

Costly Contracts and Consumer Credit*

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Abstract

This paper explores the implications of technological progress in consumer lending. The model features households who differ in endowment risk. The borrower's risk type is private information, and intermediaries observe a noisy signal of each borrower's default risks. To offer a lending contract, an intermediary incurs a fixed cost. Each lending contract is comprised of an interest rate, a borrowing limit and a set of eligible borrowers. Technological improvements which lead to more accurate signals of a borrowers type or lower the cost of offering a contract increase the number of contracts offered and the extension of credit to riskier households. This results in higher aggregate levels of defaults and borrowing. To corroborate the predictions of the model, we examine data on credit card borrowing reported by households in the Survey of Consumer Finance. We find that the number of different credit card interest rates reported (one measure of the "number" of contracts) increases and that the empirical density of credit card interest rates has become much more disperse since 1983. We also document that lower income households' share of outstanding credit card debt has increased since 1983.

Keywords: Consumer Credit, Endogenous Financial Contracts, Bankruptcy.

JEL Classifications: E21, E49, G18, K35

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1 Introduction

This paper explores the implications of improvements in consumer lending technology for the unsecured consumer credit market. As we discuss in more detail in Section 1.1, there is substantial evidence of significant technological change in consumer credit markets (Barron and Staten (2003), Berger (2003), Evans and Schmalnsee (1999)). These innovations are widely held to have played a key role in the rapid increase in usage and borrowing on credit cards over the past thirty years (Mann (2006)). A number of authors have argued that the diffusion and increased use of credit cards have played a key role in the rise in bankruptcy and unsecured consumer borrowing (White (2007), Ellis (1998)). This argument has been buttressed by recent quantitative incomplete market models of bankruptcy which have argued that changes in the supply of credit appear to have played a significant role in the rise of bankruptcies and unsecured borrowing over the past 30 years (Athreya (2004), Livshits, MacGee, and Tertilt (2007a)).

One limitation of this literature is that it relies on reduced form ways of modeling financial innovation. Athreya (2004) and Livshits, MacGee, and Tertilt (2007a) model financial innovation as impacting consumer lending via two adhoc channels: a fall in the cost (“stigma”) of bankruptcy and reduced transaction cost of lending. As a result, this literature has relatively little to say about how improved information technology may have changed the set of consumer credit contracts offered or facilitated the extension of credit to riskier borrowers by more accurate pricing of borrowers default risk (Barron and Staten (2003)). More generally, surprisingly little work has been done to evaluate whether the theoretical predictions of credit market innovations or to document the changes.

To address this gap, we develop a simple incomplete markets model of bankruptcy to analyze the qualitative implications of improved credit technology on the equilibrium set of lending contracts. Following the consumer credit industry definition, we define a credit contract as an interest rate, a credit limit and a set of risk types

which the lender will accept.¹ The model incorporates two elements which play a key role in determining the conditions of credit contracts: asymmetric information about borrowers risk of default and a fixed cost to create each contract offered by lenders. This fixed cost of creating contracts means that some pooling of different observable risk types is optimal. Asymmetric information – which we introduce by assuming that lenders observe a noisy signal of a borrowers true default risk while the borrower is perfectly informed about their type – allows us to explore the effects of variations in the extent of adverse selection on consumer credit markets. We use this framework to analyze the effect of technological change which improves the accuracy of signals (thus mitigating adverse selection) as well as reductions in the fixed cost of creating contracts. Comparing these predictions to the data allows us to evaluate the plausibility of stories which emphasize the role of credit market innovations in the rise of unsecured borrowing and bankruptcies, as well as to assess the welfare consequences of these innovations.

While asymmetric information is a common element of credit markets models, fixed costs of contract design are relatively unexplored. This is somewhat surprising since texts targeted at credit market practitioners discuss significant fixed costs associated with developing consumer credit contracts. According to Lawrence and Solomon (2002), a prominent consumer credit industry handbook, the development of a consumer lending product development involves selecting the target market, researching the competition in the target market, designing the terms and conditions of the product, (potentially) testing the product², brand creation through advertisements, point-of-sale promotions and mass mailings, forecasting profitability, preparing a formal documentation of the product, an annual formal review of the product, and providing well-trained customer service tailored specifically to the needs of the prod-

¹The standard definition of a product in the consumer loan industry is “a collection of loans or lines of credit governed by *standard terms and conditions*.” (Lawrence and Solomon (2002, p. 23))

²This involves the actual testing costs plus the delay induced by testing. The typical testing period in this industry is eighteen month (Lawrence and Solomon 2002).

uct.³ To a large extent, these costs are fixed for each product, rather than a function of the number of loans. Even after the initial product launch, account maintenance requires additional fixed costs, such as customer data base maintenance, costs involved in changing in the terms of the product, etc. Finally, it is worth noting that fixed costs are consistent with the fact that credit contracts are a differentiated product, with each product tailored to a specific segment of the market.

The model environment builds on the classic contribution of Jaffee and Russell (1976). Borrowers live for two periods, and have a stochastic endowment in the second period. Borrowers are heterogeneous with respect to their probabilities of different endowment realizations. To offer a lending contract (comprised of a bond price, a borrowing limit, and a set of eligible consumer types), an intermediary incurs a fixed cost. There is free entry into the credit market, so that in equilibrium each contract earns zero profit. We assume that with probability α , this signal is accurate and with complementary probability $1 - \alpha$ the signal is a random draw from the distribution of households types. Our equilibrium concept (which we largely formalize in the timing of the lending game) builds on work by Hellwig (1987), who discusses under what condition (pooling) equilibria exist in environments similar to ours.

We show that this environment generates a finite set of contracts. This is driven by the assumption that there is a fixed cost of contracts which implies that *some* “pooling” is optimal. A pooling contract offers cost savings per borrower, since the fixed cost can be spread across more consumers. The cost to the lowest risk types

³A similar process is described in other industry guidebooks. For example, Siddiqi (2006), outlines the development process of credit risk *scorecards*. A scorecard is a mapping from individual characteristics to a risk score for a particular subset of the population. Large issuers develop their own “custom scorecards” based on data from their own customers, while some firms use purchased data. Because of industry change as well as changes to the overall economic environment, scorecards are constantly updated (a scorecard is usually developed on data that’s up to two years old), i.e. there is not one “true” mapping that once developed becomes a public good. Siddiqi (2006) gives an of a financial company that outsourced scorecard development and purchased ten different cards at an average cost of \$27,000 a card.

within a pool of a larger pool however, is that expanding the pool to include higher risk types increases the interest rate by increasing the average default premium. With free entry of intermediaries, these two forces lead to a finite set of contracts for any (strictly positive) fixed cost. Since a disproportionate share of the fixed cost is paid by lower risk types, this equilibrium features a form of cross-subsidization of borrowing by higher risk types within each contract segment.

We use the model to analyze the qualitative implications of two mechanisms via which improved information technology may have impacted credit markets. The first mechanism we explore is that improved information technology reduced adverse selection problems by improving the ability of lenders to predict prospective borrowers default risk, which facilitated the expansion of credit. The second possibility we consider is that improved information technology reduced the cost of designing and marketing financial contracts, which led to more contracts being offered, each targeted at smaller subsets of the population.

We find that technological improvements which make signals about a borrowers type more accurate lead to an increase in the number of contracts offered. The increase in the number of contracts leads to the extension of credit to riskier households. This generates more unsecured borrowing and an increase in defaults, since the “new” borrowers are more likely to default. Risk based pricing is increased both due to a reduction in the misclassification of high risk borrowers as low risk types as well a reduction in the measure of households served by each contract shrinks, which reduces the extent of cross-subsidization. We further find that technological improvements which lower the cost of offering a contract also generates an increase in the number of contracts, more risk based pricing and an extension of credit to riskier households.

The model also generates interesting insights into the possible relationship between the risk free interest rate and the average borrowing interest rate. In an influential paper, Ausubel (1991) documented that the decline in the risk-free rate in the U.S. in the 1980s was not accompanied by a decline in the average credit card rate. This led to a debate over whether or not the credit card industry was competitive. We

show in our model that a decline in the risk free rate can sometimes lead to higher average borrowing interest rate. The mechanism is that a decline in the risk free rate makes borrowing more attractive, and can thus lead to an increase in the number of contracts offered in equilibrium. Since new contracts are offered to riskier borrowers, the average borrowing interest can increase if the average risk premium on borrowing increases by more than the fall in the risk-free rate.

The second task we tackle in this paper is to assemble extensive data on the number of unsecured consumer credit contracts targeted at specific types (groups) of borrowers. To measure the number and distribution of credit contracts across consumers we look at two specific features of credit contracts: the interest rate and credit limit. We pay particular attention to the distribution of credit card interest rates. Using data from the Survey of Consumer Finance, we document a large increase in the number of different credit card interest rates reported by households since 1983. More strikingly, the empirical density of credit card interest rates has become much “flatter” since 1983. While in 1983 nearly 55% of households reported they faced the same credit rate (18%), by the late 1990s no single credit card interest rate was reported by more than 15% of households. We also document a similar pattern in data on interest rates for 24-month consumer loans and credit cards from surveys of banks conducted by the Board of Governors. These shifts in the distribution of interest rates have also been accompanied by increased lending to lower income households. These features – an increase in contract variety, an increased spread between the lowest and highest interest rates offered, and an expansion of credit to lower income consumers – are all consistent with the predictions of our model.

The equilibrium model of bankruptcy that we use is related to recent work on equilibrium models of consumer bankruptcy.⁴ Both Livshits, MacGee, and Tertilt (2007b) and Chatterjee, Corbae, Nakajima, and Rios-Rull (2005) outline dynamic equilibrium models where interest rates vary with borrowers’ characteristics, and show that for reasonable parameter values, these models can match the level of U.S.

⁴See Athreya (2005) for a more detailed survey.

bankruptcy filings and debt-income ratios. Livshits, MacGee, and Tertilt (2007a) argue that a rise in income and expense (such as uninsured medical expenses) plays a small role in accounting for the rise in filings and unsecured credit. Instead, they find that a decline in the cost (stigma) associated with bankruptcy together with a decline in the transactions cost of borrowing can account for both the dramatic increase in consumer bankruptcy filings and increased unsecured borrowing by consumers. In recent work, Chatterjee, Corbae, and Rios-Rull (2007) and Chatterjee, Corbae, and Rios-Rull (2006) present the first formal model of the role of credit histories and credit scoring in supporting the repayment of unsecured credit.

Closely related to the story we explore is recent work by Narajabad (2008), Drozd and Nosal (2008), Sanchez (2008), and Athreya, Tam, and Young (2008) who also explore whether improved information technologies led to an extension of credit to riskier borrowers. Narajabad (2008) formalizes this mechanism in a model without adverse selection, since he assumes that consumers do not know their own riskiness, while lenders see a noisy signal on a borrowers type. In a relevant empirical contribution, Edelberg (2006) examines PSID and SCF data and finds that the risk-based pricing of consumer loans has increased over the past twenty years.

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 sets up the general model. In Section 3 we characterize the set of equilibrium contracts, while in Section 4 we explore the implications of improved signal accuracy and a decline in the fixed cost. Section 5 examines data on the terms of consumer unsecured borrowing (especially interest rates). Section 7 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 related to the rapid improvements in information technology, which has significantly reduced the cost of processing information and led

to large increases in information sharing on borrowers between financial intermediaries (Barron and Staten (2003), Berger (2003), Evans and Schmalnsee (1999)). It has been argued that this has increased the analysis of the relationship between borrower characteristics and loan performance by lenders to better price loans (Barron and Staten 2003). Despite the existence of a broad descriptive literature on financial innovation, there are very few empirical studies documenting the extent of it quantitatively.⁵ Here we briefly outline some suggestive evidence of significant technological innovations, especially in the credit card market where most of the expansion of unsecured consumer credit has taken place. To summarize, crucial innovations in the credit card industry include the following:

- The development of improved credit-scoring techniques to identify and then monitor creditworthy customers, during the 1970s. These systems became increasingly widely used during the 1980s and 1990s.⁶
- Increased use of computers to process information to facilitate customer acquisition, designing credit cards, marketing, as well as monitoring repayment, and debt collection.
- Increased securitization of credit card debt (starting in 1987).

There are two direct pieces of evidence that suggest that technological innovations related to shifts in the cost of processing information have diffused and become widely used. First, there was a substantial spread of credit scoring throughout the consumer credit industry during the 1980s and 1990s (McCorkell (2002), Engen (2001), Asher

⁵Frame and White (2004) in a recent survey of the literature on financial innovation noted that: “A striking feature of this literature [...] is the *relative dearth of empirical studies* that [...] provide a quantitative analysis of financial innovation.”

⁶The most prominent player is Fair Isaac Cooperation, the developer of the FICO score. Fair Isaac started building credit scoring systems in late 1950s, although the first credit card scoring system was not delivered until 1970. In 1975 Fair Isaac introduced the first behavior scoring system to predict credit risk related to existing customers. In 1981 the Fair Isaac credit bureau scores were introduced. For details see: http://en.wikipedia.org/wiki/Fair_Isaac

(1994)).⁷ Several authors have argued that the development and spread of credit scoring was necessary for the growth of the credit card industry (Evans and Schmalensee (1999), Johnson (1992)). The diffusion of credit scoring is reflected in usage figures reported by the American Banking Association (ABA). The fraction of large banks using credit scoring as a loan approval criteria increased from half in 1988 to nearly seven-eighths in 2000, and 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 to adopt credit scoring than smaller banks (Berger (2003)), banks of any size can access this technology by purchasing scores from other providers.⁸ Barron and Staten (2003) argue that credit cards companies during the early 1990s rapidly expanded their use of risk based pricing, which led to substantial declines in interest rates for low risk customers and increased interest rates for higher risk consumers. There is also evidence that the adoption of automated credit scoring systems decreased the time and cost required to evaluate loan applications (Mester (1997)).

The second (related) piece of direct evidence is the rapid increase in information on borrowers collected by credit bureaus and purchased by lenders. For every credit-using person in the United States, there is at least one (more likely three) credit bureau files (Hunt 2002). 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. This reflects the widespread adoption of credit scoring to evaluate loan applicants. The information in these files is widely used by lenders, as more than 2 million credit

⁷Credit scoring is the evaluation of the credit risk of loan applicants using historical data and statistical techniques ((Mester 1997)). Credit scores are used both to evaluate initial loan applications, and to adjust the interest rates and credit limits of revolving (credit card) debts (up and down).

⁸Further support for the significant impact of credit scoring on lending comes from studies of small business lending. Frame et al (2001) find that the adoption of credit scoring by banks to evaluate small business loans led to lending, while Berger, Frame and Miller (2002) found that credit scoring led to the extension of credit to "marginal applicants" at higher interest rates.

reports are sold by credit bureaus in the U.S. daily (Riestra (2002)).⁹

There has also been significant innovations in how credit card companies finance their operations. Beginning in 1987, credit card companies began to securitize their portfolio of credit card receivables. As can be seen from Table 1, by 2005 nearly half of all balances are now securitized. This has led to a reduction in the costs of financing credit card operations.

Table 1: Measures of Technological Progress in the Financial Sector

Measure of Innovation	then	and now	Source
Credit scoring as loan approval tool*	50% (1988)	85% (2000)	ILR 2000
Credit Reports issues	400 mln (1989)	700 mln (2001)	Riestra (2002)
Credit Card Payments	10.4 bln (1995)	15 bln (2000)	Berger (2003)
Fully automated loan processing*	12% (1988)	29% (2000)	ILR 2000
Mail solicitations	1.1 bln (1990)	5.23 bln (2004)	Synovate**
Securitization as a share of all credit card balances held by banks	26.7% (1991)	48.3% (2005)	Fed [§]

* for large banks

** *Mail Monitor*, Synovate, as cited in Federal Reserve Board (2006).

§ Federal Reserve Board (2006)

However, not all technological progress in the financial sector was directly related to a better assessment of credit risk. Other innovations took place that simply increased the efficiency of designing credit cards, marketing credit cards, and processing accounts. Some of this progress can be thought of a reduction in the cost of credit per account, while other parts may be interpreted as a reduction in the fixed cost of entering this market with a differentiated product.

⁹In Canada and the U.S., credit bureaus report data on borrowers payment history, the stock of current debt and any public judgments (such as bankruptcy).

2 Model Environment

We analyze a two period small open economy with incomplete markets. The economy is populated by a continuum of borrowers each of whom faces stochastic income in period 2. Markets are incomplete in that only non-contingent contracts can be issued. Borrowers can default on contracts and incur exogenous costs associated with bankruptcy. Financial intermediaries are competitive and have access to funds at an exogenously given (risk-free) interest rate. The creation of each financial contract (characterized by a lending rate, a borrowing limit and eligibility requirement for borrowers) requires the payment of a fixed cost χ .

2.1 People

The economy is populated by a continuum of 2-period lived households. For simplicity, we assume that borrowers 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^i , is stochastic. The endowment can take on one of two possible values: $y_2^i \in \{y_h, y_l\}$, where $y_h > y_l$. Households differ in their probability ρ_i of receiving the high endowment y_h . The expected value of income of household i is

$$E_i y_2 = (1 - \rho_i) y_l + \rho_i y_h$$

We identify households with their type ρ_i . ρ is distributed uniformly on $[a, 1]$, where $a \geq 0$. Households know their own type.

2.2 Signals

While each household knows their own type, other agents can only observe a public signals, σ_i , regarding household i 's type. With probability α , this signal is accurate:

$\sigma_i = \rho_i$. With complementary probability $(1 - \alpha)$, the signal is an independent draw from the ρ distribution ($U[a, 1]$). Thus, α is the precision of the public signal.

2.3 Bankruptcy

There is limited commitment by borrowers. We model this as a bankruptcy system, whereby borrowers can 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 bankrupt borrowers.

2.4 Financial Market

Financial markets for borrowing and lending are competitive. Financial intermediaries can borrow (or save) from the (foreign) market at the exogenously given interest rate r . Financial intermediaries accept deposits from savers 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.

Throughout the paper, we assume that $\beta < \frac{1}{1+r} = \bar{q}$, so that households want to borrow as much as possible (at actuarially fair prices), and never want to save. What limits the households' ability to borrow is their inability to commit to repaying loans.

Financial intermediaries must incur a fixed cost χ in order to offer a non-contingent lending contract to (an unlimited number of) households. Endowment-contingent contracts are ruled out (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 promise to pay L in period 2), and $\underline{\sigma}$ is the minimal value of public signal that makes a household eligible for the contract.¹⁰

¹⁰Alternatively, we can specify the contract as just (L, q) and have the eligibility set (characterized by $\underline{\sigma}$) be an equilibrium outcome.

Intermediaries observe the public signal about a household's type, but not the actual type. Households are allowed to accept only one contract, so the intermediaries know the total amount being borrowed. Intermediaries forecast the default probability of loan applicant, and decide to whom to grant loans.

Profit maximization implies that intermediaries never offer loans to types on which they would make negative expected profits, which implies that the expected value of repayments cannot be lower than the cost of the loan to the intermediary.

In equilibrium, free entry implies that intermediaries earn zero expected profits on their *loan portfolio*. The bond price incorporates the fixed cost of offering the contract, so that in equilibrium the operating profits of each contract equal the fixed cost.

2.5 Timing

The timing of events in the financial markets is as follows:¹¹

- 1.a. Intermediaries pay fixed costs χ of entry and announce their contracts. While this stage can be modeled as simultaneous move game, we prefer to think of it as sequential – the stage does not end until no new intermediary wants to enter (having observed the contracts already being offered).
- 1.b Households observe all offered contracts and choose which one to apply for (realizing that some intermediaries may choose to exit the market).¹²
- 1.c Intermediaries, who paid the entry cost, decide whether to stay in the market and advance loans to qualified applicants or to exit the market.¹³

¹¹This timing is necessary for the existence of (partially) pooling equilibria in the environment with imperfect public signals. (Hellwig 1987) discusses the key role of timing in guaranteeing existence of equilibrium.

¹²To simplify the analysis, we could introduce ϵ cost of sending an application, so that each household applies only for a single contract which will be offered in equilibrium.

¹³This stage is not necessary in the environment with perfect signals (Section 3.2) but is essential to ensure existence of equilibria under asymmetric information.

1.d Loans are advanced to qualified applicants by lenders who remain in the market.

We can further split this stage into two sub-stages: Successful applicants are notified, and then they make their choice of lenders.

2.a Households realize their endowments in period 2, and make their default decisions.

2.b Non-defaulting households repay their loans.

2.6 Equilibrium

We defer the complete definition of equilibrium – which involves specifying agents’ beliefs on and off the equilibrium path – to Section 3. Abstracting from the question of beliefs, a standard (non-game-theoretic) equilibrium satisfies the following conditions.

An *equilibrium*¹⁴ is a set of active contracts $\mathcal{K}^* = \{(q_k, L_k, \underline{\sigma}_k)_{k=1, \dots, N}\}$ and consumer contract decision rules $\kappa(\rho, \mathcal{K}) \in \mathcal{K} \cup \{(0, 0, 0)\}$ for each type ρ such that

1. Given $\{(q_k, L_k, \underline{\sigma}_k)_{k \neq j}\}$ and consumer contract 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 chooses which contract (if any) to accept so as to maximize expected utility. Note that a consumer of type ρ can choose a contract k only if $\rho \geq \underline{\sigma}_k$.

3 Characterizing Equilibrium

We focus on a pure strategy equilibrium with pooling within the public types. A contract is characterized by $(L, q, \underline{\sigma})$, where L is the maximum face value of the loan,

¹⁴This is a description of a competitive equilibrium that comes out of the (sequential) game specified in section 2.5. For a full description of (sequential) equilibrium, which also includes the set of beliefs of all players (entrants and households) on and off the equilibrium path, see Section ??.

q is the per-unit price of the loan (so that qL is the amount advanced in period 1 in exchange for promise to pay L in period 2), and $\underline{\sigma}$ is the minimal value of public signal that makes a household eligible for the contract.

3.1 Characterizing Equilibrium Contracts

We begin by characterizing the face value of possible equilibrium contracts. Contracts in the model can vary along two key dimensions: the face value L to be repaid in period 2, and bond price q . The key result is that all possible lending contracts are characterized by one of two face values. The risk-free borrowing contract has a face value equal to the cost of bankruptcy in the low income state, so households are always willing to repay this contract in equilibrium. Risky-lending contracts have the maximum face value such that in the high income state borrowers are always willing to repay. 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, the first result is that free entry leads to zero profits net of the cost of offering contracts.

Proposition 3.1. *All contracts offered earn exactly χ profits (valued as of period 1).*

Proof. Profits of less than χ preclude entry in the pure strategy equilibrium. Profits of more than χ would generate entry of a competing contract with better terms. \square

The second result is that the face value of all risky contracts is the same. This result is tied to the fact that separating contracts are not an equilibrium outcome of the game.

Proposition 3.2. *There are at most two types of contracts offered in equilibrium: risk-free contract with $L = \gamma y_l$ and $\underline{\sigma} = a$, and N risky contracts with $L = \gamma y_h$. Risky contracts are repaid by all households who realize high endowment y_h in period 2.*

Proof. The risk-free contract with $L = \gamma y_l$ dominates all other risk-free contracts (and thus generates the highest possible profit). Risky contracts with $L > \gamma y_h$ cannot be offered as they would never be repaid.

The more interesting result is that no risky contracts with $L' < \gamma y_h$ are offered. It is clear that, keeping the price q constant, all households who would apply for (L', q) would prefer $(\gamma y_h, q)$, and it would generate greater profits for the lender. However, there is potential for cream-skimming by offering a smaller loan L' with a slightly better price $q' > q$ (such that $q'L' < qL$) so that (L', q') is preferred to (L, q) by households with high unobservable type ρ . Households with a low ρ would prefer (L, q) , since they are less likely to repay and hence are willing to promise the larger repayment L in exchange for the larger advance qL . Such cream-skimming is never an equilibrium outcome, due to the specific timing introduced in Section 2.5. If an entrant attempts to cream-skim from an existing contract by offering a contract (L', q') that is preferred to the existing contract only by the better types, the equilibrium of that subgame has the incumbent contract exiting the market (having realized that the “good” customers have applied for the new contract). As a result, the “bad” customers (with low unobservable ρ) also apply for the new contract, even though they prefer the terms of the incumbent contract. Thus, “cream-skimming” fails, and the entrant makes lower profit than would the incumbent who was “cream-skimmed” (since both $q' > q$ and $L' < L$). Since the incumbent contract was exactly recovering the fixed cost χ , such an entry is unprofitable. \square

Proposition 3.3. *Every lender offering a risky contract at price q rejects an applicant iff the expected profit from that applicant is negative.*

Corollary 3.4. *When $\alpha = 1$ (and hence, $\sigma_i = \rho_i$), every lender offering a risky contract at price q rejects an applicant iff $\rho < \underline{\rho}(q) = \frac{q}{\chi}$.*

This implies that the “riskiest” household accepted by a risky contract makes no contribution to overhead cost χ . If a risk-free contract is offered in equilibrium, the eligibility set for that contract is unrestricted.

Proposition 3.5. *The interval of public types served by each risky contract is of size $\sqrt{\frac{2\chi(1-a)}{\alpha\bar{q}\gamma y_h}}$.*

Proof. This result basically follows from Propositions 3.2 and 3.3 and the assumption of uniform distribution of types. From Proposition 3.3, we know that the lowest public type accepted, $\underline{\sigma}$, will generate exactly 0 expected profits. Any public type greater than that, $\sigma = \underline{\sigma} + \delta$, will generate positive profits of $\frac{\delta\bar{q}\gamma y_h}{\alpha}$ per customer.

It is critical to note that the participation cutoff $\bar{\rho}(q_k)$ is the same for all public types within the k -contract. \square

Proposition 3.6. *With α sufficiently high, we can support the equilibria with partial pooling within public types.*

Proof. What we have to show is twofold: 1) that there is no profitable deviation (by other intermediaries) which would unravel the pooling equilibrium, and 2) that the participation cutoff is above the target group: $\bar{\rho}(q_k) \geq \sigma_{k-1}$.

(1) A profitable deviation which could unravel the pooling equilibrium would offer an alternative contract that is attractive only to “good” (private) types. In our environment, such deviation would include slightly lower face value of the debt L' with slightly (but sufficiently) better price q' . What rules out such deviation is our timing which includes application and exit stages (see 1.b and 1.c in Section 2.5). If such a deviation were introduced, the households would recognize that the original pooling contract is no longer viable and would not be offered in equilibrium. Thus, both “good” and “bad” private types would apply for the new (deviation) contract, thus making it unprofitable ex-ante.

(2) In the case $\alpha = 1$, we determine the number of contracts by effectively comparing $\bar{\rho}(q_k)$ with $\underline{\rho}_{k-1}$. Since everything is continuous in *alpha*, the inequalities $\bar{\rho}(q_k) > \sigma_{k-1}$ should still hold when *alpha* is close enough to 1. We may lose the last risky contract, especially if $\bar{\rho}(q_K) = \underline{\rho}_{K-1}$ held with equality for the last contract under *alpha* = 1. \square

3.1.1 Household Problem and Participation Constraints

Given a choice between multiple risky contracts, households always prefer the risky contract with the highest q that they are eligible for. Thus, the households' decision problem can be characterized as choosing between the best risky contract (if one exists) offered that will accept them, the risk-free contract and autarky (conditional on the risk-free contract and a risky contract being offered to them in equilibrium). We formalize this choice problem in three household participation constraints.

We begin by considering the participation constraints of households with accurate signals ($\sigma_i = \rho_i$). The problem of a consumer of type ρ with public signal $\sigma = \rho$ can be expressed as:

$$\max \{v_\rho(q, L), v_\rho(q_{rf}, L_{rf}), v_\rho(0, 0)\},$$

where the value of an arbitrary risky contract (q, L) is

$$v_\rho(q, L) = qL + \beta (\rho(y_h - L) + (1 - \rho)(1 - \gamma)y_l), \quad (3.1)$$

the value of a risk-free contract (q_{rf}, L_{rf}) is

$$v_\rho(q_{rf}, L_{rf}) = q_{rf}L_{rf} + \beta (\rho y_h + (1 - \rho)y_l - L_{rf}), \quad (3.2)$$

and the value of autarky is

$$v_\rho(0, 0) = \beta (\rho y_h + (1 - \rho)y_l). \quad (3.3)$$

The easiest participation constraint to analyze is that comparing autarky and the risk-free contract. Comparing equations (3.2) and (3.3) shows that, regardless of the loan size, the risk free contract dominates autarky whenever

$$q_{rf} \geq \beta \quad (3.4)$$

This has a straightforward interpretation. The risk-free contract will be accepted whenever the number of people who might accept the risk-free contract (and the value of pledgable income γy_l) is high enough relative to the fixed cost so that the bond price is greater than the discount factor.

We now turn to the two participation constraints involving the risky contract. A household will prefer the risky contract (q, L) to autarky whenever $v_\rho(q, L) \geq v_\rho(0, 0)$. This reduces to

$$q \geq \beta \left(\rho + (1 - \rho) \frac{\gamma y_l}{L} \right). \quad (3.5)$$

for all ρ in the eligibility set who are not eligible for a better risky contract. For the risk-free household ($\rho = 1$), this collapses to $q \geq \beta$.

Finally, if the risk-free contract is offered in equilibrium (and thus preferred to autarky), households face a choice between a risky and the risk-free contracts. The risky contract then has to satisfy $v_\rho(q, L) \geq v_\rho(q_{rf}, L_{rf})$, which reduces to

$$q \geq (q_{rf} - \beta) \frac{\bar{L}_{rf}}{L} + \beta \left(\rho + (1 - \rho) \frac{\gamma y_l}{L} \right) \quad (3.6)$$

for all ρ in the eligibility set.

These constraints have important implications for the set of equilibrium contracts. First, consider a risky contract (q, L) offered to households in an interval $[\underline{\rho}, \bar{\rho}]$. Recall that the risky contracts have $L > \gamma y_l$ (otherwise the contract would be risk-free), which implies that $\frac{\gamma y_l}{L} < 1$, and the right-hand side of both equation (3.5) and (3.6) are increasing in ρ . Hence, we only need to check the participation constraint for the least risky type in an interval covered by a risky contract since if a participation constraint does not bind for the highest type in the interval, $\bar{\rho}$, it will not bind for any household $\rho < \bar{\rho}$. Second, note that as one moves from one risky interval to a riskier contract, q decreases. This makes the left-hand side of equations (3.5) and (3.6) smaller, which makes it less likely that the risky contract for that risk bin will be preferred to the risk-free contract or autarky.

Imperfect signals complicate households' participation decisions. Since the right-hand side of the participation constraints above is increasing in ρ , households with signals greater than their true type ($\sigma_i > \rho_i$) will always accept the risky contracts they are eligible for if households with $\sigma_i = \rho_i$ find it optimal to accept them. On the other hand, households with public signals below their true type ($\sigma_i < \rho_i$) may choose to opt out of the risky contracts offered to them and choose autarky or the

risk-free contract (if it is offered in equilibrium).

Exploiting the monotonicity of the incentive constraint (3.5) in ρ , we can specify the highest true type that would choose a risky contract (L, q) over autarky:

$$\bar{\rho}_{aut}(q, L) = \frac{qL - \beta\gamma y_l}{\beta(L - \gamma y_l)}. \quad (3.7)$$

Analogously, the highest type that would prefer a risky contract (L, q) to the risk-free contract (L_{rf}, q_{rf}) (where in equilibrium $L_{rf} = \gamma y_l$) is

$$\bar{\rho}_{rf}(q, L) = \frac{qL - (q_{rf} - \beta)L_{rf} - \beta\gamma y_l}{\beta(L - \gamma y_l)} = \frac{qL - q_{rf}\gamma y_l}{\beta(L - \gamma y_l)}. \quad (3.8)$$

3.1.2 The Set of Equilibrium Contracts

As can be seen from Proposition 3.2, all risky contracts have the same face value, $L = \gamma y_h$, and differ only in the price (and eligibility set). We order these contracts by the riskiness of the clientele served by the contract, from the least to the most risky. We assume throughout our characterization that there is a strictly positive cost $\kappa > 0$ of creating a contract.

The equilibrium is characterized by a finite number N of risky contracts, which serve consecutive intervals $[\underline{\sigma}_n, \underline{\sigma}_{n-1})$ of public types (which we continue to order from the best to the worst types targeted), and a possible risk-free contract, all of which generate operating profit of exactly χ . Each of these contracts has a bond price q_n and an acceptance set of public types. In addition, one has to specify the set of true types $([a, \bar{\rho}(q, L)])$ that accept a risky contract when their public type falls into the eligibility set for that risky contract. Furthermore, the set of potential customers for a risk free contract includes not only all the households who are not eligible for risk-free contracts, but also households with public signals less than their true type who choose not to accept risky contracts they are eligible for.

Proposition 3.7. *The risky contracts are of the form $(q_n, L, \underline{\sigma}_n)$, where $L = \gamma y_h$,*

$$\underline{\sigma}_n = 1 - n \sqrt{\frac{2\chi(1-a)}{\alpha \bar{q} L}}. \quad (3.9)$$

The first contract serves the interval $[\underline{\sigma}_1, 1]$, and each subsequent contract serves the interval $[\underline{\sigma}_n, \underline{\sigma}_{n-1}]$. If the participation constraints of borrowers with $\sigma < \rho$ does not bind ($\bar{\rho}(q_n, L) \geq 1$), then $q_n = \bar{q}(\alpha \underline{\sigma}_n + (1 - \alpha) \frac{1+a}{2})$. If the participation constraints of borrowers with $\sigma < \rho$ does bind, then

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

where $\bar{\rho}_n = \bar{\rho}(q_n, L)$ is given by equation (3.7) or (3.8).

Proof. (1) We start with the case where the participation constraints of borrowers with $\sigma < \rho$ do not bind. Clearly, intermediaries only accept applicants who deliver non-negative expected profit. That implies that for any contract with price q , the marginal type $\underline{\sigma}$ satisfies

$$\left(\alpha \underline{\sigma} + (1 - \alpha) \frac{1 + a}{2} \right) \bar{q} = q. \quad (3.10)$$

We now use the free entry condition to pin down the equilibrium values:

$$\left(\alpha \int_{\underline{\sigma}_n}^{\underline{\sigma}_{n-1}} \frac{\rho}{1 - a} d\rho + (1 - \alpha) \frac{\underline{\sigma}_{n-1} - \underline{\sigma}_n}{1 - a} \frac{1 + a}{2} \right) \bar{q} - \frac{\underline{\sigma}_{n-1} - \underline{\sigma}_n}{1 - a} q_n = \frac{\chi}{L} \quad (3.11)$$

Using equation (3.10) to eliminate q_n , and rearranging:

$$\underline{\sigma}_{n-1} - \underline{\sigma}_n = \sqrt{\frac{2\chi(1 - a)}{\alpha \bar{q} L}} \quad (3.12)$$

(2) Noisy signals create the possibility of adverse selection. Households with signals $\sigma > \rho$ will always accept a contract that a $\sigma = \rho$ type would. However, high types with low signals ($\sigma < \rho$) may choose not to borrow via the risky contract they are eligible for and opt for the risk-free contract or autarky.

Note that this is not an issue for the first risky contract (q_1, \bar{L}) . For each risky contract (q_n, \bar{L}) with $n \geq 2$, let $\bar{\rho}_n$ denote the cutoff such that all households with $\rho \geq \bar{\rho}_n$ (and $\sigma \in (\underline{\sigma}_n, \underline{\sigma}_{n-1}]$) would not purchase contract (q_n, L) . Suppose that the participation constraint of high types with low signals does not bind for the first $n - 1$

contracts, but binds for contract n . The n^{th} contract covers households with public types in the interval $(\underline{\sigma}_n, \underline{\sigma}_{n-1}]$, where the cut-offs are given by:

$$\underline{\sigma}_{n-1} = \frac{1}{\alpha} \left(\frac{q_{n-1}}{\bar{q}} - (1 - \alpha) \frac{1 + a}{2} \right) \quad (3.13)$$

$$\underline{\sigma}_n = \frac{1}{\alpha} \left[\frac{q_n}{\bar{q}} \left(\alpha + (1 - \alpha) \frac{\bar{\rho}_n - a}{1 - a} \right) - (1 - \alpha) \frac{(\bar{\rho}_n)^2 - a^2}{2(1 - a)} \right] \quad (3.14)$$

The operating profit can be decomposed into the contributions from households with accurate and inaccurate signals. The zero profit condition $\Pi_n = \chi$ is given by:

$$\begin{aligned} 0 = \Pi_n - \chi &= \frac{\bar{q}L}{1 - a} \left(\alpha \frac{(\underline{\sigma}_{n-1})^2 - (\underline{\sigma}_n)^2}{2} + (\underline{\sigma}_{n-1} - \underline{\sigma}_n)(1 - \alpha) \frac{(\bar{\rho}_n)^2 - a^2}{2(1 - a)} \right) \\ &\quad - \frac{q_n L}{1 - a} (\underline{\sigma}_{n-1} - \underline{\sigma}_n) \left(\alpha + (1 - \alpha) \frac{\bar{\rho}_n - a}{1 - a} \right) \end{aligned}$$

Using equation (3.14) to eliminate q_n yields:

$$\underline{\sigma}_{n-1} - \underline{\sigma}_n = \sqrt{\frac{2\chi(1 - a)}{\alpha\bar{q}L}} \quad (3.15)$$

Note that this is the same as when the participation constraints of high types with low signals does not bind. Hence, the only effect of binding incentive constraint of high types with low σ binds is to reduce the bond price of a risky contract. This follows from equation (3.15), and from comparing (3.13) and (3.14). \square

The equilibrium set of contracts can be solved explicitly by considering several cases. Since the possibility of adverse selection complicate the bond prices (equation (3.14)), one has to simultaneously solve a system of non-linear equations for the cut-offs for the risk-free participation and the bond prices for each risky contract as well as for the risk-free bond price.

3.2 Perfectly Informative Signals ($\alpha = 1$)

We now briefly discuss the (simpler) special case of complete information regarding households' risk types ($\alpha = 1$). This is an interesting special case to explicitly consider for several reasons. First, this environment corresponds to a static version of papers

such as Livshits, MacGee, and Tertilt (2007b) and Chatterjee, Corbae, Nakajima, and Rios-Rull (2005) which abstract from adverse selection. Second, abstracting from adverse selection helps to illustrate the workings of the model. To save on notation in this section, we will set a , the lower bound on the probability of high income realization, to 0. That is, $\rho \sim U[0, 1]$.

3.2.1 Characterizing Equilibrium with $\alpha = 1$

The characterization of equilibrium is the same as discussed earlier. Hence, we briefly discuss the key equations where $\alpha = 1$. First, note that in the absence of private information, the equations characterizing the contracts are considerably simplified.

Theorem 3.8. *Finitely many (N) risky contracts are offered. Each contract ($q_n, L = \gamma y_h$) serves borrowers in the interval $\rho \in (\rho_n, \rho_{n-1}]$, where*

$$\begin{aligned}\rho_n &= 1 - n\sqrt{\frac{2\chi}{\gamma y_h \bar{q}}} \\ q_n &= \bar{q}\rho_n\end{aligned}$$

If risk-free contract ($q_{rf}, L_{rf} = \gamma y_l$) is offered, it serves borrowers with $\rho \in [0, \rho_N]$, and

$$q_{rf} = \bar{q} - \frac{\chi}{\gamma y_l \rho_N}. \quad (3.16)$$

To construct an equilibrium, one needs to check the household participation decisions to solve for N and for whether the risk-free contract is offered in equilibrium. This process is straightforward when $\alpha = 1$, since one no longer needs to track the measure of types with lower public signals than their true types who decline the best risky contract they are offered. Combining the household participation constraint (3.4) with the expression for the risk-free bond price (3.16), one can solve for the minimum length of the interval (not served by risky contracts) that makes the risk-free contract viable. Letting the upper-cutoff for this interval be denoted by $\bar{\rho}_{rf}$

$$\begin{aligned}\beta = q_{rf} &= \bar{q} - \frac{\chi}{\bar{\rho}_{rf} L_{rf}} \\ \rho_{rf} &= \frac{\chi}{(\bar{q} - \beta) L_{rf}}\end{aligned} \quad (3.17)$$

To solve for N , one has to find the (first) risky contract for which the household participation constraint with respect to either autarky or the risk-free contract is violated. Recall that for any risky contract serving the interval $(\underline{\rho}, \bar{\rho}]$ we only need to check the participation constraint of the individual with the highest type, $\bar{\rho}$. Further, if $\underline{\rho} \geq \bar{\rho}_{rf}$, then we have to check the household $\bar{\rho}$'s participation constraint with respect to the risk-free contract (serving $[0, \underline{\rho}]$). Conversely, if $\underline{\rho} < \bar{\rho}_{rf}$, we check the value of the risky contract against the autarky participation constraint (3.5).

This observation allows us to put an upper bound on the number of risky contracts offered in equilibrium by considering only the autarky participation constraint.

Theorem 3.9. *Assume that $\beta \frac{y_L}{y_H} + \bar{q} > 1$. Taking participation constraints into account, the number of risky contracts offered in equilibrium, N , cannot exceed*

$$\bar{N} = \text{int} \left(\frac{(\bar{q} - \beta) \sqrt{\frac{\gamma y_h \bar{q}}{2\chi}} - \beta \left(1 - \frac{y_L}{y_H}\right)}{\beta \frac{y_L}{y_H} + \bar{q} - 1} \right)$$

Proof. We want to find that largest N that is consistent with firm maximization and household participation. In other words, what is the largest n that satisfies

$$\rho_n = 1 - n \sqrt{\frac{2\chi}{y_h \gamma \bar{q}}} \text{ and } q_n = \bar{q} \rho_n$$

and does not violate the household participation constraint for all types in $(\rho_n, \rho_{n-1}]$? Since the autarky participation constraint (equation 3.5) must always hold (and since when the risk-free contract is offered, the autarky constraint is slacker), checking the autarky constraint will give the upper bound on the number of possible contracts. As discussed above, it suffices to check the participation constraint only for type ρ_{n-1} . Recalling that the autarky-risky participation constraint is $\beta \left(\frac{\gamma y_l (1 - \rho)}{L} + \rho \right) \leq q$, we have that contract n will satisfy the participation constraint for ρ_{n-1} if and only if:

$$\beta \left(\frac{\gamma y_l (1 - \rho_{n-1})}{L} + \rho_{n-1} \right) \leq \bar{q} \rho_n$$

Substituting $\rho_n = 1 - n \sqrt{\frac{2\chi}{y_h \gamma \bar{q}}}$ from Theorem 3.8, simplifying and collecting terms:

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

Table 2: Parameters used in the Numerical Example

β	γ	y_h	y_l	\bar{r}	χ	a
0.75	0.25	3	0.4	4%	0.0001	0

Under the condition that $\beta \frac{y_l}{y_H} + \bar{q} > 1$, this inequality can be rewritten as:

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

The equilibrium number of contracts cannot exceed the largest n that satisfies the inequality above. □

Clearly, this bound \bar{N} is weakly decreasing in χ .

4 Implications of Technological Progress

We now ask what is the impact of financial market innovations on the set of contracts offered in equilibrium and the cross-sectional pattern of borrowing and defaults. We focus on the comparative static implications of three different channels. First, what is the effect of increased signal accuracy on the number and price of contracts offered in equilibrium? Second, what is the effect of changes in the fixed cost of creating contracts? Finally, we explore the implications of reductions in the cost of funds.

Given the highly stylized nature of the model, we focus on the qualitative predictions of the model. We provide most comparative statics results in the form of theorems. To better illustrate the results, we also present a numerical example. Since the example is intended to help illustrate how the qualitative features of the model (i.e. direction of change) matches up with the data, the parametrization is chosen for simplicity rather than to match any quantitative facts. The example parameters are given in Table 2.

4.1 Improvements in Signal Accuracy

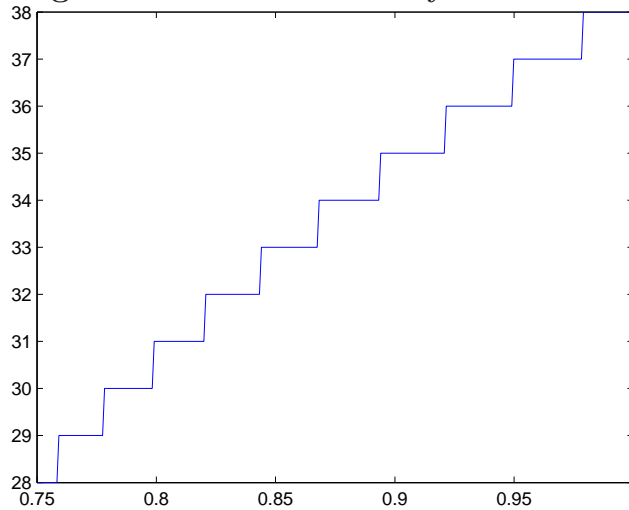
We begin by exploring the implications of improved signal accuracy. This comparative static exercise is motivated by improved credit evaluation technologies such as credit scoring. In addition to presenting some general results, we also illustrate the working by varying $\alpha \in [0.75, 0.9999]$ while holding fixed the other parameters.

Total borrowing and defaults depend upon the fraction of population who borrow via a risky contract. This depends upon three factors: the number eligible for each contract, the number of people who accept each contract they are offered and the number of contracts. The qualitative relationship between α and each of these factors is easy to characterize. First, the measure of household eligible for *each individual* contract is decreasing in α . This follows directly from equation 3.15, as the length of the interval eligible for each risky contract is strictly decreasing in α . The intuition is simply that increased signal accuracy reduces the incentive for agents to pool by increasing the return on reducing cross-subsidization via a smaller pool of public types.

The fraction of eligible borrowers who accept the risky contracts they are offered is increasing in α . An increase in signal accuracy reduces the adverse selection problem by shrinking the fraction of misclassified high risk types eligible for the contract. This lowers the default premium (thus increasing the bond price), which reduces the fraction of low risk types with (incorrect) high risk public signals who decline the offered contract. The final channel via which signal accuracy impacts the equilibrium is the number of risky contracts offered. The number of risky contracts is non-decreasing in α . For a *sufficiently large* change in α , the number of risky contracts offered in equilibrium increases. As Figure 1 illustrates, this implies that the number of contracts is an increasing step function in α .

The interaction between shrinking interval length and the increased number of contracts determines the total fraction of the population with *access* to risky borrowing. As Figure 2 illustrates, whenever α declines enough to generate an additional risky contract in equilibrium, the total measure of households *eligible* to borrow via risky

Figure 1: Number of Risky Contracts



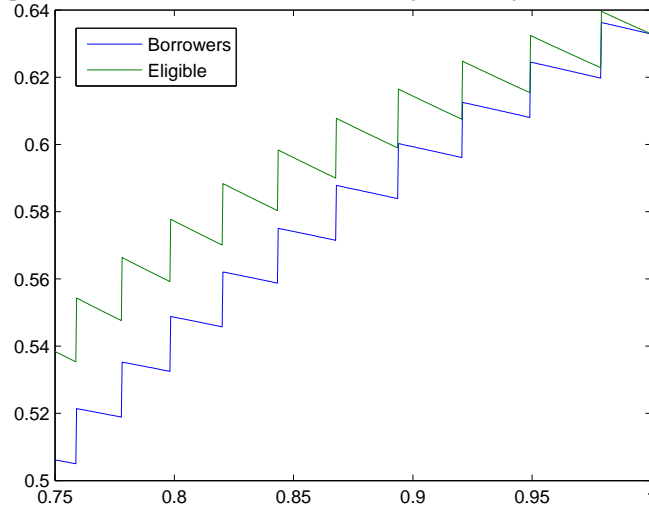
contracts increases. However, when α declines by less than this amount, the length of each contract interval shrinks, which reduces the fraction of the population with access to risky borrowing.

An increase in the measure of households eligible to borrow goes hand in hand with an increase in the fraction of households borrowing. The increase in the measure of households borrowing strictly exceeds the increase in the fraction of the population eligible to borrow. This reflects the fact that more accurate signals reduce the degree of adverse selection in the economy caused by low risk types with high(er) risk public signals declining to borrow via the risky contract they are eligible for. This can be seen from Figure 2 where for a low signal accuracy roughly 54% of the population has access to borrowing but only 51 % borrows, while for perfect signals over 63 % of the population has access to risky credit and all eligible households borrow.¹⁵

The increase in the number of households eligible to borrow and in the fraction of eligible households who borrow leads to an increase in borrowing and defaults. The expansion of credit to more borrowers in this environment involves the extension of

¹⁵Recall that the model also allow for a small risk-free loan which is repaid with certainty. These loans are not part of the picture.

Figure 2: Measure Served by Risky Contracts

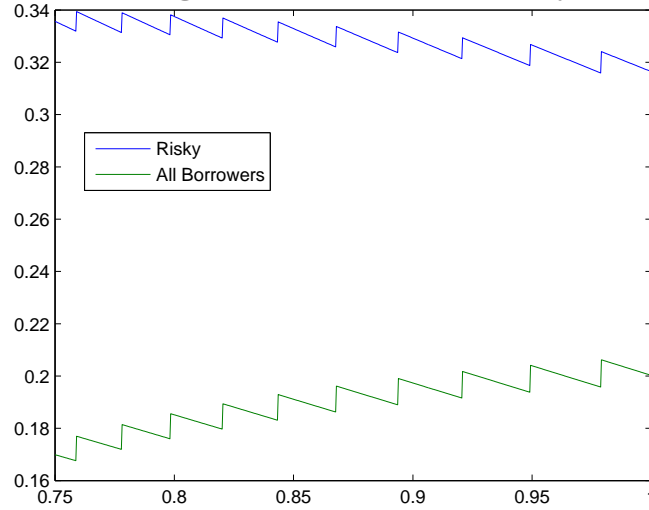


credit to public types with higher default risk than existing borrowers. This tends to increase the average default rate of all borrowers. However, the rise in defaults is partially muted by the fact that improvements in signal accuracy lead to a reduction in the number of high risk people who borrow on terms offered to low risk borrowers. As a result, the default rate (and the default premium) of contracts offered to existing borrowers decreases with improvements in signal accuracy.

The overall effect of these forces is reflected in the average default rate of borrowers. As Figure 3 illustrates, the average default rate on risky contracts spikes up whenever a new contract is introduced. However, improvements in signal quality also tend to lower the average default rate by reducing the number of high risk households whose public type classifies them as low risk. In this example, this effect dominates so that improvements in signal quality leads to a slightly lower average default rate on the risky contract. However, total defaults and the average default rate for all borrowers (which in this example is all households) is increasing in α . This is driven by the fact that the increase in the measure of households borrowing via risky (instead of risk-free) contracts dominates the decline in the default rate on risky contracts.

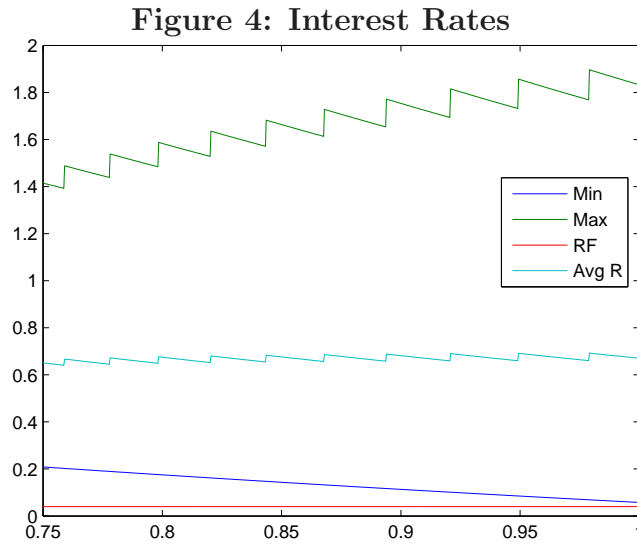
The shifts in default rates shows up in the distribution of interest rates. As α

Figure 3: Average Default Rate on Risky Contracts



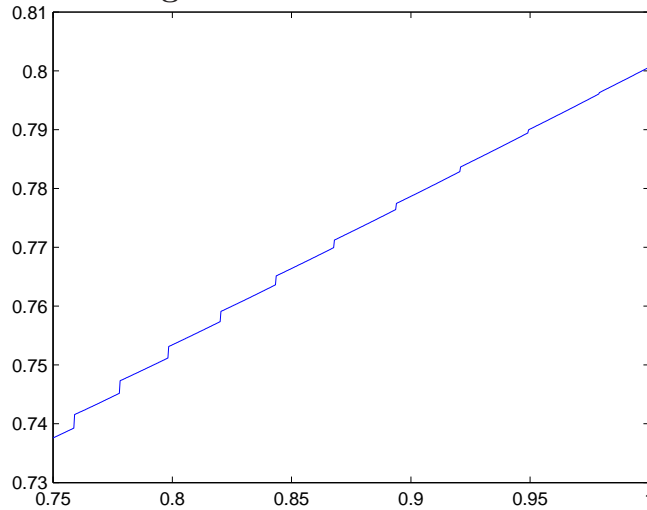
increases, the measure of consumers eligible for each risky interval decreases. The increased accuracy of the signal also implies that fewer high risk borrowers (low ρ types) are incorrectly classified as low risk public types. Both of these two forces combine to drive down the interest rate ($r_1 = \frac{1}{q_1} - 1$) on the lowest risk risky-contract. Since both of these forces are independent of the number of contracts, this implies that the interest rate on the lowest risk types is strictly decreasing in α , as illustrated in Figure 4. As a result, the interest rate on the lowest risk risky contract tends towards the risk-free interest rate in the economy. The maximum interest rate in the economy depends upon these forces as well as on the number of contracts offered. As can be seen from Figure 4, so long as an increase in α is not large enough to generate the entry of an additional contract, the highest borrowing interest rate in the economy decreases. This reflects the “dropping” of the riskiest borrowers from the eligibility set for the riskiest contract, which lowers the default premium. However, since the entry of a new contract involves the extension of credit to high risk households previously excluded from risky borrowing, the interest rate on the (new) riskiest contract is increasing in α . The average interest rate (weighted by the face value of borrowing) in the economy reflects these forces, and varies relatively little with α . One additional

effect that matters here is that increases in α lead to an increase in the acceptance rate of risky contracts, which increases the share of these contracts in the calculation of the average interest rate in the economy. Finally, it is worth noting that the risk free interest rate in this economy increases slightly with α . This is driven by a reduction in the fraction of the population borrowing via the risk-free contract, which means that the fixed cost of offering this contract is spread over a smaller base.



The ratio of overhead costs to total borrowing is increasing in α , as can be seen from Figure 5. Since an increase in the accuracy of the signal generates an increase in the number of contacts, the total spent on overhead costs increases. What drives the increase in overhead costs as a share of the face value of lending is that on average the decrease in the measure of each household served by a contract exceeds the reduction in the measure of eligible households who opt not to borrow due to adverse selection. As a result, in this example, improvements in credit technology lead to an increase in average overhead costs. This suggests that cost of operations of banks (or credit card issuers) might not be a good measure of technological progress in the banking sector. Figure 5 also illustrates that overhead costs are relatively small in this example, and are equal to less than 1 % of the face value of outstanding debt.

Figure 5: Overhead Costs



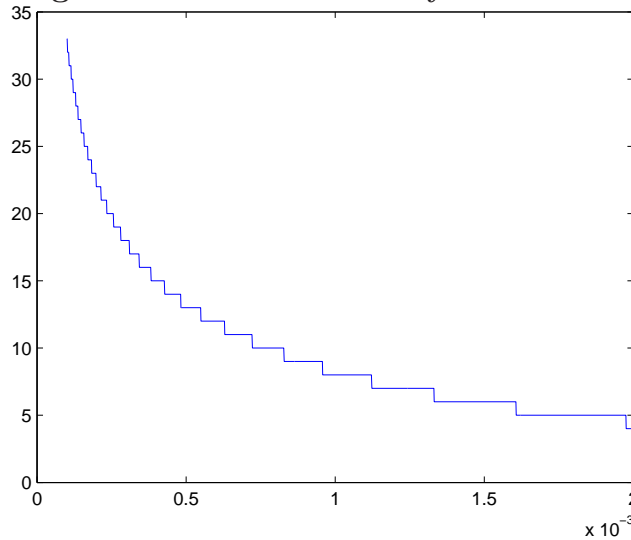
4.2 Decline in Cost of Contract χ

We now consider another possible channel via which financial innovation may have impacted the set of equilibrium contracts: a decline in the fixed cost of offering a contract. As previously discussed, credit contracts are a differentiated product, where each product is tailored to a specific segment of the market. Credit contracts have become more and more differentiated over time (i.e. tailored to finer and finer segments of the population) – as we discuss in Section 5.1. One mechanism which could generate increased market segmentation would be a decline in the fixed cost of designing a particular credit product (contract).¹⁶ Unfortunately, direct evidence on the decline in such a fixed cost is hard to obtain – other than by pointing to general evidence on productivity increases in the credit sector. To the extent that productivity increased in those industries that deliver these services, it seems plausible to believe that these fixed costs have been falling over time.

¹⁶The rise of information technology has also made it easier for companies to offer contracts to a wider geographical area. For example, large credit card providers such as Citi and MBNA offer cards nationally, whereas early credit cards were offered by regional banks. In this model, this would act as an increase in the market size which has a similar effect to a fall in χ .

A change in the fixed cost χ of creating a contract affects both the measure of households served by each contract and the number of contracts offered. The length of the interval served by *each* contract increases in χ . This follows directly from equation 3.15. Intuitively, higher (lower) values of the fixed cost increases (decreases) the benefits of spreading the fixed cost over a larger pool of agents relative to the cost of cross-subsidization of the lowest risk borrowers in a contract pool. The number of contracts N is weakly decreasing in χ . For a *sufficiently large* increase (decrease) in χ , the number of risky contracts offered in equilibrium decreases (increases). This follows from Theorem 3.9, which states that the maximum number of contracts is weakly decreasing in χ . The effect of varying χ in our numerical example is illustrated in Figure 6, which shows that the number of contracts is a non-decreasing step function in χ . The intuition for the step function is that for small enough changes in χ , adding a new contract is not profitable.

Figure 6: Number of Risky Contracts



Since total borrowing and defaults depend upon the fraction of population covered by a risky contract, $(1 - \rho_N)$, the interaction between shrinking interval length and the increased number of contracts is key. The size of the group served by each contract is locally increasing in χ almost everywhere. This corresponds to the number of risky

contracts remaining the same and the number of households served by each contract increasing. However, globally, the fraction served by risky contracts is decreasing in χ as can be seen from the fact that both the upper and the lower bounds of the interval are decreasing in χ . As Figure 7 illustrates, whenever χ declines enough to generate an additional risky contract in equilibrium, the total measure of households borrowing via risky contracts increases. However, when χ declines by less than this amount, the only effect is to shrink the length of each interval – which reduces the fraction of the population with risky borrowing. The next theorem provides theoretical bounds for the contract coverage.

Theorem 4.1. *Assume that $\beta \frac{y_L}{y_H} + \bar{q} > 1$. Then the fraction of households served by risky contracts in equilibrium*

$$(1 - \rho_N) \in \left(\frac{\bar{q} - \beta - (\beta + \bar{q} - 1) \sqrt{\frac{2\chi}{\gamma y_h \bar{q}}}}{\beta \frac{y_L}{y_H} - 1 + \bar{q}}, \frac{\bar{q} - \beta - \beta \left(1 - \frac{y_L}{y_H}\right) \sqrt{\frac{2\chi}{\gamma y_h \bar{q}}}}{\beta \frac{y_L}{y_H} - 1 + \bar{q}} \right].$$

Proof. This follows directly from Theorem 3.9. □

The number of risky contracts is thus key to how aggregate borrowing and defaults vary with χ . The reason is that the fraction of the population with access to risky contracts is increasing in the number of risky contracts offered. From the definitions of aggregates in Section A.2, it follows that total defaults and total risky borrowing are increasing in the fraction of the population served by risky contracts. Basically, the previous theorem establishes a weak monotonicity of ρ_N in χ : as contract costs fall enough, the fraction of people covered by risky contracts increases. Building on this, we can now write several additional results on how aggregates behave as a function of contract coverage, $1 - \rho_N$.

Theorem 4.2. *The number of total defaults strictly decreases in ρ_N .*

Proof. Total defaults are given by

$$\int_{\rho_N}^1 (1 - \rho) d\rho = 1/2 - \rho_N + \frac{\rho_N^2}{2}$$

This is strictly decreasing in ρ_N as long as $\rho_N < 1$.

q.e.d.

Theorem 4.3. *Aggregate risky borrowing strictly decreases in ρ_N .*

Aggregate risky borrowing (in period 1 dollars) is:

$$\int_{\rho_N}^1 \bar{q}Ld\rho = (1 - \rho_N)\bar{q}L$$

This clearly decreases in ρ_N .

q.e.d.

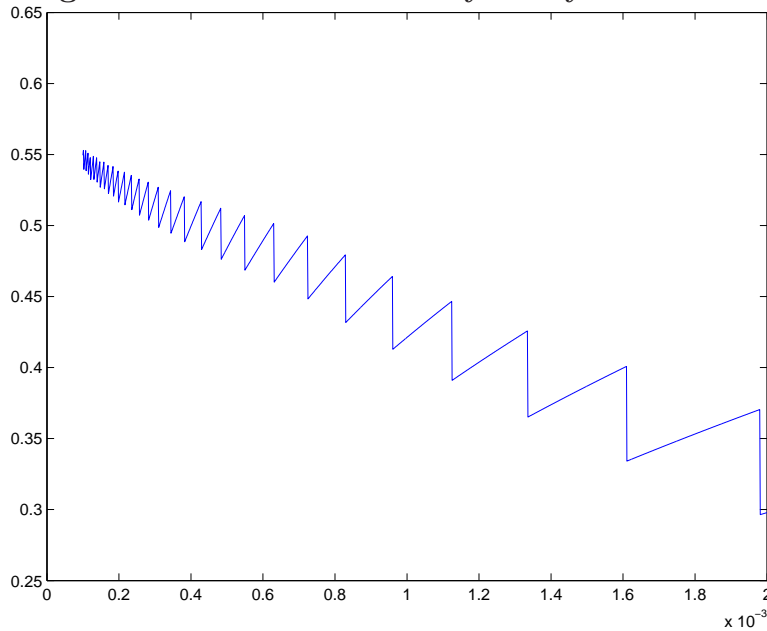
An increase in the number of contracts goes hand in hand with an expansion of credit to more (and riskier) people. This can be seen from Figure 7 where for a high fixed cost only 30% of the population is able to borrow, while for a low fixed cost, about 55% of the population has access to credit.¹⁷ The overall effect on borrowing and defaults is straightforward. Whenever χ decreases enough to increase N , total borrowing and defaults increase. In the model, this also implies that borrowing by lower income (riskier in model) households increases. As a result, defaults increase at a faster rate than debt and the share of risky debt held by lower income households increases.

A fall in χ also reduces the extent of cross-subsidization. The reason is that the lowest risk household in each contract interval “subsidizes” the highest risk households in that pool $\rho \in (\rho_n, \rho_{n-1}]$. The shrinking of each contract interval shrinks the amount of cross-subsidization and hence leads to more accurate risk-based pricing. This pattern can be seen by looking at the bond prices in the example. As χ declines and the number of contracts increases, the model generates both more disperse interest rates and higher average borrowing interest rate. The expansion of credit to higher risk borrowers is accompanied by an increase in the bond price offered to existing borrowers. This can be seen in Figure 8, which plots the average, largest and smallest risky interest rates as a function of χ .

Total overhead costs as a percentage of borrowing are shown in Figure 9. In the example, even though χ falls by a factor of 1:20, total overhead costs (as % of debt) fall only by a factor of 1:4. The reason that a fall in χ lowers overhead costs by

¹⁷Recall that the model also allow for a small loan which is repaid with certainty. These loans are not part of the picture.

Figure 7: Measure Served by Risky Contracts



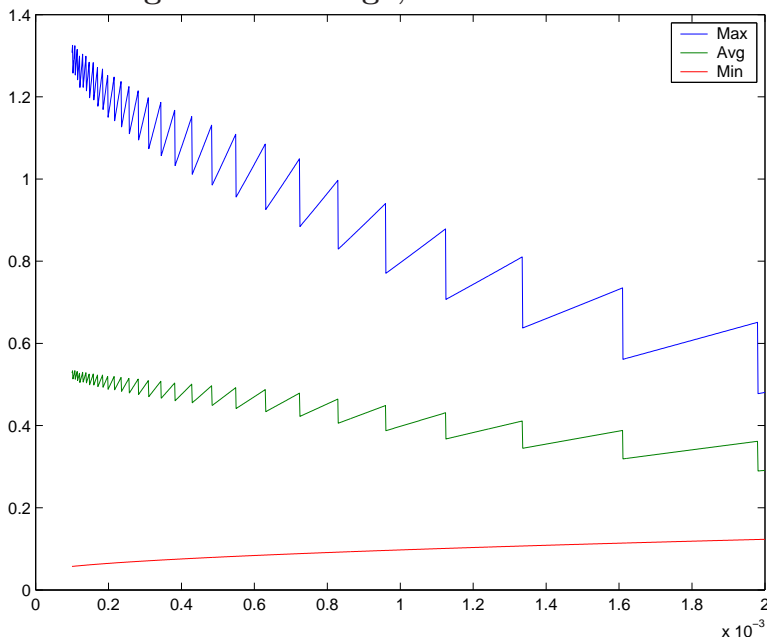
less than proportional is that even though fixed costs per contract are falling, fewer borrowers are now “sharing” a contract, so that each borrower has to pay a larger share of the overhead. This suggests that cost of operations of banks (or credit card issuers) might not be a good measure of technological progress in the banking sector.

4.3 Decline in Risk Free Rate – Increase in \bar{q}

In an influential paper, Ausubel (1991) documented that the decline in risk-free interest rates in the U.S. in the 1980s were not accompanied by a decline in the average credit card rates reported by the Board of Governors. This led some to claim that the credit card industry was characterized by imperfect competition. In contrast, others such as Evans and Schmalnsee (1999) argued that significant 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 credit card industry.

To explore the implications of our model for this debate, we consider the effect

Figure 8: Average, Max and Min r



of a decline in the risk free interest rate on the number of contracts and average borrowing interest rates. For simplicity, we focus our attention on the perfect signal case ($\alpha = 1$).

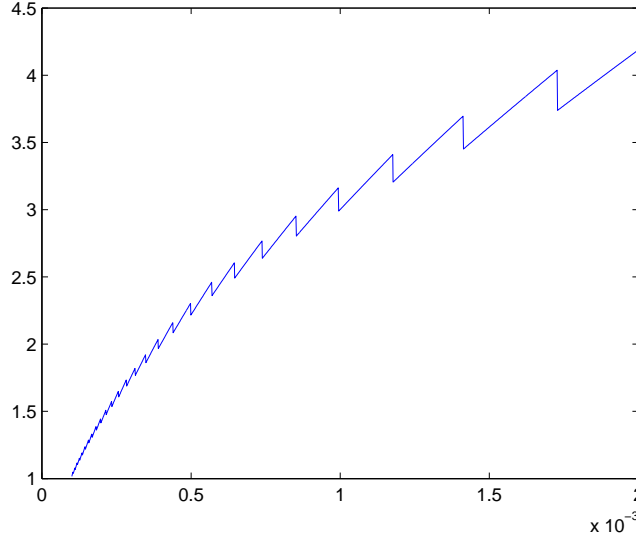
We begin by considering the effect of a rise in \bar{q} on the existing contracts. To see this, recall that from Theorem 3.8 that each of N risky contracts offered in equilibrium $(q_n, \gamma y_h)$ serves borrowers in the interval $\rho \in (\rho_n, \rho_{n-1}]$, where

$$\rho_n = 1 - n \sqrt{\frac{2\chi}{y_h \gamma \bar{q}}} \quad \text{and} \quad q_n = \bar{q} \rho_n$$

It follows directly that ρ_n is decreasing in \bar{q} and χ , so that an increase in the risk-free bond price reduces the length of each risky contract interval. In addition, the risky bond price is increased.

The main determinant of the average borrowing interest rate is the change in the total number of contracts. As with a change in the fixed cost χ , a sufficiently large rise in the risk free bond price generates an expansion of the number of risky contracts. This leads to an increase in the total measure of risky borrowers, and pulls

Figure 9: Overhead Costs as Percent of Borrowing

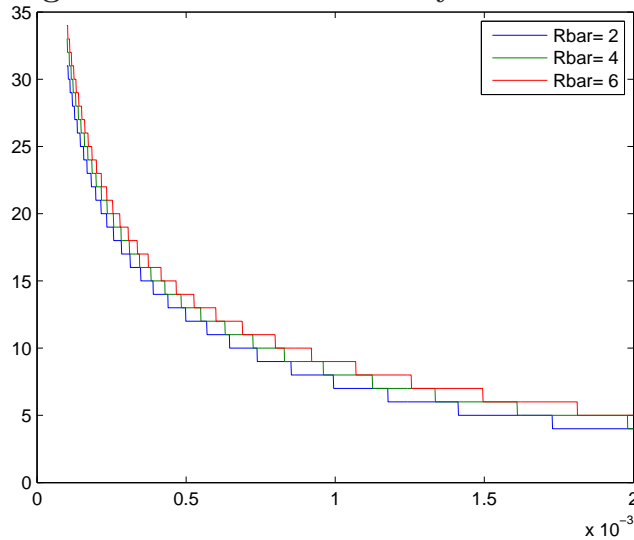


in borrowers who are riskier than existing borrowers. This generates a rise in defaults. As a result, average borrowing interest rates decline less than proportionally.

To illustrate this, we extend our numerical example and compare the equilibrium associated with three different risk free interest rates $\bar{r} = 2\%, 4\%, 6\%$ (and corresponding bond prices 0.943, 0.962, 0.980). Figure 11 plots the number of risky contracts for value of χ for each \bar{q} . The figure shows that the number of risky contracts is weakly increasing in the risk free bond price.

To illustrate the effect of variations in the risk-free rate on the average borrowing interest rate we plot the average risky bond prices for each value of χ . The figure shows that the effect of a shift in the risk free rate on the average borrowing rate depends upon the level of the fixed cost. When the cost of creating contracts is high and there are very few risky contracts offered, the average borrowing bond price tends to be positively related to the risk free rate. In contrast, for lower values of χ , lower risk free bond prices can have higher average borrowing interest rates. The reason is that the extensive margin effect of extending credit to riskier households can dominate the reduction in interest rates for existing borrowers.

Figure 10: Number of Risky Contracts

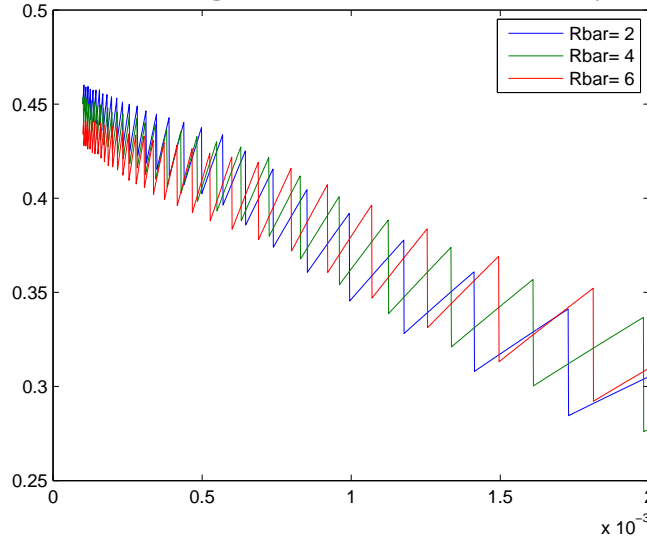


5 Unsecured Consumer Credit Facts

In this section, we document several changes in the distribution of the terms at which households access consumer credit. Surprisingly, although it is commonly asserted that the past 30 years have witnessed increased segmentation of the consumer credit market and increased expansion of credit to lower income households, relatively little work has been undertaken to document whether significant changes in the distribution of borrowing, consumer credit contracts and access to credit across households have occurred. In Section 6 we use these facts to help evaluate the predictions of the theoretical model presented in Section 4.

We focus our attention on the credit card market. Credit card borrowing currently accounts for the majority of unsecured borrowing in the United States and has increased dramatically over the past 30 years. Moreover, credit cards are a relatively recent innovation which have become widely used over the past thirty years. While the first bank credit cards were issued during the mid 1960s, by the early 1990s more than 6,000 US institutions issued general purpose credit cards (Canner and Luekett (1992)). Another reason to focus on credit cards is that the cost structure of credit

Figure 11: Average Interest Rate on Risky Bonds



card issuers differs substantially from that of other lenders.¹⁸ This suggests that information technology which lower the cost of originating loans may have a much larger impact on credit card operations than on other consumer lending.

We examine three dimensions of consumer credit: access (whether a consumer has a credit card), the interest rate and the credit limits offered to borrowers. While credit cards do vary along other dimensions, we abstract from these potential differences due to data limitations .¹⁹

Before examining shifts in the distribution across consumers, we report the trends in the mean level of credit card limits, borrowing and interest rates in Table 3.²⁰

¹⁸Canner and Luckett (1992) report that operating costs accounted for nearly 60 percent of the costs of credit card operations, but less than 20 percent of mortgage lending.

¹⁹The extent to which credit cards provide cash back on purchases, purchase insurance, insurance on car rental, etc, also appear to have varied over time. For example, in the late 1970s, annual fees became common, while during the late 1980s and early 1990s many cards removed or reduced annual fees and introduced benefits such as travel or car rental insurance (Canner and Luckett (1992)).

²⁰The SCF asks whether a household has a credit card, and the amount borrowed. The SCF also reports the interest rates for the primary card used to borrow on in 1983, and in 1995 and subsequent surveys. In addition, the SCF also contains data on the outstanding balance and (starting in 1989)

While credit cards became more widely held over the 1980s and 1990s, the fraction of people with cards who used their card to borrow funds only increased slightly. The average credit limit and outstanding balance, both in absolute levels and relative to income, increased over this time period. Much of the growth in access to credit card borrowing took place between 1983 and 1998. In contrast, the average (nominal) interest rate on credit card borrowing has declined significantly, with much of the decline taking place after 2001.

Table 3: Mean Values of Limits and Interest Rates Credit Cards, SCF

Variable	1983	1989	1995	1998	2001	2004
Have CC	43%	56%	66%	68%	73%	72%
CC Bal > 0	51%	52%	56%	55%	54%	56%
Credit Limit	NA	7,077	10,366	12,846	13,552	15,424
Credit Limit/Income	NA	0.19	0.34	0.41	0.37	0.41
Balance (all HH)	497	952	1,340	1,695	1,452	1,860
Balance (HH bal > 0)	971	1,828	2,393	3,096	2,706	3,312
Int Rate (all HH)	18.05%	NA	14.51%	14.46%	14.36%	11.49%
Int Rate (HH bal > 0)	18.08%	NA	14.14%	14.48%	14.20%	11.81%

Source: Survey of Consumer Finance. Values are in constant 2004 U.S. \$, deflated using the CPI.

The aggregate trends may mask significant shifts in the distribution of access to unsecured borrowing across households. To address this, we use the Survey of Consumer Finance to examine how the distribution across households has changed. We also draw upon data on interest rates offered by banks and credit card issuers collected by the Federal Reserve Board, as the distribution of interest rates across lenders also provide useful information about the distribution of terms of borrowing facing households. Based on these data sources, we document three key facts:

- Increased variety in credit contracts
- More risk-based pricing

on the credit limit on credit cards.

- Increased access and borrowing by lower income households

5.1 Increased Variety in Consumer Credit Contracts

The simplest measure of variety is the number of different products offered. The analog of a product in consumer credit markets is a credit contract, typically characterized by a loan size (or credit line) and an interest rate. The Survey of Consumer Finance asked questions about the interest rate paid on credit card accounts, which we use to count the number of *different* interest rates. The data reported in Table 4 shows a substantial increase in variety, with the number of different rates roughly tripling between 1983 and 2004.²¹

Table 4: Number of Different Credit Card Interest Rates, SCF

Year	All Households	Households with Positive Credit Card Debt
1983	78	47
1995	142	118
1998	136	115
2001	222	155
2004	211	145

Source: Survey of Consumer Finance.

A more nuanced view of variety comes from examining the variance of interest rates across households. Since we are comparing trends in dispersion of variables with different (and changing) means, we compute the coefficient of variation (CV).²² Table 5 reports the CV for the interest rate, credit limit, and actual balance for six

²¹It is worth emphasizing that this measure likely significantly understates the increased variety of credit card contracts, as both Furletti (2003) and Furletti and Ody (2006) argue that credit card providers have made increased use of features such as annual fees, different penalty fees for late payments and other features such as purchase insurance to provide differentiated products.

²²This is important for two reasons. First, variables such as credit limits should increase over time due to growth in real GDP. Second, the decline in nominal interest rates has shifted down mean borrowing interest rates, which will show up as a decline in the variance of interest rates.

different waves of the SCF. We find a substantial increase in the variability of credit card interest rates across households over time: the CV in interest rates almost triples during the 1983-2004 time period. On the other hand, there is little evidence of a trend in heterogeneity in credit limits and balances over time, although there has been an increase in the dispersion of credit limits relative to income and balances of households who borrow on their credit cards. However, in terms of levels, both credit limits and borrowing are more disperse than interest rates.

Table 5: Coefficient of Variation of Different Credit Card Interest Rates, SCF

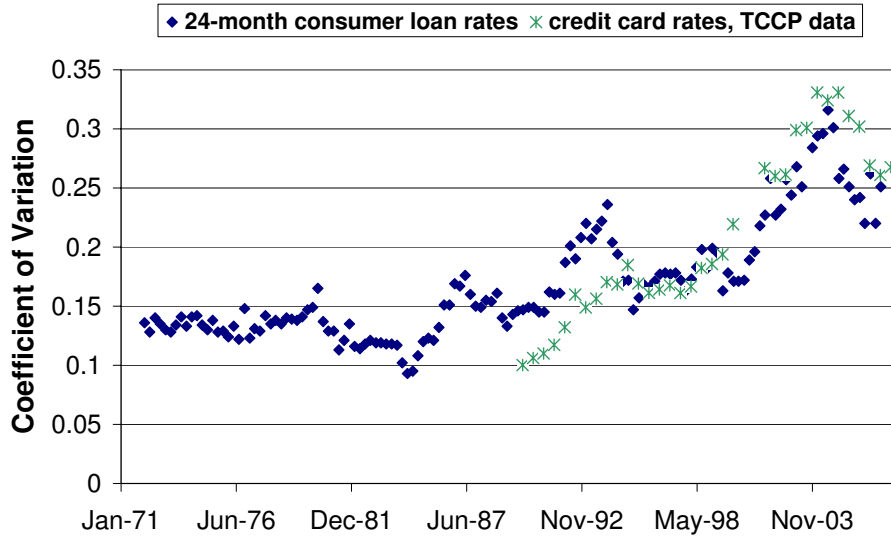
Variable	1983	1989	1995	1998	2001	2004
Credit Limit	NA	1.60	1.33	1.45	1.64	1.49
Credit Limit/Income	NA	1.27	1.60	1.85	1.53	1.82
Int Rate (all HH)	0.22	NA	0.30%	0.32%	0.37%	0.56%
Int Rate (HH bal > 0)	0.21	NA	0.32	0.35	0.40	0.56
Balance (all HH)	1.80	2.22	2.28	2.35	2.87	2.29
Balance (HH bal > 0)	1.08	1.45	1.58	1.60	1.99	1.59

Source: Survey of Consumer Finance. Standard deviations are weighted.

The increased dispersion of borrowing interest rates can also be seen using data collected by the Board of Governors directly from banks on interest rates on 24-month consumer loans from a bank survey as well data on credit card interest rates from a survey of credit card issuers starting in 1990.²³ We find a large increase in the dispersion of interest rates. As can be seen from Figure 12, 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 over time also occurs in credit cards. This finding is consistent with increased banks specialization in different segments of the market.

²³We use data from the Quarterly Report of Interest Rates on Selected Direct Consumer Installment Loans (LIRS) and the Terms of Credit Card Plans (TCCP). The data has to be interpreted with caution, since every bank is asked to report only *one* interest rate (the most commonly used one) and hence likely understates the number of loan options faced by consumers. See the Appendix for a more detailed discussion of these data.

Figure 12: CV Consumer Interest Rates

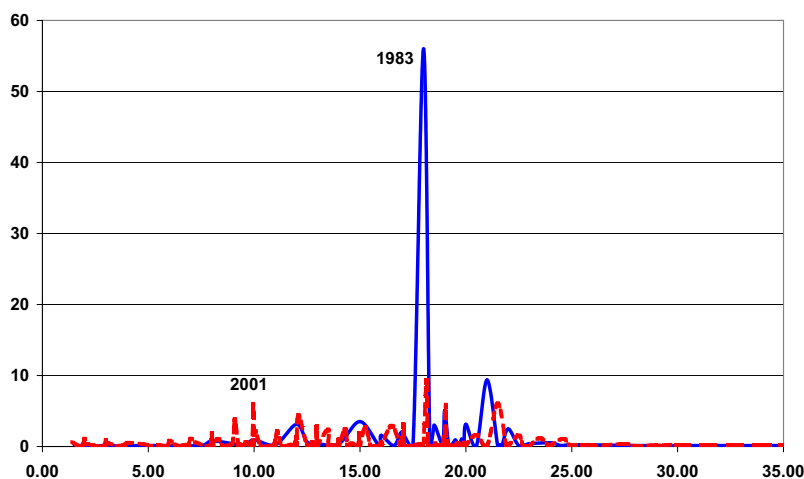


Even more details about shifts in the terms of borrowing across households over time can be gleaned from changes in the empirical distribution of interest rates across households. Figure 13 displays the fraction of households reporting different interest rates in the SCF (essentially, a normalized histogram) for two different years: 1983 and 2001. This figure clearly shows the increase in interest rate dispersion between these two cross-sections. It is striking that in 1983 more than 50% of households faced a rate of *exactly* 18%. The distribution in 2001 is strikingly “flatter” than the 1983 distribution (the comparison with other years is similar). A very similar figure also emerges for the distribution of interest rates offered by different banks (not reported here).

Another feature of the increased dispersion is that although the average (nominal) interest rate has declined over time, the maximum rate charged by banks has actually increased, as can be seen from Figure 14. This points towards an expansion of credit to riskier households.

To summarize, the evidence suggests three important changes in credit and interest heterogeneity during the last two decades of the 20th century:

Figure 13: Credit Card Interest Rate Distribution

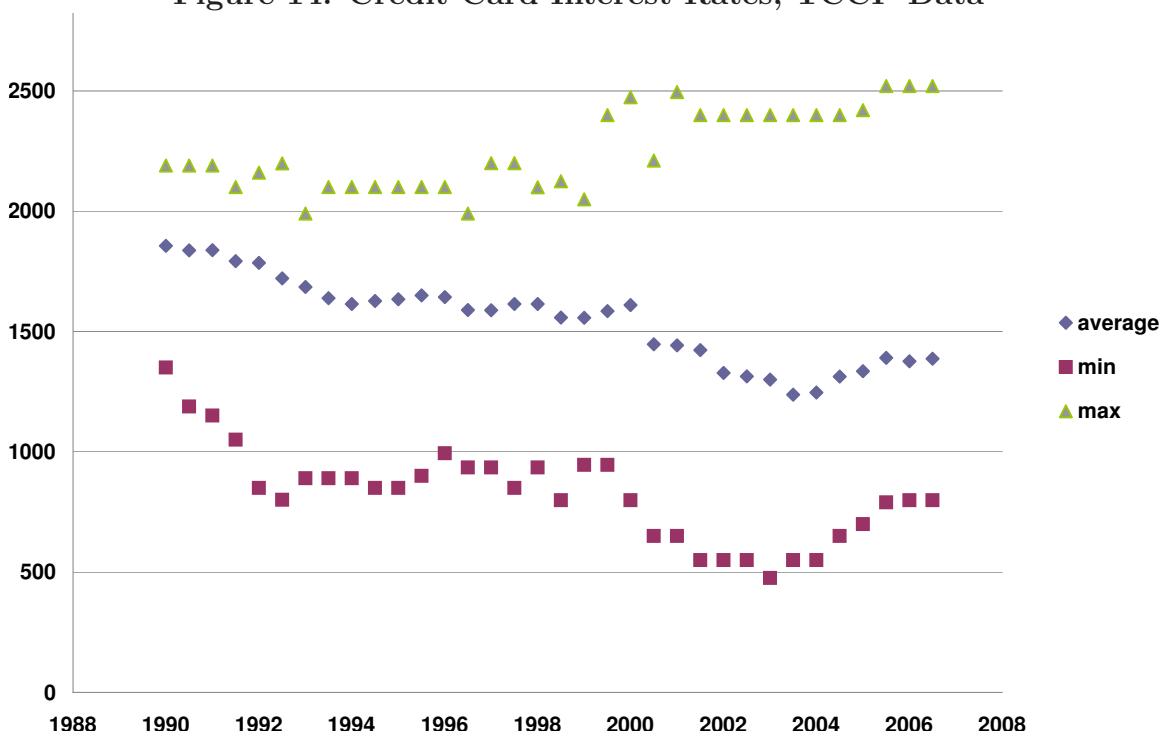


1. An increase in interest rate heterogeneity (both across banks and consumers):
 - (a) the number of different borrowing interest rates has gone up
 - (b) an increase in the dispersion of borrowing interest rates
2. A “flattening” of the distribution of borrowing interest rates (both across banks and consumers).
3. Increased spread between the minimum and maximum borrowing interest rates

5.2 Risk Based Pricing

One coarse way of seeing whether the dispersion of interest rates is related to increased risk based pricing is to compare the distribution of interest rates of delinquent and non-delinquents. The SCF asks households if they have been delinquent on a debt payment in the past year. Delinquency on debt is positively correlated with the probability of future default, so delinquent households should be riskier on average than non-delinquents. As can be seen from Figure 15 in 1983, the distributions for

Figure 14: Credit Card Interest Rates, TCCP Data

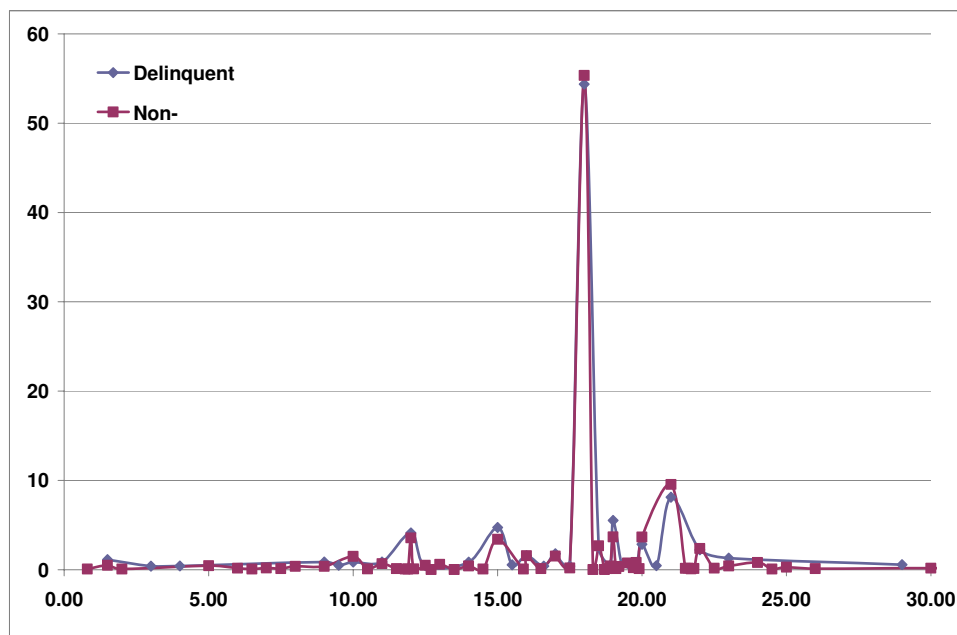


delinquents and non-delinquents was nearly identical. However, by 2001, the delinquent distribution has considerable mass to the right of the non-delinquent interest distribution. This supports the view that the increase in credit card contracts has led to more accurate pricing of borrowers default risk.

We are not the first to document an increase in risk-based pricing. 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 made increased use of risk based pricing. The timing of the change also 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 Luekett (1992)). The rise in risk-based pricing is also consistent with the entry and expansion of monoline lenders such as Capital One which target specific sub-groups of borrowers with credit card plans priced on their risk characteristics

(Mann (2006)).²⁴

Figure 15: Delinquency and Credit Card Interest Rates 1983



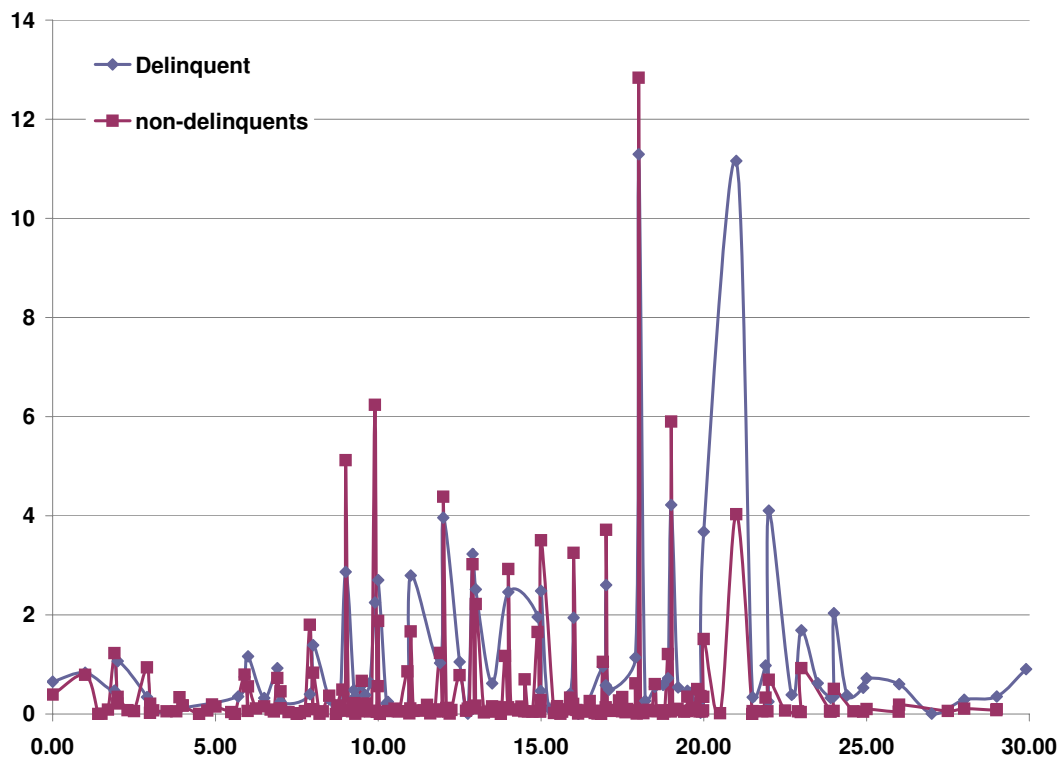
5.3 Increased Access/Borrowing on Credit Cards by Lower Income Households

Lower income and riskier households have increased access to credit cards. Table 6 reports the fraction of each income quintile who have a credit card and the fraction of those with a credit card who use them to borrow. The table shows the well known fact that credit card penetration increased most rapidly for lower income households during the 1980s and 1990s.

The increase in the number of lower income borrowers has been accompanied with a significant increase in their share of total credit card debt outstanding. Figure 17 graphs the cdf for the share of total credit card balances held by various percentiles

²⁴Furletti 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.

Figure 16: Delinquency and Credit Card Interest Rates 2001



of the earned income distribution. As can be seen from the graph, the fraction of credit debt held by lower income households has increased significantly over the past twenty years. For example, the fraction of debt held by the bottom 30% (50 %) of the earnings distribution nearly doubled from 6.1 % to 11.2% (16.8 % to 26.6%). Given that the value of total credit card debt also increased, this figure implies that lower income household access (and use) of credit card debt has increased significantly.

Figure 17 is consistent with the conclusions of numerous papers (for example, see Black and Morgan (1999), Kennickell, Starr-McCluer, and Surette (2000), Durkin (2000)) that the most rapid increase in credit card usage and debt has been among the poorest households. To the extent that lower income groups are riskier, this evidence suggests that borrowing by riskier households has increased over the 1983 - 2004 period.

Table 6: Percent HH with Bank Credit Card, U.S.

Income Quint	1983	1989	1995	1998	2001	2004
Lowest	11%	17%	28%	29%	38%	38%
Balance	40%	43%	57%	59%	60%	61%
2 nd Lowest	27%	36%	54%	58%	65%	61%
Balance	49%	46%	57%	58%	59%	60%
Middle	41%	62%	71%	72%	79%	77%
Balance	58%	56%	58%	58%	61%	64%
2 nd Highest	58%	64%	84%	86%	88%	87%
Balance	55%	60%	60%	60%	55%	57%
Highest	79%	82%	95%	95%	95%	96%
Balance	47%	46%	50%	45%	38%	44%

Source: Survey of Consumer Finance.

6 Model Predictions and the Data

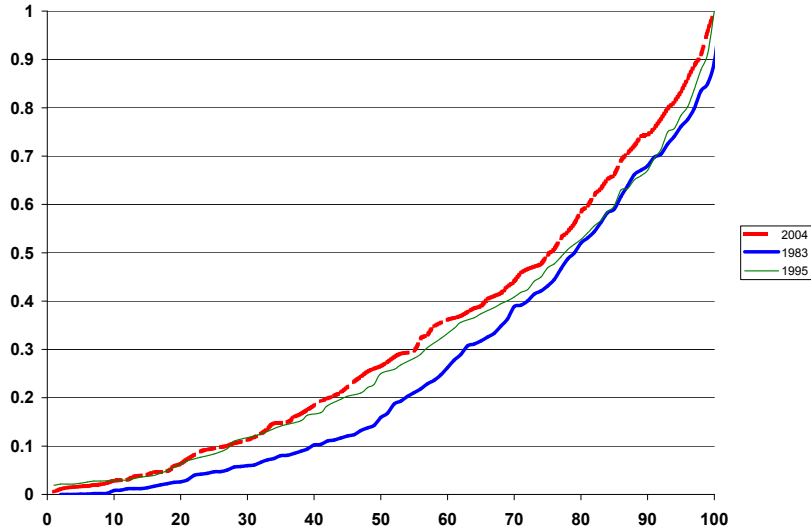
We now turn to the question of whether the qualitative predictions of improved technology are consistent with the observed changes in both aggregate borrowing and defaults as well as with the cross-sectional changes in consumers access to unsecured credit.

Table 7 summarizes the qualitative implications of the two main mechanisms via which improved information technology may have impacted credit markets explored in this paper: improved accuracy of lenders forecast of borrowers default risk and a reduction in the overhead costs of designing and marketing financial contracts.²⁵ The table also reports some key changes observed in the data.

We find that our simple model is qualitatively consistent with almost all of the empirical facts established in Section 5. This suggests that information technology driven innovations in consumer lending technology are likely an important factor behind the significant rise in unsecured borrowing and defaults over the past thirty years.

²⁵We focus here on changes in α and χ that are large enough to increase borrowing. As discussed in Section 4, for small changes, these implications are not always true.

Figure 17: CDF Credit Card Borrowing vs Earned Income



7 Conclusion

This paper examines whether improved information technology has played a key role in the rapid changes in unsecured credit markets over the past thirty years. To do so, we develop a simple incomplete markets model with bankruptcy to analyze the qualitative implications of two mechanisms for the set of credit contracts offered in equilibrium. We also assemble data on how the number of credit card contracts and the distribution of credit card borrowing has changed over time so as to evaluate the model predictions.

We find that improvements in information technology which facilitate improved accuracy of lenders forecasts of borrowers default risk or the overhead costs of creating

Table 7: Comparison Model vs. Data

	Δ in Model		Δ in Data
	$\alpha \uparrow$	$\chi \downarrow$	(over time)
Defaults/Population	\uparrow	\uparrow	\uparrow
Defaults/Borrowers	?	\uparrow	\uparrow
Debt/Income	\uparrow	\uparrow	\uparrow
Borrowers/Population	\uparrow	\uparrow	\uparrow
Debt/Borrower	—	—	\uparrow
# interest rates	\uparrow	\uparrow	\uparrow
max r	\uparrow	\uparrow	\uparrow
min r	\downarrow	\downarrow	\downarrow
CV (r)	\uparrow	\uparrow	\uparrow
debt share low income	\uparrow	\uparrow	\uparrow

and offering contracts have significant implications for the set of contracts offered in equilibrium. For sufficiently large changes, these channels imply that technological change leads to an increased variety of credit contracts, with each contract targeted to a smaller subsets of the population. This increase in the number of contracts leads to an expansion of credit to more households, and involves the extension of credit to riskier households. As a result, these technological innovations can lead to an increase in aggregate borrowing and defaults. We also find that the predictions of both these channels are qualitatively consistent with changes observed in the U.S. in both the aggregate and cross-sectional pattern of borrowing and defaults over the past twenty-five years.

This findings of this paper suggests that interpretations of events in the unsecured credit market using a “standard” competitive framework may be misleading. We find that the introduction of even a small fixed cost of creating a contract leads to significant deviations from the predictions of the standard competitive framework.

For example, the predicted relationship between the mean borrowing interest rate and the risk-free costs of funds changes dramatically with fixed costs of contracts, as the extensive margin of changes in the number of contracts leads to an ambiguous relationship between the cost of funds and average borrowing interest rates. This suggests that further explorations of the channels highlighted in our framework in a serious quantitative model could be a promising avenue for future research.

References

- ATHREYA, K. (2004): “Shame as it Ever Was: Stigma and Personal Bankruptcy,” *Federal Reserve Bank of Richmond Economic Quarterly*, 90(2), 1–19.
- (2005): “Equilibrium Models of Personal Bankruptcy: A Survey,” *Federal Reserve Bank of Richmond Economic Quarterly*, 91(2), 73–98.
- ATHREYA, K., X. S. TAM, AND E. R. YOUNG (2008): “A Quantitative Theory of Information and Unsecured Credit,” Unpublished Manuscript, Federal Reserve Bank of Richmond.
- AUSUBEL, L. (1991): “The Failure of Competition in the Credit Card Model,” *American Economic Review*, 81(4), 50–81.
- BARRON, J. M., AND M. STATEN (2003): “The Value of Comprehensive Credit Reports,” in *Credit Reporting Systems and the International Economy*, ed. by M. J. Miller, pp. 273–310. MIT Press.
- BERGER, A. (2003): “The Economic Effects of Technological Progress: Evidence from the Banking Industry,” *Journal of Money, Credit and Banking*, 35(2), 141–176.
- BLACK, S., AND D. MORGAN (1999): “Meet the New Borrowers,” *Federal Reserve Bank of New York Current Issues in Economics and Finance*, 5(3), 1–6.

- CANNER, G. B., AND C. A. LUCKETT (1992): “Developments in the Pricing of Credit Card Services,” *Federal Reserve Bulletin*, pp. 652–666.
- CHATTERJEE, S., D. CORBAE, M. NAKAJIMA, AND J.-V. RIOS-RULL (2005): “A Quantitative Theory of Unsecured Consumer Credit with Risk of Default,” *Federal Reserve Bank of Philadelphia Working Paper 05-18*.
- CHATTERJEE, S., D. CORBAE, AND J.-V. RIOS-RULL (2006): “A Finite-Life Private-Information Theory of Unsecured Debt,” *Journal of Economic Theory*, forthcoming.
- (2007): “A Theory of Credit Scoring and Competitive Pricing of Default Risk,” *University of Texas at Austin, mimeo*.
- DROZD, L., AND J. NOSAL (2008): “Competing for Customers: A Search Model of the Market for Unsecured Credit,” Unpublished Manuscript, University of Wisconsin.
- DURKIN, T. A. (2000): “Credit Cards: Use and Consumer Attitudes, 1970-2000,” *Federal Reserve Bulletin*, pp. 623–634.
- EDELBERG, W. (2006): “Risk-based pricing of interest rates for consumer loans,” *Journal of Monetary Economics*, 53(8), 2283–2298.
- ELLIS, D. (1998): “The Effect of Consumer Interest Rate Deregulation on Credit Card Volumes, Charge-Offs and the Personal Bankruptcy Rate,” *FDIC Bank Trends*, 98(5).
- ENGEN, J. (2001): “Blind Faith,” *Banking Strategies*.
- EVANS, D., AND R. SCHMALNSEE (1999): *Paying with Plastic: The Digital Revolution in Buying and Borrowing*. MIT Press, Cambridge, Massachusetts.
- FEDERAL RESERVE BOARD (2006): “Report to the Congress on Practices of the Consumer Credit Industry in Soliciting and Extending Credit and their Effects on

- Consumer Debt and Insolvency,” submitted to the Congress pursuant to section 1229 of the Bankruptcy Abuse Prevention and Consumer Protection Act of 2005, http://www.federalreserve.gov/Pubs/reports_other.htm.
- FRAME, W. S., AND L. J. WHITE (2004): “Empirical Studies of Financial Innovation: Lots of Talk, Little Action,” *Journal of Economic Literature*, pp. 116–144.
- FURLETTI, M. (2003): “Credit Card Pricing Developments and Their Disclosure,” *Federal Reserve Bank of Philadelphia – Discussion Paper Payment Cards Center*.
- FURLETTI, M., AND C. 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*.
- HELLWIG, M. (1987): “Some Recent Developments in the Theory of Competition in Markets with Adverse Selection,” *European Economic Review*, 31, 319–325.
- HUNT, R. A. (2002): “The Development and Regulation of Consumer Credit Reporting in America,” *Federal Reserve Bank of Philadelphia Working Paper No. 02-21*.
- JAFFEE, D., AND T. RUSSELL (1976): “Imperfect Information, Uncertainty and Credit Rationing,” *Quarterly Journal of Economics*, 90, 651–666.
- 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*, pp. 1–.
- LAWRENCE, D., AND A. SOLOMON (2002): *Managing a Consumer Lending Business*. Solomon Lawrence Partners, New York.
- LIVSHITS, I., J. MACGEE, AND M. TERTILT (2007a): “Accounting for the Rise in Consumer Bankruptcies,” *NBER WP 13363*.

- (2007b): “Consumer Bankruptcy: A Fresh Start,” *American Economic Review*, pp. 402–418.
- MANN, R. J. (2006): *Charging Ahead: The Growth and Regulation of Payment Card Markets*. Cambridge University Press.
- MESTER, L. (1997): “What’s the Point of Credit Scoring,” *Federal Reserve Bank of Philadelphia Business Review*, pp. 3–16.
- NARAJABAD, B. N. (2008): “Information Technology and the Rise of Household Bankruptcy,” *Unpublished Manuscript, Rice University*.
- RIESTRA, A. (2002): “Credit Bureau in Today’s Credit Markets,” *European Credit Research Institute Research Report No. 4*.
- ROTHSCHILD, 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, J. (2008): “The Role of Information in Consumer Debt and Bankruptcy,” *Unpublished Manuscript, Federal Reserve Bank of Richmond*.
- SIDDIQI, N. (2006): *Credit Risk Scorecards – Developing and Implementing Intelligent Credit Scoring*. John Wiley & Sons, Inc., Hoboken, New Jersey.
- WHITE, M. (2007): “Bankruptcy Reform and Credit Cards,” *NBER Working Paper No. 13265*.
- WILSON, C. (1977): “A Model of Insurance Markets with Incomplete Information,” *Journal of Economic Theory*, 16, 167–207.

A Data Appendix

The Survey of Consumer Finance asked questions on the credit card interest rate of respondents. The questions asked were for the card with the largest balance (1995 - 2004), while the 1983 survey asked for the best guess of the average annualized interest respondent would pay on the bank or store card he uses most often if the full amount was not paid. One issue that affects the number of different rates reported is that in the later years the SCF imputed values for respondents who did not report an interest rate. To count the number of different interest rates, we drop imputed values. The sample size for the various years does increase, but by much less than the reported number of different interest rates.

Year	HH Count	HHs with non-imputed LOC rate	HHs with non-imputed CC rate	HHs with positive CC balance
1983	4103	-	2196	768
1989	3143	263	-	-
1992	3906	282	-	-
1995	4299	251	2458	1072
1998	305	279	2386	1029
2001	4442	265	2523	1085
2004	4519	440	2458	1185

When computing the CDF of credit card debt held by percentiles of the earned income distribution, we define earned income to be the sum of Wages + Salaries + Professional Practice, Business, Limited Partnership, Farm + Unemployment or Worker's Compensation.

A.1 Board of Governor Interest Rate Data

We use data collected by the Board of Governors directly from banks on the interest rate for various financial contracts. The Board of Governors conducts a bank survey

asking banks for information on interest rates charged to consumers. In principle, interest rate information is available for general consumer loans (both 12 and 24 months), automobile loans, credit cards, and mobile home loans. However, not all interest rates are available over a long time series and in several instances the wording of the question on the bank questionnaire has changed over time which makes the data difficult to compare over time. The longest consistent time series that is available is the interest rate charged on 24-months consumer loans. The data is collected in a quarterly survey (in February, May, August and November) and is available from February 1972 until February 2007.²⁶ Precisely, the survey asks about the most common rate (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. These loans are typically used for consolidation of debts, medical attention, taxes, vacations, and general personal and family expenditures, including student loans currently being repaid. It excludes all home improvement loans, and all loans secured primarily by real estate.

The data has to be interpreted with caution since every bank is asked to report only *one* interest rate (the most commonly used one) and hence does not necessarily represent an accurate picture of all loan options faced by consumers. For example, taking the most extreme case, each bank could offer a large menu of interest rates and the menu itself could be expanding over time, yet, the most common rate could be identical across banks and unchanging over time.

A.2 Definition of Aggregate Measures

Here we briefly define the main aggregates we are interested in.

Given the number of risky contracts N and the length of the interval served by each risky contract, the fraction of the population eligible to borrow via risky contracts is

²⁶This information is collected on form FR 2835. The data is coded as item LIRS7808 by the Board.

$\frac{1-\rho_N}{1-a}$. Since some households with $\sigma < \rho$ may choose not to accept the risky contract they are offered, the fraction of the population with risky borrowing is:

$$\alpha \frac{1-\rho_N}{1-a} + \frac{(1-\alpha)}{1-a} \sum_{j=1}^N [(\sigma_{j-1} - \sigma_j) \frac{(\bar{\rho}_j - a)}{1-a}] \quad (\text{A.1})$$

Note that if the participation constraint of types with lower public signals than their true type never binds (so $\bar{\rho}_j = 1$ for all contracts j), this collapses to $\frac{1-\rho_N}{1-a}$.

Total Defaults equals the total number of households who borrowed using the risky contract and experienced low income (y_l) in the second period of life. Given the assumption that households are uniformly distributed over the interval, defaults are

$$\frac{\alpha}{1-a} \left(1 - \rho_N - \frac{1-\rho_N^2}{2} \right) + \frac{(1-\alpha)}{1-a} \sum_{j=1}^N [\sigma_{j-1} - \sigma_j] \frac{1}{1-a} \left(\bar{\rho}_j - a - \frac{(\bar{\rho}_j)^2 - a^2}{2} \right)$$

Total borrowing is the sum of risky and risk-free borrowing. We report this in terms of the present value of the amount borrowed at date 1, rather than the face value. Hence, *Total Risky Borrowing* in units of the period 1 good is given by²⁷

$$\sum_{j=1}^N \frac{(\sigma_{j-1} - \sigma_j)}{1-a} q_j L \left(\alpha + (1-\alpha) \left[\frac{(\bar{\rho}_j - a)}{1-a} \right] \right)$$

where $\sigma_0 = 1$. If the risk free contract is offered in equilibrium, then the *Total Risk-Free Borrowing* is

$$q_{rf} L_{rf} \left[\frac{1}{1-a} - \sum_{j=1}^N \frac{(\sigma_{j-1} - \sigma_j)}{1-a} \left(\alpha + (1-\alpha) \left[\frac{(\bar{\rho}_j - a)}{1-a} \right] \right) \right]$$

The total amount of borrowing is the sum of risky and risk-free borrowing.

We define the average *risk premium* using the default rate on a risky contract, expressed in terms of the face value of the debt in period 2. The number of defaults on contract j is

$$D_j = \alpha \frac{\sigma_{j-1} - \sigma_j}{1-a} \left(1 - \frac{\sigma_{j-1} + \sigma_j}{2} \right) + (1-\alpha) \frac{\sigma_{j-1} - \sigma_j}{1-a} \frac{1}{1-a} \left(\bar{\rho}_j - a - \frac{(\bar{\rho}_j)^2 - a^2}{2} \right)$$

²⁷This is the (present value of) the amount borrowed at date 1, rather than the face value of debt outstanding at $t = 2$.

The face value of defaults on contract j is the product of $\text{Defaults}_j L$. The fraction of the face value of debt not repaid is D_j .

In the model, bond prices (interest rates) are lower (higher) than the risk-free both due to defaults and due to overhead costs associated with creating and making loans. The *Average Overhead on Contract $_j$* is measured as a fraction of the amount borrowed:

$$\text{Average Overhead on Contract}_j = \frac{\chi}{\frac{(\sigma_{j-1} - \sigma_j)}{1-a} q_j L \left(\alpha + (1 - \alpha) \left[\frac{(\bar{p}_j - a)}{1-a} \right] \right)}$$

We use the term *average* overhead because different households may pay more or less than the average overhead. The reason is that the low default risks within a contract type effectively cross-subsidize higher default risks by paying a larger share of the overhead costs.

Finally, the *Total Overhead* cost of making risky loans is simply the number of contracts times the cost per contract ($N\chi$). If the risk-free contract is offered, total overhead costs is $(N + 1)\chi$.