Institute, the Social Science and Humanities Research Council (Livshits, MacGee) and the National Science Foundation SES-0748889 (Tertilt) for financial support. Wendi Goh, Vuong Nguyen, and Alex Wu provided excellent research assistance. MacGee thanks the Federal Reserve Bank of Cleveland for their support during the writing of this paper. The views expressed herein are those of the authors and not necessarily those of the Federal Reserve Bank of Cleveland, the Federal Reserve System, or the National Bureau of Economic Research.

Costly Contracts and Consumer Credit
Igor Livshits, James MacGee, and Michèle Tertilt
NBER Working Paper No. 17448
September 2011
JEL No. E21,E49,G18,K35

ABSTRACT

Financial innovations are a common explanation of the rise in consumer credit 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 to create each contract offered by lenders. Innovations which reduce the fixed cost or ameliorate asymmetric information have large extensive margin effects via the entry of new lending contracts targeted at riskier borrowers. This results in more defaults and borrowing, as well as increased dispersion of interest rates. Using the Survey of Consumer Finance and interest rate data collected by the Board of Governors, we find evidence supporting these predictions, as the dispersion of credit card interest rates nearly tripled, and the share of credit card debt of lower income households nearly doubled.

Igor Livshits
Department of Economics
University of Western Ontario
Social Science Centre
London, Ontario N6A5C2
livshits@uwo.ca

James MacGee
Department of Economics
University of Western Ontario
London, Ontario Canada NCA 5C2
jmacgee@uwo.ca

Michèle Tertilt
Department of Economics
University of Mannheim
L7, 3-5
68131 Mannheim
Germany
and NBER
tertilt@uni-mannheim.de

1 Introduction

Financial innovations are frequently cited as playing an essential role in the dramatic rise in credit card borrowing over the past thirty years. By making intensive use of improved information technology, it is argued that lenders were able to more accurately price risk and to offer loans more closely tailored to the risk characteristics of different groups (Mann 2006; Baird 2007). This dramatic 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 I) over the past thirty years (White 2007).

Surprisingly little theoretical work, however, has explored the implications of financial innovations for unsecured consumer loans, or compared these predictions to the data. We address this gap by developing a simple incomplete markets model of bankruptcy to analyze the qualitative implications of improved credit technology. Further, to assess the model predictions, we assemble cross-sectional data on the evolution of credit card debt in the U.S. from the early 1980s to the mid 2000s.

Our model incorporates two frictions which play a key role in shaping credit contracts: asymmetric information about borrowers' default risk and a fixed cost to create a credit contract. While asymmetric information is a common element of credit market models, fixed costs of contract design have been largely ignored by the academic literature.[1] This is surprising, as texts targeted at practitioners discuss significant fixed costs associated with consumer credit contracts. According to Lawrence and Solomon (2002), a prominent consumer credit handbook, the development of a consumer lending product involves selecting the target market, researching the competition, designing the terms and conditions of the product, (potentially) testing the product, forecasting profitability, preparing formal documentation, as well as an annual review of the product. Even after the initial launch, there are additional overhead costs, such as customer data base maintenance, that vary little with the number of customers.[2] Finally, it is worth noting that fixed costs are consistent with the observation that consumer credit contracts are differentiated but rarely individual specific.

[1]Notable 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.

[2]A similar process is described in other guidebooks. For example, Siddiqi (2006), outlines the development process of credit risk *scorecards* which map individual characteristics (for a particular demographic group) into a risk score. Large issuers develop their own "custom scorecards" based on customer data, while some firms use purchased data. Because of changes to the economic environment, scorecards are frequently updated, so there is not one "true" risk mapping that once developed is a public good.

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 receiving 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 of 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 offered, so that some "pooling" is necessary to spread the fixed cost across multiple types of borrowers. Working against larger pools is that bigger pools requires a broader range of risk types, which leads to larger gaps between the average default rate of the pool and the default risk of the least risky pool members. With free entry of intermediaries, these two 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 financial innovations which may have had a significant impact on credit card lending over the past thirty years: (i) reductions in the fixed cost of creating contracts; (ii) increased accuracy of the lenders' predictions of borrowers' default risk (which mitigates adverse selection); and (iii) a reduced cost of lenders' funds. As we discuss in Section 1.1, the first two innovations capture the idea that better and cheaper information technology reduced the cost of designing financial contracts, and allowed lenders to more accurately price borrowers' risk. The third channel is motivated by the increased use of securitization (which reduced lenders' costs of funds) as well as lower costs of servicing consumer loans as a result of improved information technology.

All three forms of financial innovation lead to significant changes in 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 served by existing contracts. In the model, the new contract margin dominates the local effect of smaller pools, so that new contracts lead to an increase in 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 their interest rate, which leads to improved risk-based pricing. This pricing effect is especially pronounced when the accuracy of the lending technology improves, as fewer high risk borrowers are misclassified as low risk.

One dimension along which improved risk assessment differs from the other innovations 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. On the other hand, an increase in signal accuracy reduces the number of misclassified high risk types who are offered loans targeted at low risk borrowers, which acts to lower defaults. In our numerical example, these two effects roughly offset each other, so that improved risk assessment leaves the average default rate of *borrowers* essentially unchanged.

To evaluate these predictions, we examine changes in the distribution of credit card debt and interest rates, using data from the Survey of Consumer Finance from 1983 to 2004. We find that 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 interest rate (18%), by the late 1990s no credit card 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 (such as recent delinquencies) and interest rates has tightened since the early 1980s. Finally, we find that the largest increase in access to credit cards has been for lower income households, whose share of total credit card debt more than doubled.

The model also provides novel insights into competition in consumer credit markets. 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." In contrast, this episode is consistent with our competitive framework. The extensive margin is key to understanding why our predictions differ from Ausubel (1991). 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. This extensive margin channel also provides insight into recent empirical work by Dick and Lehnert (2010). They find that increased competition, due to interstate bank deregulation, contributed to the rise in bankruptcies. Our model suggests a theoretical mechanism that could account for this observation. By lowering barriers to interstate banking, deregulation acts to expand market size, which effectively lowers 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 has interesting implications for the debate over the welfare implications of financial innovations. In our environment, while financial innovations increase average (*ex ante*) welfare, they are not Pareto improving, as changes in the size of each contract result in some households being pushed into higher interest rate contracts. Moreover, the competitive equilibrium allocation is in general not efficient, as it features a greater product variety (more contracts) and less cross-subsidization than would be chosen by a social planner who weights all households equally. As a result, in equilibrium more resources are consumed by the financial sector 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).[3] Livshits, MacGee, and Tertilt (2010) and Athreya (2004) use this framework to 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.[4] Un-

[3]Chatterjee, Corbae, and Rios-Rull (2010) and Chatterjee, Corbae, and Rios-Rull (2008) extend this work and formalize how credit histories and credit scoring support the repayment of unsecured credit.

[4]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.

like our paper, they abstract from how financial innovations change equilibrium loan contracts and the pricing of borrowers default risk, and model financial innovation in an ad hoc way as a fall in the "stigma" of bankruptcy and lenders cost of funds.

Closely related in spirit is complementary work by Narajabad (2010), Sanchez (2010), Athreya, Tam, and Young (2008), and Drozd and Nosal (2008). Narajabad (2010), Sanchez (2010) and Athreya, Tam, and Young (2008) 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., a shift in the intensive margin), which increases their probability of defaulting. Drozd and Nosal (2008) examine a reduction 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 the intensive margin. Second, our tractable framework allows us to analyze three different types of financial innovations, and provides interesting insight into the mechanisms linking lending environment and the degree of dispersion in credit contracts. Our analysis also suggests new interpretations of "competition" in consumer credit markets, the Ausubel (1991) puzzle, and the effects of relaxing geographic restrictions to credit market competition.

Also related to this paper is recent work on competitive markets with adverse selection. Adams, Einav, and Levin (2009), Einav, Jenkins, and Levin (2010) and Einav, Jenkins, and Levin (2009) find that subprime auto lenders face both 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 **?**) 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 incorporation of fixed costs of creating contracts.

The remainder of the paper is organized as follows. Section 1.1 documents technological progress in the financial sector over the last couple decades, Section 2 outlines the general model. In Section 3 we characterize the set of equilibrium contracts, while Section 4 examines the implications of financial innovations. Section 5 compares these predictions to data on the evolution of credit card borrowing. Section 6 concludes.

1.1 Financial Innovation

It is frequently asserted that the past thirty years have witnessed the diffusion and introduction of numerous innovations in consumer credit markets (Mann 2006). Many of these changes are attributed to improved information technology, which has led to increased information sharing on borrowers between financial intermediaries (Barron and Staten 2003; Berger 2003; Evans and Schmalensee 1999). Here we briefly outline several important innovations in the credit card market (which largely accounts for the rise in unsecured consumer debt): the development and diffusion of improved credit-scoring techniques to identify and monitor creditworthy customers;[5] increased use of computers to process information to facilitate customer acquisition, design credit card contracts, and monitor repayment; and the increased securitization of credit card debt.[6]

The development of automated credit scoring systems played an important role in the growth of the credit card industry (Evans and Schmalensee 1999; Johnson 1992). Credit scoring refers to the evaluation of the credit risk of loan applicants using historical data and statistical techniques (Mester 1997). Credit scoring technology figures centrally in credit card lending for two reasons. First, it decreased the cost of evaluating loan applications (Mester 1997). Second, it led to increased analysis of the relationship between borrower characteristics and loan performance, and thus led to increased risk based pricing. This resulted in substantial declines in interest rates for low risk customers and increased rates for higher risk consumers (Barron and Staten 2003).[7]

Improvements in computational technology led to credit scoring becoming widely used during the 1980s and 1990s (McCorkell 2002; Engen 2000; Asher 1994). The fraction of large banks using credit scoring as a loan approval criteria increased from half in 1988 to nearly seven-eights in 2000. Further, the fraction of large banks using fully automated loan processing (for direct loans) increased from 12 percent in 1988 to nearly 29 percent in 2000 (Installment Lending Report 2000). While larger banks are more likely than smaller banks to create their own credit scores, banks of any size have been using this technology by purchasing scores from other providers (Berger 2003). In fact, credit

[5]The most prominent is Fair Isaac Cooperation, the developer of the FICO score, who started building credit scoring systems in the late 1950s. In 1975 Fair Isaac introduced the first behavior scoring system, and in 1981 introduced the Fair Isaac credit bureau scores. See: http://en.wikipedia.org/wiki/Fair_Isaac.

[6]While references to financial innovation are common, few empirical studies attempt to quantitatively document its extent: "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))

[7]A similar finding holds for small business loans, where bank adoption of credit scoring led to the extension of credit to "marginal applicants" at higher interest rates (Berger, Frame, and Miller 2005).

bureaus have increasingly collected information on borrowers and have been selling the information to lenders. The number of credit reports issued has increased dramatically from 100 million in 1970 to 400 million in 1989, to more than 700 million today. The information in these files is widely used by lenders (as an input into credit scoring), as more than two million credit reports are sold daily by U.S. credit bureaus (Riestra 2002).[8]

The reduction in information processing costs may have also lowered the cost of designing and offering unsecured loan contracts. As discussed earlier, deciding on the target market and terms of credit products is typically data intensive as it involves statistical analysis of large data sets. In addition, the cost of maintaining and processing different loan products is also information intensive, so that improved information technology both reduced the fixed cost of maintaining differentiated credit products and lowered the cost of servicing each account.

There has also been significant innovations in how credit card companies finance their operations. Beginning in 1987, credit card companies 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 has led to reduced financing costs for credit card lenders (Furletti 2002; Getter 2008).

2 Model Environment

We analyze a two-period small open economy populated by a continuum of borrowers, who face 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, incur a fixed cost to design each financial contract (characterized by a lending rate, a borrowing limit and eligibility requirement for borrowers) and observe a (potentially) noisy signal of borrowers' risk types.

[8] U.S. credit bureaus report borrowers' payment history, debt and public judgments (Hunt 2006).

2.1 People

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

$$c_1 + \beta E c_2.$$

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 $y_h > y_l$. 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 $[0, 1]$.[9] While each household knows their type, other agents observe a public signal, σ, regarding a household'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 ($U[0, 1]$).

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

2.2 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.

2.3 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

[9] The characterization of equilibria is practically unchanged for an arbitrary support $[a, b] \subseteq [0, 1]$.

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 the minimal public signal that makes a household eligible for the contract. 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. We exempt the risk-free contract $(\gamma y_l, \overline{q}, 0)$ from paying the entry cost.[10] Households can accept only one loan, so intermediaries know the total amount borrowed.

2.4 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.

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 whether to advance loans to qualified 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.

[10] In 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.

2.5 Equilibrium

We study (pure strategy) Perfect Bayesian Equilibria of the extensive form game described in Subsection 2.4. 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 3.2.

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 $\mathcal{K}^* = \{(q_k, L_k, \underline{\sigma}_k)_{k=1,\ldots,N}\}$ 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 $\sigma \geqslant \underline{\sigma}_k$.

3 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 3.2 we show that including asymmetric information leads to remarkably similar equilibrium outcomes.

3.1 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 3.1. *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: $\overline{q}\rho L - qL = 0$, where $\rho\overline{q}L$ 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 3.2. *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 $\rho = \frac{q}{\overline{q}}$.*

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 3.3. *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:

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

Using $q_n = \underline{\sigma}_n\bar{q}$ and $L = \gamma y_h$ from Lemmata 3.1 and 3.2, 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 3.3 shows that the measure of households pooled in each contract increases in the fixed cost χ and 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

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

and the value of the risk-free contract is

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

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

$$q \geqslant (\bar{q} - \beta)\frac{\gamma y_l}{L} + \beta\left(\rho + (1-\rho)\frac{\gamma y_l}{L}\right) \tag{3.1}$$

Note that the right-hand side of equation (3.1) 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 3.4. *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, then 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 (3.1) 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 3.3, 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 following theorem characterizes the entire set of equilibrium contracts. It follows directly from Lemmata 3.1-3.4.

Theorem 3.5. *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 $\rho < \underline{\sigma}_N$.*

3.2 Incomplete Information

We now characterize equilibria with asymmetric information. We focus on "pooling" equilibria which closely resemble the compete information equilibria of Section 3.1.[11] 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 behavior 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 (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:

$$\hat{\rho}_n = \frac{q_n y_h - \overline{q} y_l}{\beta(y_h - y_l)}. \tag{3.2}$$

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 II 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 3.6. *In a "pooling" equilibrium, the interval of public types served by each risky contract is of size* $\sqrt{\frac{2\chi}{\alpha\overline{q}\gamma y_h}}$.

[11] In 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.

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.

$$\int_0^{\theta} E\pi(\underline{\sigma}+\delta)d\delta = \chi \tag{3.3}$$

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:

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

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:

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

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

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

Since the expected profit for type $\underline{\sigma}$ is zero, this simplifies to $E\pi(\underline{\sigma}+\delta)=\alpha\delta\overline{q}\gamma y_h$. Plugging this into equation (3.3), we have $\int_0^{\theta}\alpha\overline{q}\gamma y_h\delta d\delta=\chi$. It follows that $\theta=\sqrt{\frac{2\chi}{\alpha\overline{q}\gamma y_h}}$. $\square$

The expression for the length of the interval (of public types) served closely resembles the complete information case in Lemma 3.3. 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 3.6 illustrates, this is driven by two effects that exactly offset each other: lower-ranked contracts have fewer borrowers accepting, but make up for it by higher profit per borrower. As a result, the profitability of a type $(\underline{\sigma} + \delta)$ is the same across contracts $(= \alpha\delta\overline{q}\gamma y_h)$.

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 $\hat{\rho}_n \geqslant \underline{\sigma}_{n-1}$. That is, no accurately labeled customer ever opts out of a risky contract in equilibrium. Combining Lemma 3.6 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 3.7. *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*

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

where $\hat{\rho}_n$ is given by equation (3.2)*. If the participation constraints of mislabeled borrowers do not bind ($\hat{\rho}_n = 1$), this simplifies to* $q_n = \overline{q}\left(\alpha\underline{\sigma}_n + (1-\alpha)\frac{1}{2}\right)$.

To verify that this "pooling" allocation is indeed an equilibrium, we need to verify that there is no possible 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 here, as it forces potential entrant to "skim" enough people to cover the fixed cost. See Appendix A for a detailed description of both the possible deviation and verification procedure.

By numerically ruling out these deviations we establish not only that "pooling" is an equilibrium, but also that it is the unique equilibrium. Given our timing assumptions, if a "separating" equilibrium existed, it would rule out "pooling" as an equilibrium, since "separating" is preferred by the best customers (highest ρ's). The uniqueness within the class of "pooling" equilibria follows from the very same argument that guarantees the uniqueness of equilibria under complete information (Section 3.1).

4 Implications of Financial Innovations

In this section, we analyze the model implications for three channels via 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 total borrowing, defaults, interest rates and the composition of borrowers. We find that financial innovations significantly impacts the extension 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 the innovations we consider have different implications for changes in the ratio of overhead cost to total loans and the average default rate of borrowers.

4.1 Decline in the Fixed Cost

It is widely agreed that information processing costs have declined significantly over the past 30 years (Jorgenson 2001). This has facilitated the increased use of data intensive analysis to design credit scorecards for new credit products (McNab and Taylor 2008). A natural way of capturing this in our model is via lower fixed costs, χ. We use the analytical results from Section 3.1, as well as an illustrative numerical example (see Figure III), to explore how the model predictions vary with χ.[12] 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 III.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

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

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 3.5, 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 III.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 the measure of borrowers (compare Figure III.C with III.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 more quickly, leading to higher default rates (see Figure III.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 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 III.F).

There are two key points to take from Figure III.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.[13] 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 of particular interest 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 increased 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 higher bankruptcies. [14]

4.2 Decline in Risk Free Rate

Another channel via which financial innovations may have impacted consumer credit is by lowering lenders cost of funds, either via securitization or lower loan processing costs. 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 measure served by each contract. The length of each contract is $\sqrt{\frac{2\chi}{\alpha y_h \gamma \bar{q}}}$, 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 IV.A and B).

[13]Add scalar for density to interval length expression?

[14]Bank deregulation, as well as improved information technology, are likely explanations for the increased role of large credit card providers who offer cards nationally, whereas early credit cards were offered by regional banks.

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 IV.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 IV.F). As a result, the average interest rate on risky loans declines by less than 1 point in response 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 (1999) 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.[15] As Figure IV.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.

4.3 Improvements in Signal Accuracy

The last innovation we consider is an improvement in lenders' ability to assess borrowers' default risk. This is motivated by the improvement and diffusion of credit evaluation technologies such as credit scoring (see Section 1.1), which maps naturally into an increase in signal accuracy, α. We again use our numerical example to help illustrate the model predictions (see Figure V).[16]

Variations in signal accuracy (α) impact who is *offered* and who *accepts* risky loans. As in Sections 4.1 and 4.2, the measure offered a risky loan depends upon the number and "size" of each contract. From Theorem 3.7, the measure eligible for each contract

[15]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.

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

$(\sqrt{\frac{2\chi}{\alpha\bar{q}\gamma y_h}})$ is decreasing in α (see Figure V.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 V.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 V.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 V.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 4.1).

$$\text{Defaults} = \underbrace{\alpha\left(1-\underline{\sigma}_N-\frac{1-\underline{\sigma}_N^2}{2}\right)}_{\text{Correctly Classified}}+\underbrace{(1-\alpha)\sum_{j=1}^{N}\left(\underline{\sigma}_{j-1}-\underline{\sigma}_j\right)\left(\hat{\rho}_j-\frac{(\hat{\rho}_j)^2}{2}\right)}_{\text{Misclassified}} \tag{4.1}$$

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 on average riskier than the correctly classified. In our example, this results in the average default rate of borrowers varying little in response to α, so that total defaults increase proportionally to the total number of (risky) borrowers.

Figure V.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 to 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 V.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 in this example technological progress (in the form of an increase in α) causes an increase in overhead costs.

4.4 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 III, IV and V 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. Formally, we consider the problem of a social planner that 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.[17] 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 3.2), 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 (3.1) binds). Since this allocation "wastes" fewer resources on fixed costs, average consumption is higher.

This inefficiency is not directly related to adverse selection problems, as the equilibrium is inefficient even in the perfect information case.[18] Instead, the source of this inefficiency is analogous to the *business stealing effect* of entry models with fixed costs (e.g., see Mankiw and Whinston (1986) where the competitive equilibrium suffers from excess entry. Borrowers would like to commit to larger pools (greater cross-subsidization) ex-ante (before their type has been realized); but ex post some borrowers prefer the competitive contracts. This highlights the practical challenges of policies to improve upon the competitive allocation. Any such policy would make some borrowers worse off and would essentially require a regulated monopolist lender.

5 Comparing the Model Predictions to the Data

We now ask whether the model predictions for the effect of financial innovations (reduced cost of contract design, more accurate risk assessment, and reduced funding costs) are consistent with developments in the unsecured consumer credit market over the past thirty years. Given the rich cross-sectional predictions of our model, we focus primarily on the degree of segmentation of consumer credit and changes in borrowing

[17] See the supplemental web appendix for the explicit representation and solution characterization.

[18] Since 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).

across income groups. Our conclusion is that the key model predictions for technological innovations – increased market segmentation, improved risk-based pricing and the extension of credit to riskier households – are borne out in the data.

5.1 Aggregate Trends

As discussed in Section 4, the model predicts that "sufficiently large" financial innovations (i.e. increases in α, decreases in χ or $\bar{q}$) increase debt and defaults. This is consistent with the surge in consumer bankruptcies and unsecured borrowing observed in the U.S. during the past thirty years (see Figure I). The available data on aggregate overhead costs, however, suggest that a decline in the fixed cost alone is not the sole driving force. The model predicts that reductions in the fixed cost lead to a decline in 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 either reduced funding costs $\bar{q}$, or more accurate risk assessment (increases in α), but not a decline in χ.

5.2 Cross-Sectional Predictions and the Data

The model has interesting cross-sectional implications for the impact of financial innovations on the degree of credit market segmentation, the relationship between borrower risk and interest rates and the extensive margin of who has access to borrowing.[19]

To evaluate these predictions, we examine U.S. data on the distribution of credit card debt and interest rates over the 1980s and 1990s. We focus on credit cards for several reasons. First, most unsecured borrowing occurs via credit cards (Livshits, MacGee, and Tertilt 2010). Second, while credit cards are a recent innovation (dating from the mid 1960s), they have become widely used. Ownership of a bank credit card has increased from 43% of households in 1983 to 72% in 2004 (see Table 1), while the fraction carrying a positive balance has nearly doubled from about 22% in 1983 to 40% in 2004. Third, as

[19] The model-implied changes refer to those that result from an increase in α, a decrease in χ or lower cost of funds. We focus on changes that are large enough to increase the number of contracts offered, i.e. we ignore small changes that sometimes (locally) have the opposite implications.

Table 1: Survey of Consumer Finances

	1983	1989	1995	1998	2001	2004
% Population has card	43%	56%	66%	68%	73%	72%
% Population has balance	22%	29%	37%	37%	39%	40%

Source: Authors' calculations, based on SCF

discussed in Section 1.1, improvements in information technology are frequently cited as a key factor in the growth and evolution of the credit card industry.[20]

We focus on three key model predictions of the effect of financial innovation: (i) an increase in the "variety" (number) of credit contracts, (ii) an increase in risk-based pricing, i.e. interest rates that are more finely tailored to people's types, and (iii) increased access to borrowing for more risky people. We find that all three model predictions for the impact of financial innovations are broadly consistent with the data.

5.2.1 Increased Variety in Consumer Credit Contracts

All three financial innovations that we consider predict an increase in the number of risky contracts. In our model, this increase in product variety appears as an increase in the number of different interest rates offered. We find a similar trend in the data: the number of different credit card interest rates offered to consumers has increased, while the distribution (across borrowers) has become more dispersed.

We use data from the Survey of Consumer Finance (SCF) on the interest rate paid on credit card accounts to count the number of different interest rates reported in various years. The second and third columns of Table 2 show that the number of different interest rates reported nearly tripled between 1983 and 2004.[21] As the table shows, this has been accompanied by increased dispersion of rates across households: the coefficient of variation (CV) also nearly tripled.[22]

[20]Improvements in information technology which reduce operating costs are likely to have a large impact of credit cards since operating costs account for nearly 60 percent of the costs of credit card operations, compared to less than 20 percent of mortgage lending (Canner and Luckett (1992)).

[21]This likely understates the increase in variety, as Furletti (2003) and Furletti and Ody (2006) argue that credit card providers make increased use of features such as annual fees and purchase insurance to differentiate their products, while Narajabad (2010) documents increased dispersion in credit limits

[22]Since 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.

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 Finance.

We also find increased dispersion in borrowing interest rates from survey data collected from banks by the Board of Governors on 24-month consumer loans (starting in 1971) and credit card interest rates (starting in 1990).[23] As can be seen from Figure 6(a), the CV for 24-month consumer loans increases from roughly 1.5 in the early 1970s to about 3.0 by the late 1990s. A similar increase also occurs in credit cards.

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 6(b)). This increased gap between the average and the maximum rate points is consistent with the comparative statics of the model.

Further details about the large shift in the distribution of credit card interest rates can be gleaned from the empirical density of interest rates across households. Figure VII 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%.[24] The 2001 distribution (and other recent years) is notably "flatter" than that of 1983. Indeed, by 2001, no interest rate was reported by more than 12% of households.[25]

[23]We 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 a more details. Since each bank can report only one (the most common) interest rate this likely understates the increase in options.

[24]This refers to the raw data: Figure VII aggregates interest rates into bins of one percentage points.

[25]A similar pattern holds for the distribution of interest rates on 24-months consumer loans.

5.2.2 Increased Risk Based Pricing

A second key prediction of all three financial innovations is that more contracts should be accompanied by better risk-based pricing. To see whether interest rates more accurately reflect household risk, we compare the SCF distribution of interest rates for households who were delinquent on at least one debt payment in the past year to non-delinquents. Delinquency on debt is positively correlated with the probability of future default, so delinquent households should be riskier than non-delinquents (Gross and Souleles 2002). The top panel of Figure VII shows that the distributions of interest rates for delinquents and non-delinquents was nearly identical in 1983. However, by 2001, the delinquent interest rate distribution has considerable mass to the right of the non-delinquent interest distribution (see bottom panel of Figure VII). This suggests that credit card 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 more different credit card plans "targeted at selected subsets of consumers, and many charge[d] lower interest rates" (Canner and Luckett 1992).[26]

5.2.3 Expansion of Credit to Lower Income Households

In the model, financial innovations lead to an extension of credit to riskier borrowers. We use SCF data to examine access to credit cards by income quintiles. Not surprisingly, we find a strong positive relationship between credit card ownership and borrowing for all years. However, the positive relationship between credit card ownership/borrowing and income in the SCF has become less pronounced in recent years. For example, in 1983 only 11% (4%) of households in the lowest income quintile owned a credit card (carried a balance), versus 79% (37%) in the highest quintile. This gap narrowed considerably during the 1990s. By 2004, card ownership for the lowest income quintile more than tripled from 11% to 38% in 2004, while penetration for the top quintile increased to 96%.

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 6(c) plots the

[26] Furletti and Ody (2006) report that credit card issuers also have made increased use of fees as ways to impose a higher price on riskier borrowers.

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.[27] To the extent that lower income groups are riskier, these findings suggest that borrowing by riskier households has increased over the past two decades.

6 Conclusion

This paper develops a qualitative incomplete markets model to explore the effect of financial innovations on unsecured consumer credit markets. This allows us to derive predictions for how commonly discussed financial innovations, based on improved information technology, impacts equilibrium credit contracts, borrowing, and defaults. To evaluate these predictions, we assemble cross-sectional data on credit card interest rates and the distribution of credit card borrowing over the past thirty years.

Our findings support the view that financial innovations (likely due to improvements in information technology) in the credit card market played a key role in the rise in unsecured borrowing and bankruptcies over the past thirty years. Our model predicts that financial innovations lead to more credit contracts, with each contract targeted at smaller groups, and 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 surprisingly consistent with changes in the aggregate and cross-sectional pattern of borrowing and defaults in the U.S. over the past twenty-five years.

The model implies 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 predictions of the standard competitive framework. This suggests that incorporating fixed costs into a quantitative model could be a promising avenue for future research.

[27] Black and Morgan (1999), Kennickell, Starr-McCluer, and Surette (2000), Durkin (2000) also find that the most rapid increase in credit card usage and debt has been among lower income households.

References

Adams, William, Liran Einav, and Jonathan Levin. 2009. "Liquidity Constraints and Imperfect Information in Subprime Lending." *American Economic Review* 99 (March): 49–84.

Allard, Marie, Jean-Paul Cresta, and Jean-Charles Rochet. 1997. "Pooling and Separating Equilibrium in Insurance Markets with Adverse Selection and Distribution Costs." *The Geneva Papers on Risk and Insurance Theory* 22:103–120.

Asher, Joe. 1994. "Look What Credit Scoring Can Do Now." *ABA Banking Journal*, May, 51–52.

Athreya, Kartik. 2001. "The Growth of Unsecured Credit: Are We Better Off?" *Economic Quarterly* 87 (3): 11–33 (Summer).

———. 2004. "Shame as it Ever Was: Stigma and Personal Bankruptcy." *Federal Reserve Bank of Richmond Economic Quarterly* 90 (2): 1–19 (Spring).

Athreya, Kartik, Xuan S. Tam, and Eric R. Young. 2008. "A Quantitative Theory of Information and Unsecured Credit." Working Paper 08-06, Federal Reserve Bank of Richmond Working Paper Series.

Ausubel, Lawrence. 1991. "The Failure of Competition in the Credit Card Market." *American Economic Review* 81 (4): 50–81.

Baird, Douglas G. 2007. "Technology, Information and Bankruptcy." *University of Illinois Law Review*, pp. 305–322.

Barron, John M., and Michael Staten. 2003. "The Value of Comprehensive Credit Reports." In *Credit Reporting Systems and the International Economy*, edited by Margaret J. Miller, 273–310. MIT Press.

Berger, Allan. 2003. "The Economic Effects of Technological Progress: Evidence from the Banking Industry." *Journal of Money, Credit and Banking* 35 (2): 141–176.

Berger, Allan, W.S. Frame, and N. Miller. 2005. "Credit Scoring and the Availability, Price and Risk of Small Business Credit." *Journal of Money, Credit and Banking* 37 (2): 191–222.

Bisin, Alberto, and Piero Gottardi. 2006. "Efficient Competitive Equilibria with Adverse Selection." *Journal of Political Economy* 114 (3): 485–516.

Black, Sandra, and Donald Morgan. 1999. "Meet the New Borrowers." *Federal Reserve Bank of New York Current Issues in Economics and Finance* 5 (3): 1–6 (February).

Brito, Dagobert, and Peter Hartley. 1995. "Consumer Rationality and Credit Cards." *Journal of Political Economy* 103 (April): 400–433.

Canner, Glenn B., and Charles A Luckett. 1992. "Developments in the Pricing of Credit Card Services." *Federal Reserve Bulletin*, September, 652–666.

Chatterjee, Satyajitt, Dean Corbae, Makoto Nakajima, and José-Víctor Ríos-Rull. 2007. "A Quantitative Theory of Unsecured Consumer Credit with Risk of Default." *Econometrica* 75 (6): 1525–1589.

Chatterjee, Satyajitt, Dean Corbae, and Jose-Victor Rios-Rull. 2008. "A Finite-Life Private-Information Theory of Unsecured Debt." *Journal of Economic Theory* 142:149–177.

———. 2010. "A Theory of Credit Scoring and Competitive Pricing of Default Risk." *University of Texas at Austin, mimeo.*

Dick, Astrid, and Andreas Lehnert. 2010. "Personal Bankruptcy and Credit Market Competition." *Journal of Finance* 65 (April): 655–686.

Drozd, Lukasz, and Jaromir Nosal. 2008. Competing for Customers: A Search Model of the Market for Unsecured Credit. Unpublished Manuscript, University of Wisconsin.

Dubey, Pradeep, and John Geanakoplos. 2002. "Competitive Pooling: Rothschild Stiglitz Reconsidered." *Quarterly Journal of Economics* 117:1529–1570.

Durkin, Thomas A. 2000. "Credit Cards: Use and Consumer Attitudes, 1970-2000." *Federal Reserve Bulletin*, September, 623–634.

Edelberg, Wendy. 2006. "Risk-based pricing of interest rates for consumer loans." *Journal of Monetary Economics* 53 (8): 2283–2298 (November).

Einav, Liran, Mark Jenkins, and Jonathan Levin. 2009, July. "The Impact of Information Technology on Consumer Lending." unpublished manuscript, Stanford University.

———. 2010, January. "Contract Pricing in Consumer Credit Markets." unpublished manuscript, Stanford University.

Engen, John R. 2000. "Blind Faith." *Banking Strategies* 76, no. 6.

Evans, David, and Richard Schmalensee. 1999. *Paying with Plastic: The Digital Revolution in Buying and Borrowing*. Cambridge, Massachusetts: MIT Press.

Federal Reserve Board. 2006, June. Report to the Congress on Practices of the Consumer Credit Industry in Soliciting and Extending Credit and their Effects on Consumer Debt and Insolvency. http://www.federalreserve.gov/Pubs/reports_other.htm.

Frame, W. Scott, and Lawrence J. White. 2004. "Empricial Studies of Financial Innovation: Lots of Talk, Little Action." *Journal of Economic Literature*, March, 116–144.

Furletti, Mark. 2002. "An Overview of Credit Card Asset-Backed Securities." *Federal Reserve Bank of Philadelphia – Discussion Paper Payment Cards Center*, December.

———. 2003. "Credit Card Pricing Developments and Their Disclosure." *Federal Reserve Bank of Philadelphia – Discussion Paper Payment Cards Center*, January.

Furletti, Mark, and Christopher Ody. 2006. "Another Look at Credit Card Pricing and Its Disclosure: Is the Semi-Annual Pricing Data Reported by Credit Card Issuers to the Fed Helpful to Consumers and Researchers?" *Federal Reserve Bank of Philadelphia – Discussion Paper Payment Cards Center*, July.

Getter, Darryl. 2008, February. "The Credit Card Market: Recent Trends, Funding Cost Issues, and Repricing Practices." Crs report for congress, Congressional Research Services.

Gross, D., and N. Souleles. 2002. "An Empirical Anaylsis of Personal Bankruptcy and Delinquency." *The Review of Financial Studies* 15 (1): 319–347.

Guerrieri, Veronica, Robert Shimer, and Randall Wright. 2010. "Adverse Selection in Competitive Search Equilibrium." *Econometrica* 78 (6): 18231862.

Hellwig, Martin. 1987. "Some Recent Developments in the Theory of Competition in Markets with Adverse Selection." *European Economic Review* 31:319–325.

Hunt, Robert A. 2006. "The Development and Regulation of Consumer Credit Reporting in America." In *The Economics of Consumer Credit: European Experience and Lessons from the US*, edited by Giuseppe Bertola and Charles Grant, 301–346. Boston: MIT Press.

Jaffee, D., and T. Russell. 1976. "Imperfect Information, Uncertainty and Credit Rationing." *Quarterly Journal of Economics* 90:651–666.

Johnson, R.W. 1992. "Legal, Social and Economic Issues in Implementing Scoring in the U.S." In *Credit Scoring and Credit Control*, edited by L.C. Thomas, J.N. Crook, and D.B. Edelman. Toronto: Clarenden Press.

Jorgenson, Dale W. 2001. "Information Technology and the U.S. Economy." *The American Economic Review* 91 (1): 1–32.

Kennickell, A., M. Starr-McCluer, and B. Surette. 2000. "Recent Changes in U.S. Family Finances: Results from the 1998 Survey of Consumer Finances." *Federal Reserve Bulletin*, January, 1–29.

Lawrence, David, and Arlene Solomon. 2002. *Managing a Consumer Lending Business*. New York: Solomon Lawrence Partners.

Livshits, Igor, James MacGee, and Michele Tertilt. 2007. "Consumer Bankruptcy: A Fresh Start." *American Economic Review*, March, 402–418.

———. 2010. "Accounting for the Rise in Consumer Bankruptcies." *American Economic Journal: Macroeconomics* 2:165193.

Mankiw, Gregory, and Michael Whinston. 1986. "Free Entry and Social Efficiency." *RAND Journal of Economics*, Spring, 48–58.

Mann, Ronald J. 2006. *Charging Ahead: The Growth and Regulation of Payment Card Markets*. Cambridge University Press.

McCorkell, Peter L. 2002. "The Impact of Credit Scoring and Automated Underwriting on Credit Availability." In *The Impact of Public Policy on Consumer Credit*, edited by Thomas Durkin and Michael Staten. Kluwer Academic Punlishers.

McNab, Helen, and Peter Taylor. 2008. *Consumer Credit Risk Management*. Global Professional Publishing.

Mester, Loretta. 1997. "What's the Point of Credit Scoring." *Federal Reserve Bank of Philadelphia Business Review*, September, 3–16.

Moss, David A., and Gibbs A. Johnson. 1999. "The Rise of Consumer Bankruptcy: Evolution, Revolution or Both?" *American Bankruptcy Law Journal* 73:311–352.

Narajabad, Borghan N. 2010. "Information Technology and the Rise of Household Bankruptcy." *Unpublished Manuscript, Rice University*.

Newhouse, Joseph. 1996. "Reimbursing Health Plans and Health Providers: Efficiency in Production Versus Selection." *Journal of Economic Literature* 34 (3): 1236–1263 (September).

Prescott, Edward C., and Robert M. Townsend. 1984. "Pareto Optima and Competitive Equilibria with Adverse Selection and Moral Hazard." *Econometrica* 52 (1): 21–45.

Riestra, Amparo San Josè. 2002, September. Credit Bureau in Today's Credit Markets. *European Credit Research Institute* Research Report No. 4.

Rothshild, M., and J. Stiglitz. 1976. "Equilibrium in Competitive Insurance Markets: An Essay on the Economics of Imperfect Information." *Quarterly Journal of Economics* 90:629–650.

Sanchez, Juan. 2010. The IT Revolution and the Unsecured Credit Market. Federal Reserve Bank of St. Louis Working Paper 2010-022A. WP 2010-022A.

Siddiqi, Naeem. 2006. *Credit Risk Scorecards – Developing and Implementing Intelligent Credit Scoring*. Hoboken, New Jersey: John Wiley & Sons, Inc.

Tufano, Peter. 2003. "Financial Innovation." Chapter 6 of *Handbook of the Economics of Finance*, edited by G.M. Constantinides, M. Harris, and R. Stulz, 307–335. Elsevier B.V.

White, Michelle. 2007. "Bankruptcy Reform and Credit Cards." *Journal of Economic Perspectives* 21:175–199.

Wilson, C. 1977. "A Model of Insurance Markets with Incomplete Information." *Journal of Economic Theory* 16:167–207.

A Verifying Equilibrium under Incomplete Information

To verify that the allocation we have characterized is indeed 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.[28] Without loss of generality, $u_1(q', L') = u_1(\bar{q}, \gamma y_l)$, which implies

$$L' = \frac{\bar{q} - \beta}{q' - \beta} \gamma y_l. \tag{A.1}$$

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

[28]Keeping 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.

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 $n = 2, \ldots, N$. 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 scenario. First, the disruption to the existing contract may be small enough that the incumbent lender chooses not to exit the market. This happens when 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 $\underline{\sigma} = \underline{\sigma}_{n-1}$.

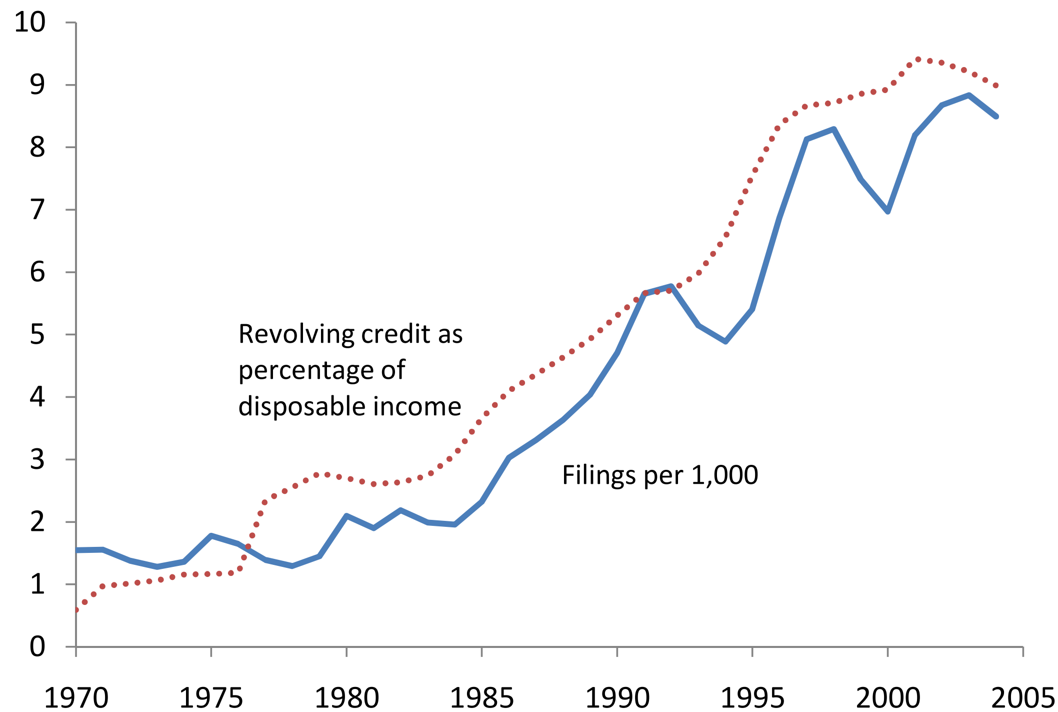
We provide the details of the numerical implementation in a separate web appendix.

B Data Appendix

The Survey of Consumer Finance 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, we drop imputed values. The sample size increases, but by much less than the reported number of different interest rates (see the online appendix for the sample size by year). In Figure 6(c), earned income is Wages + Salaries + Professional Practice, Business, Limited Partnership, Farm + Unemployment or Worker's Compensation.

Figures 6(a) and 6(b) are based on surveys asking banks about interest rates charged to consumers administered by the Board of Governors. The 24-months consumer loans series is from the *Quarterly Report of Interest Rates on Selected Direct Consumer Installment*

Loans (LIRS), and is available since February 1972 (coded as 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 is from the bi-annual (since 1990) *Terms of Credit Card Plans* (TCCP). We use series TCCP6258, including only nationally available plans. Annual response rates range from 200 to 400.



Source: Livshits, MacGee, and Tertilt (2010)

Figure I: Aggregate Facts

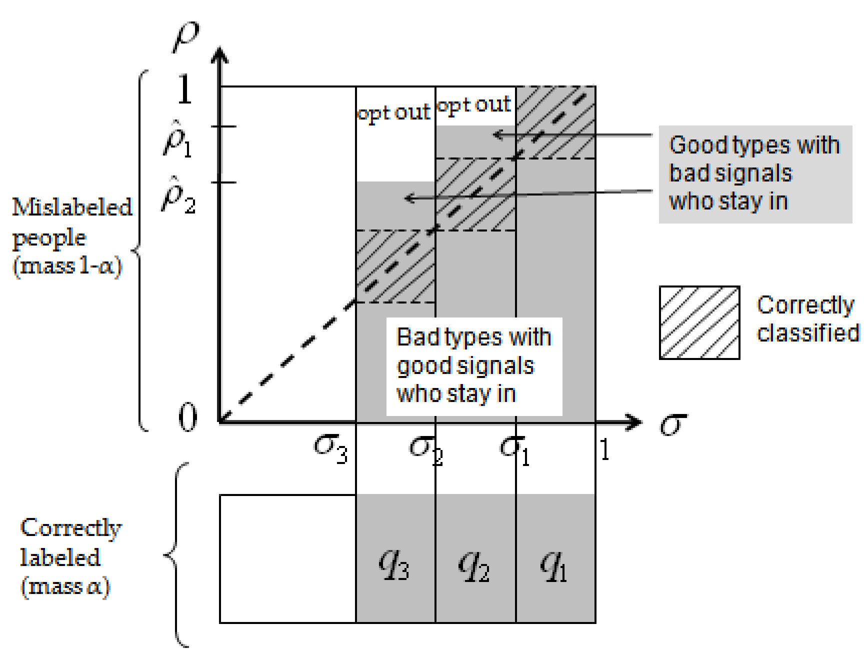


Figure II: Illustration of Equilibrium Contracts with Imperfect Information

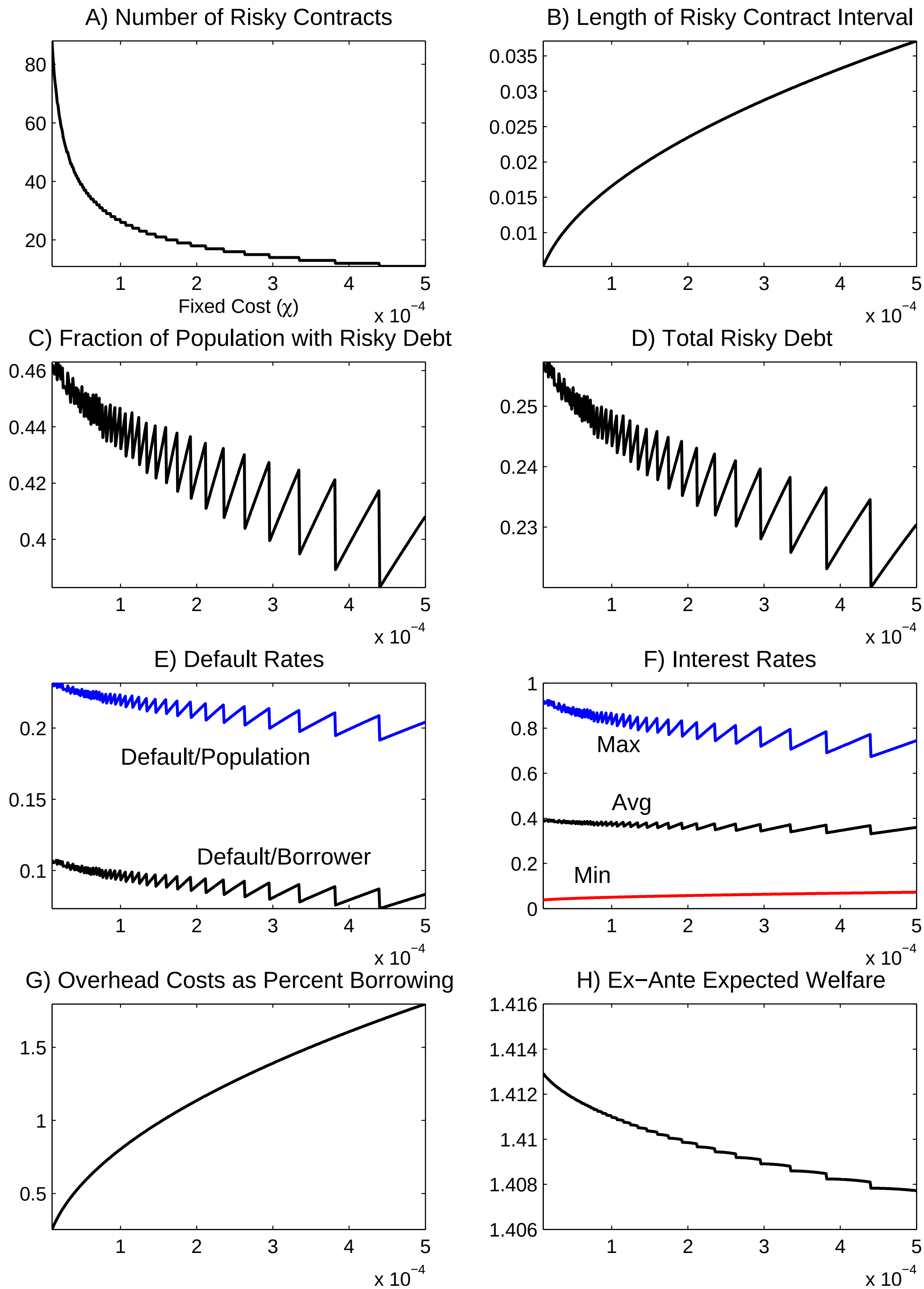


Figure III: Varying the Fixed Cost

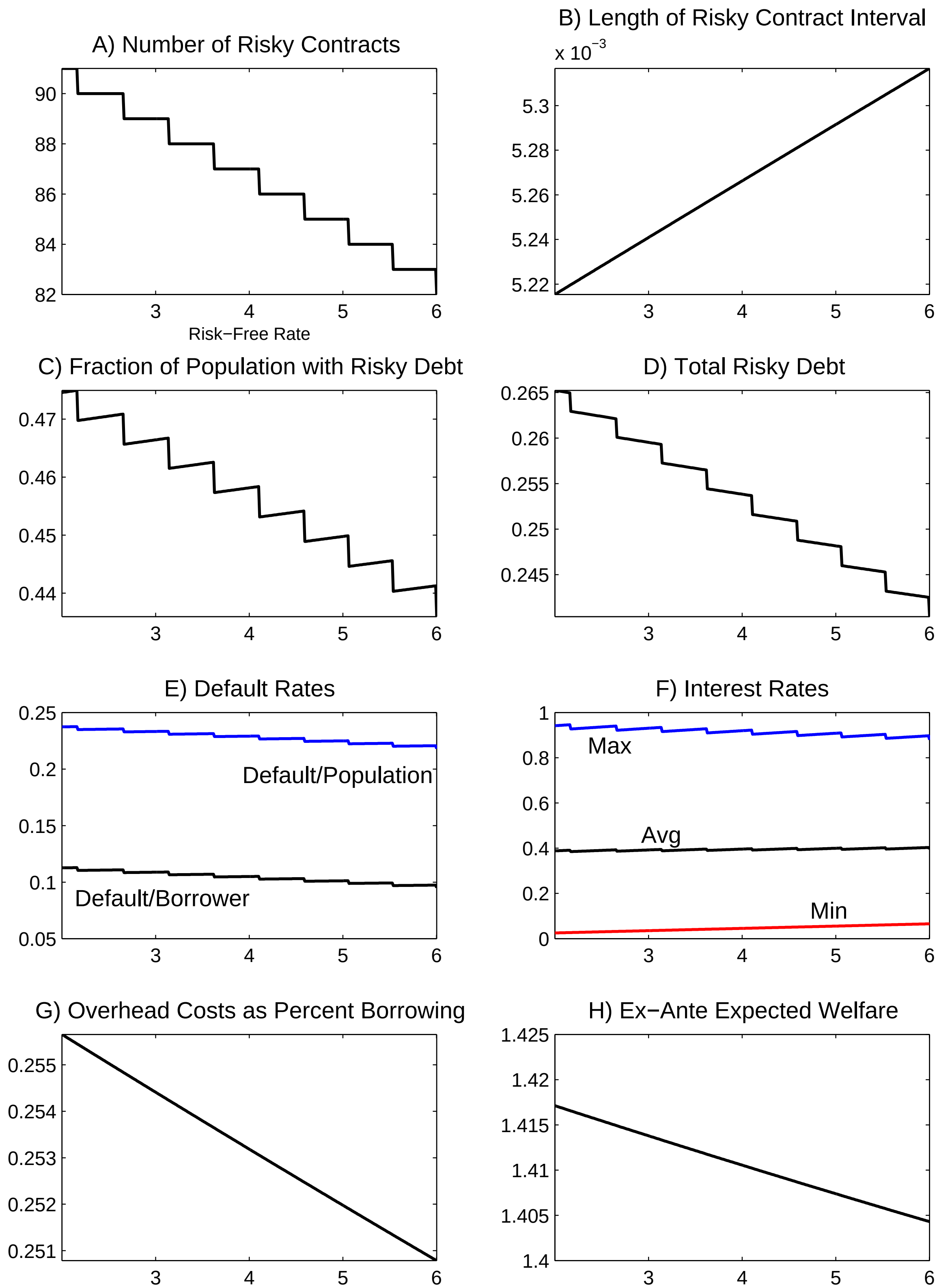


Figure IV: Varying the Interest Rate

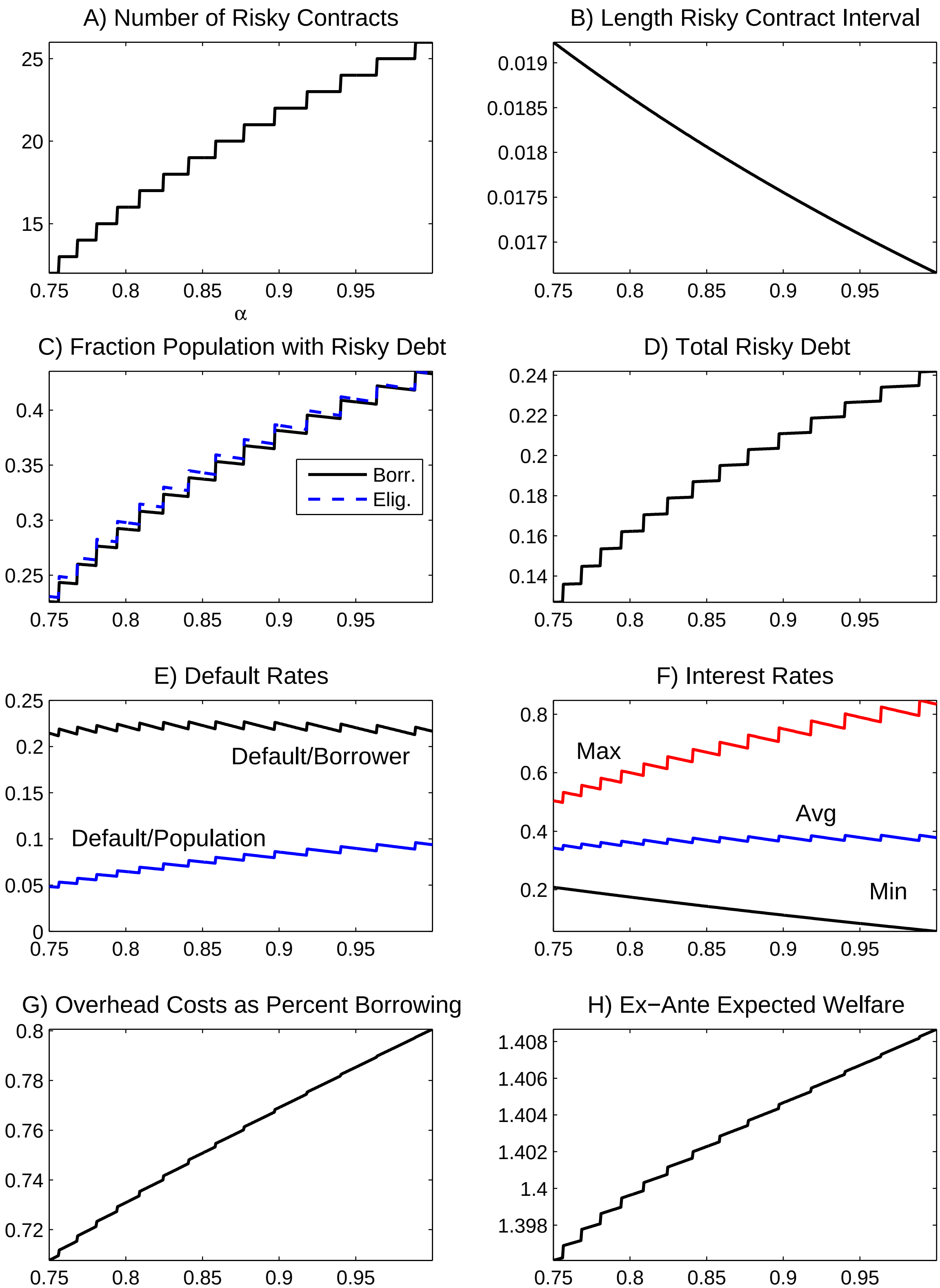
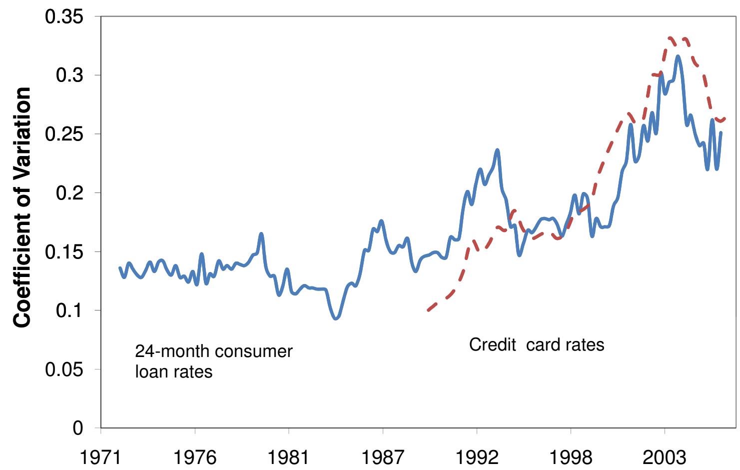
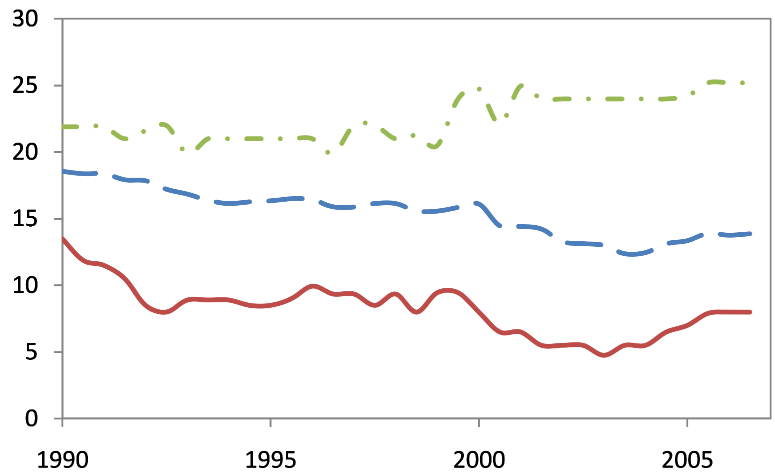


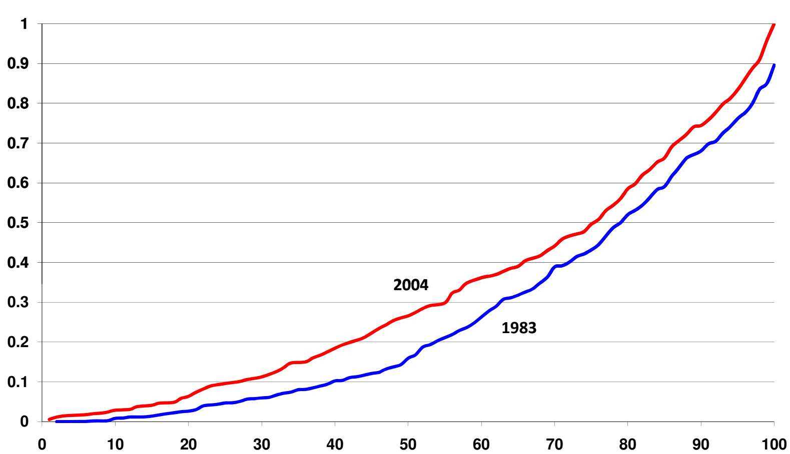
Figure V: Varying the signal accuracy



(a) *CV Consumer Interest Rates*



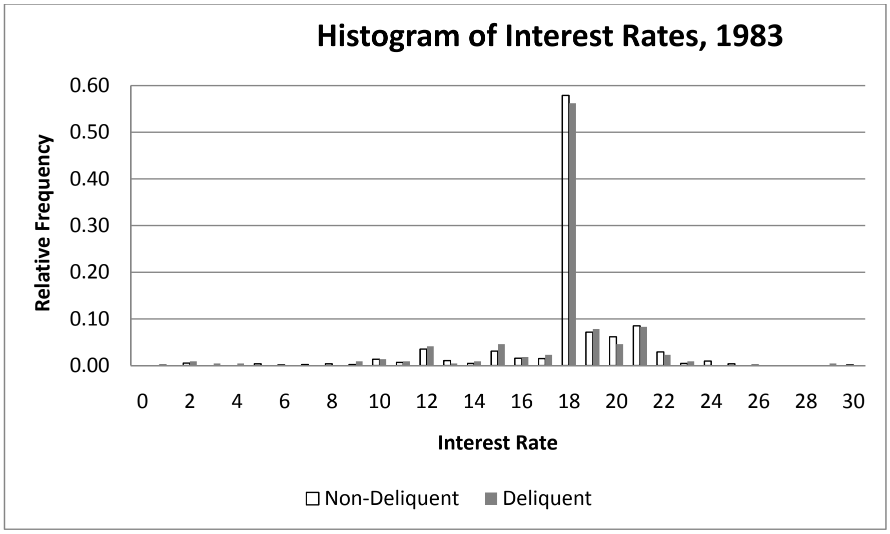
(b) *Average, Min and Max Interest Rate Across Banks*



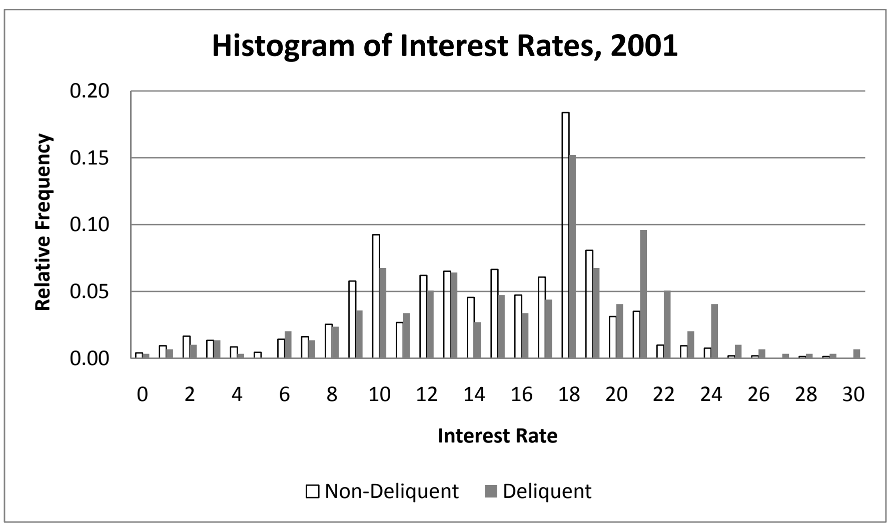
(c) *CDF Credit Card Borrowing vs Earned Income*

Figure VI: Contract Variety, based on data from SCF, TCCP and LIRS

PANEL A



PANEL B



Source: Authors' calculations based on SCF

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