Appendix: The Democratization of Credit and the Rise in Consumer Bankruptcies*

Igor Livshits
University of Western Ontario, BEROC

James MacGee
University of Western Ontario

Michèle Tertilt
University of Mannheim

June 26, 2015

Abstract

This appendix contains supplementary material for Livshits, MacGee, and Tertilt (2014). In particular, it provides further details on some of the data used, formally defines the aggregate credit variables, and provides further details on the verification of the equilibrium allocation.

*Corresponding Author: Jim MacGee, Department of Economics, University of Western Ontario, Social Science Centre, London, Ontario, N6A 5C2, fax: (519) 661 3666, e-mail: jmacgee@uwo.ca.

1 Introduction

This appendix is structured to be as consistent as possible Livshits, MacGee, and Tertilt (2014). Section 2 briefly outlines some additional background material related to the discussion in Section 2 of the paper. Section 3 provides detail regarding existence and uniqueness of the equilibrium we characterize.[1] Further details on the comparative statics results can be found in Section 4, while Section 5 provides additional details related to the empirical analysis based (primarily) on the Survey of Consumer Finances in Section 6 and 7 of Livshits, MacGee, and Tertilt (2014).

2 Credit Card Industry: Evolution and Driving Forces

The reference to the Federal Reserve Board (2007) on page 7 refers to: "Credit-scoring systems generally involve significant fixed costs to develop, but their 'operating' cost is extremely low – that is, it costs a lender little more to apply the system to a few million cases than it does to a few hundred." As another example of the fixed costs involved, Siddiqi (2006) discusses a company that outsourced scorecard development and purchased ten different cards at an average cost of $27,000 each. While FICO scores (introduced by Fair Isaac and Company) are the best known example of general purpose credit scores, Mays (2004) lists over 70 different generic credit scores.

An important input into credit scoring models is information on borrower repayment behaviour and debt portfolio. Credit bureaus play an important role by collecting borrower information which is widely used by lenders. U.S. credit bureaus report borrowers' payment history, debt and public judgments (Hunt 2006). More than two million credit reports are sold daily by U.S. credit bureaus (Riestra 2002).

In 1984, First Deposit Corporation (which later became Providian Financial Corporation) adopted a business model of developing analytic methods of targeting card offers to mispriced demographic groups (i.e., groups with relatively low default probabilities for that product). Initially developed by Andrew Kahr, their first credit card product targeted low-risk"revolvers" by dropping the annual fee, upped the interest rate to 22%, lowering the minimum monthly payment, and offering new customers a cash-advance

[1]The section numbering for Sections 3 and above differ from the paper by 1 since the Appendix lacks a counterpart to "Model Environment".

loan (at a high interest rate). Four years after opening, First Deposit had over 350,000 customers and $1 billion in credit card receivables (Nocera (1994), pp 315-324).

Capital One, currently one of the largest credit card issuers in the U.S., further extended this information-based strategy to design credit products for targeted submarkets (Clemons and Thatcher 1998). This business model was originally developed in 1988 by two consultants (Richard Fairbank and Nigel Morris) at a small regional Bank in Virginia (which was called Signet). Fairbank and Morris' business model was so successful that in 1994, Signet spun off Capital One as a separate monoline lender. Besides relying heavily on borrowers' payment history data to make credit decisions, Capital One pioneered the wide-scale use of two other innovations. First, Capital One ran numerous experiments which involved sending out offers for various products (i.e., credit cards with different terms) to consumers. Based on these experiments, specific credit products were designed for differentiated market segments. Clemons and Thatcher (2008) argue that these experiments helped Capital One identify relatively low risk customers who were being mispriced by existing credit card companies, which led to a decline in delinquency and charge-off rates during the 1992-1996 period. Second, Capital One adopted a policy of dynamically re-pricing customer accounts in response to changes in their profitability which required intensive ongoing analysis of customer data (Clemons and Thatcher 2008).

Our use of references to credit scoring in various publications to document the timing of the diffusion of new lending technologies reflects the lack of good data on the diffusion of credit scoring. This is a common challenge facing those interested in the diffusion of financial innovations: "A striking feature of this literature [...] is the *relative dearth of empirical studies* that [...] provide a quantitative analysis of financial innovation." Frame and White (2004).

Lastly, it is worth noting that the *Marquette* decision of the U.S. Supreme Court, by increasing the market size for each contract from statewide to nationwide, likely lowered the effective fixed costs of designing credit card contracts.[2]

[2] In a landmark decision in 1978 case of Marquette Nat. Bank of Minneapolis v. First of Omaha Service Corp, the U.S. Supreme Court ruled that a nationally chartered bank (from Nebraska) could make loans to customers in another state (Minnesota) charging interest rates in excess of that state's usury limit.

2.1 Notes on Figure 2

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

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

3 Existence

In this section we provide a more detailed discussion of the existence of the equilibrium we analyze. We do this first for the perfect information case ($\alpha = 1$) for which we can prove existence and uniqueness of the equilibrium characterized in the paper. For the asymmetric information case we do not have such a proof. In fact, there are parameters for which the equilibrium we have characterized does not exist. Instead, we describe a numerical procedure to verify whether the characterized equilibrium is indeed an equilibrium for given parameter values. We show that if it exists, then it is also unique.

3.1 Equilibrium with Symmetric Information: $\alpha = 1$

Here we provide a more detailed argument for uniqueness in Section 3.1.

Theorem 3.1. *The equilibrium described in Section 3.1 is the unique pure strategy equilibrium.*

Proof. The proof is inductive — we begin by establishing that the top contract is the same in all pure strategy equilibria. Taking this as given, we then come to the same conclusion regarding the next interval from the top.

Consider an arbitrary pure strategy equilibrium. Denote by (q_1^*, L_1^*) the equilibrium contract with the highest price among the risky contracts. First, observe that $L_1^* = \gamma y_h$, the loan size in the equilibrium we have characterized. If L_1^* were greater than γy_h, the loan would never be repaid, and thus would never be offered. If L_1^* were lower than γy_h, then a profitable deviation would be possible in equilibrium — a contract with the same price and eligibility set and a larger loan $L' > L_1^*$ would generate more profits than (q_1^*, L_1^*), which in turn had to generate at least χ in gross profits.

Second, $q_1^* = q_1$. If $q_1^* > q_1$, then the contract would generate gross profits less than the fixed cost of entry χ, so this cannot be part of a pure strategy equilibrium. To see this, note that (q_1, L_1) generates more profits from each customer, has a larger customer base than any such (q_1^*, L_1^*), and the gross profits from (q_1, L_1) exactly equal χ. On the other hand, if $q_1^* < q_1$, then a contract with $q' \in (q_1^*, q_1)$, $L' = \gamma y_h$, and eligibility set $[\underline{\sigma}_1', 1]$, where $\underline{\sigma}_1' \in [\frac{q'}{\bar{q}}, \underline{\sigma}_1]$, would attract (steal) all the customers with $\rho \in [\underline{\sigma}_1', 1]$ and generate more profits than (q_1, L_1). Hence, $q_1^* = q_1$.

Third, the eligibility set for (q_1^*, L_1^*) has to be $[\underline{\sigma}_1, 1]$ (plus/minus measure 0 set), since any other eligibility set would generate lower gross profits, thus falling short of recovering the fixed cost of entry, χ. Adding any type $\sigma^* < \underline{\sigma}_1 = \frac{q_1}{\bar{q}}$ would lower total profits, since the expected return on lending to such type is less than $\frac{1}{\bar{q}}$. Rejecting any type in $[\underline{\sigma}_1, 1]$ would mean foregoing positive profits (lowering the total profits).

Thus, the "top" contract in any pure strategy equilibrium is identical to contract 1 in the equilibrium characterized in Section 4.1 of Livshits, MacGee, and Tertilt (2014).

Taking the top contract as given (for interval $[\underline{\sigma}_1, 1]$), consider the second contract. Note that the argument above holds for arbitrary $b \in (0, 1]$. Thus, the same argument can be applied to establish the uniqueness of the second contract $(q_2, \gamma y_h, \underline{\sigma}_2)$ serving $[\underline{\sigma}_2, \underline{\sigma}_1)$, and so on. □

3.2 Equilibrium with Asymmetric Information: $\alpha < 1$

This subsection outlines conditions which verify that the allocation characterized in Section 4.2 of Livshits, MacGee, and Tertilt (2014) are equilibria. We also establish under which conditions the allocation characterized in the paper are in fact unique equilibria of the environment with asymmetric information.

The presence of adverse selection (introduced by mislabeled borrowers) raises well known issues with the existence and nature of competitive equilibrium. Our framework incorporates two key assumptions which help us overcome these issues. First, the model timing helps to rule out the usual "cream-skimming" deviations. Second, the presence of a fixed cost per contract helps rule out deviations targeted at individual borrower types. Intuitively, these features imply that introducing a small amount of "noise" does not dramatically alter the equilibria of the full information version.[3]

The key threat to our proposed equilibrium are "deviation contracts" that primarily target mislabeled customers who opt-out of risky equilibrium contracts in lieu of the risk-free contract. These deviation contracts are risky contracts with face value $L_d \in (\gamma y_l, \gamma y_h)$ and bond prices higher than the risky loan that its potential customers are eligible for. These contracts provide higher amounts than the risk-free contracts, but less than than the risky contract, while repaying smaller repayments than the risky contract.

For sufficiently small values of α, the pool of customers for these deviation contracts is too small to justify entry. It is worth emphasizing the key role played here by the assumption that the fixed cost χ is strictly positive. For example, if $(1-\alpha)\gamma y_h(\bar{q}-\beta) < 2\chi$, the total number of mislabeled (downwards) customers is insufficient to support a contract targeted solely at mislabelled borrowers alone, and the pooling contract considered in the paper is the unique equilibrium.[4]

As the precisions of the signal (α) and/or the fixed cost of offering a contract (χ) get smaller, the pool of mislabeled customers opting out of our standard risky contracts becomes large enough to potentially justify an entry of a smaller risky contract (with a lower interest rate). Importantly, such a deviating contract may attract borrowers from

[3]If incumbents were not allowed to exit the market in response to entry of new contracts, there would have been no risky loan contract with complete pooling across private types in equilibrium, even when "noise" is very small (α very close to 1), and even in the presence of the fixed cost χ.

[4]This sufficient condition is very loose and could be tightened somewhat even analytically, but we are ultimately interested in applying the analysis to economies (parameter values) for which the equilibrium has to be verified numerically.

multiple intervals of public types. This necessitates numerical analysis, and we lay out the algorithm in the following subsection.

Lemma 3.2. *If* $(\bar{q}-\beta)(y_h-y_l) > \left(\alpha\theta + \frac{1-\alpha}{2}\right)\bar{q}y_h$*, then all equilibria have the top risky contract* $(q_1, L, \underline{\sigma}_1) = \left(\bar{q}\left(\alpha(1-\theta)+(1-\alpha)\frac{1}{2}\right), \gamma y_h, 1-\theta\right)$*, where* $\theta = \sqrt{\frac{2\chi(1-\underline{a})}{\alpha\gamma y_h \bar{q}}}$.

Proof. The condition in the statement of the lemma ensures that the top customer prefers the risky contract to the risk-free one, and thus, that the risky contract $(q_1, L, \underline{\sigma}_1)$ is offered in equilibrium. The proof of theorem 3.1 applies to establish that all pooling (within observable types) equilibria have the same top contract. What remains to be shown is that this equilibrium (contract) is robust to "cream-skimming" deviation — entry of a contract attempting to attract customers with high private type ρ by offering a better price $q' > q_1$ (combined with a smaller loan size $L' < \gamma y_h$ in order to attract only the "right" customers).

There are two scenarios to consider. First, the disruption to the existing contract may be small enough that the incumbent lender chooses not to exit the market. This happens when incumbent's profit loss is smaller than χ. However, profits of the entrant from each switching customer are smaller than those of the incumbent (since both the price q' is higher and loan size L' is smaller). Thus the profits of the entrant are necessarily smaller than the losses of the incumbent, and thus smaller than the entry cost; making the deviation unprofitable. In the second scenario, the profit loss to incumbent from losing the best customers is larger than χ, and the incumbent lender exits the market. In this case, the entrant inherits *all* of the incumbent's customers. Since the incumbent was generating exactly χ in profits, the entrant has to be earning less than that; again making the deviation unprofitable. □

The same logic applies to every risky contract accepted by all eligible customers (that is, with $\hat{\rho} = 1$). Note that this argument provides not only verification of the equilibrium, but also insight into the uniqueness of the equilibrium — any equilibrium has to feature the exact same contract(s) serving the top public types.

When it comes to contracts with $\hat{\rho}_n < 1$, we have to consider deviations in the form of smaller risky contracts targeting misclassified individuals opting out of the incumbent contracts $(q_n, \gamma y_h, \underline{\sigma}_n)$. Such deviating contract would feature a smaller loan size $L' < \gamma y_h$ and a better interest rate $q' > q_n$ than the incumbent contract.

The most profitable of such potential deviations makes the best customer indifferent between (q', L') and the risk-free contract.[5] Without loss of generality, $u_1(q', L') = u_1(\overline{q}, \gamma y_l)$, which implies

$$L' = \frac{\bar{q} - \beta}{q' - \beta}\gamma y_l. \quad (3.1)$$

Equation (3.1) establishes a simple relation between q' and L'. The search for the most profitable deviation then amounts to searching over all possible q'. A single smaller risky loan may attract borrowers from a number of signal bins, and we thus have to calculate (and sum over) the profits generated from each of the equilibrium bins $[\underline{\sigma}_n, \underline{\sigma}_{n-1})$, for $n = 2, \dots, N$. It is important to note that any contract that attracts misclassified borrowers necessarily disrupts the existing contract (into which these borrowers were misclassified). To see this, consider a contract (q', L') with $L' < \gamma y_h$ and $q' > q_n$, which attracts borrowers with $\rho' > \hat{\rho}_n$. Since ρ' prefers this contract to the risk-free contract, so will every borrower with $\rho < \rho'$, including $\hat{\rho}_n$. Since $\hat{\rho}_n$ is indifferent between the risk-free contract and $(q_n, \gamma y_h)$, they strictly prefer (q', L') to the existing contract $(q_n, \gamma y_h)$.

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

3.3 Algorithm

The algorithm we use to verify numerically that the "pooling" equilibrium that we analyze is in fact an equilibrium is sketched below.

1. Search over q'. For each q', equation (3.1) implies the corresponding L'.

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

2. Go through the existing bins starting with $n = 2$, until including customers from bin n is unprofitable. There are two cases to consider:

   (a) Consider the first scenario: Assuming the incumbent contract is offered, find $\hat{\rho}'_n$ indifferent between $(q_n, \gamma y_h)$ and (q', L'):

$$q_n \gamma y_h + \beta(1-\gamma)\left(\hat{\rho}'_n y_h + (1-\hat{\rho}'_n) y_l\right) = q' L' + \beta\left(\hat{\rho}'_n (y_h - L') + (1-\hat{\rho}'_n) y_l (1-\gamma)\right)$$

   That is,

$$\hat{\rho}'_n \quad = \quad \frac{q_n \gamma y_h - q' L'}{\beta(\gamma y_h - L')} \quad = \quad \frac{q_n (q' - \beta) y_h - q'(\bar{q} - \beta) y_l}{\beta(q' - \beta) y_h - \beta(\bar{q} - \beta) y_l}. \tag{3.2}$$

   - If $\hat{\rho}'_n < \underline{\sigma}_{n-1}$, then dealing with the bin $[\underline{\sigma}_n, \underline{\sigma}_{n-1})$ is unprofitable for the entrant (as the deviation would not just peel off mislabelled borrowers, but also correctly classified ones, thus destroying the incumbent contract). End loop.
   - Calculate the losses to the incumbent (serving customers with $\sigma \in [\underline{\sigma}_n, \underline{\sigma}_{n-1})$) from losing customers with $\rho \in [\hat{\rho}'_n, \hat{\rho}_n]$:

$$\Delta\pi = (1-\alpha)(\underline{\sigma}_{n-1} - \underline{\sigma}_n)\gamma y_h \int_{\hat{\rho}'_n}^{\hat{\rho}_n} (\bar{q}\rho - q_n) \frac{d\rho}{1-\underline{a}} = (1-\alpha)\theta\gamma y_h \frac{\hat{\rho}_n - \hat{\rho}'_n}{1-\underline{a}} \left(\bar{q}\frac{\hat{\rho}_n + \hat{\rho}'_n}{2} - q_n\right),$$

     where $\theta = \sqrt{\frac{2\chi(1-\underline{a})}{\alpha\gamma y_h \bar{q}}}$ is the size of the interval of public types served by a single risky contract.
   - If $\Delta\pi \leq \chi$, then calculate the entrant's profits:

$$\pi'_n = (1-\alpha)\theta L' \int_{\hat{\rho}'_n}^{1} (\bar{q}\rho - q') \frac{d\rho}{1-\underline{a}} = (1-\alpha)\theta L' \frac{1-\hat{\rho}'_n}{1-\underline{a}} \left(\bar{q}\frac{1+\hat{\rho}'_n}{2} - q'\right).$$

     Incorporating equations (3.1) and (3.2), the expression becomes

$$\pi'_n = \frac{1-\alpha}{1-\underline{a}}\theta\gamma y_l \frac{\bar{q}-\beta}{2}((\bar{q}-\beta)y_l - (q_n - \beta)y_h) \frac{(q'-\beta)y_h\left(\bar{q}(q_n+\beta) - 2\beta q'\right) - (\bar{q}-\beta)y_l\left(\bar{q}(q'+\beta) - 2\beta q'\right)}{\left(\beta(q'-\beta)y_h - \beta(\bar{q}-\beta)y_l\right)^2} \tag{3.3}$$

     - If $\pi'_n < 0$, then dealing with the bin $[\underline{\sigma}_n, \underline{\sigma}_{n-1})$ is unprofitable for the entrant. End loop.
     - Otherwise, move on to the next interval.
   - If $\Delta\pi > \chi$, then we need to consider the second scenario, as the incumbent will exit the market in response to entry.

(b) If necessary, consider the second scenario: The entrant offers $(q'_n, \gamma y_h)$ to customers with $\sigma \in [\underline{\sigma}_n, \underline{\sigma}_{n-1})$. We now have to solve for q'_n and the new marginal true type $\hat{\rho}''_n$ indifferent between $(q'_n, \gamma y_h)$ and (q', L'):

$$q'_n \gamma y_h + \beta(1-\gamma)\left(\hat{\rho}''_n y_h + (1-\hat{\rho}''_n) y_l\right) = q' L' + \beta\left(\hat{\rho}''_n (y_h - L') + (1-\hat{\rho}''_n) y_l (1-\gamma)\right)$$

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

- If $\hat{\rho}''_n < \underline{\sigma}_{n-1}$, then dealing with the bin $[\underline{\sigma}_n, \underline{\sigma}_{n-1})$ is unprofitable for the entrant. End loop.
- Otherwise, calculate the entrant's profits, which consist of both π'_n from equation (3.3) (with $\hat{\rho}''_n$ instead of $\hat{\rho}'_n$) and the net profit from offering $(q'_n, \gamma y_h)$ and paying additional fixed cost χ (which turns out to be exactly 0 due to the mechanism outlined in the proof of Lemma 3.6 in the text).
  - If this "marginal" profit is negative, then dealing with the bin $[\underline{\sigma}_n, \underline{\sigma}_{n-1})$ is unprofitable for the entrant. End loop.
  - Otherwise, move on to the next interval.

3. Sum up the profits from all the bins and compare to χ. If total operating profits are less than χ, then the deviation will not take place in equilibrium.

4 Comparative Statics

In this section, we provide the formal analysis underlying the comparative statics results in Section 5 of the paper. The key comparative statics are responses of total debt and the bankruptcy rate to changes in the model parameters. We present the analytical expressions for these aggregates for the general model where $\rho \in [\underline{a}, 1]$ (in parts of the paper we present the simplified case where $\underline{a} = 0$) in subsection 4.1. The following subsections present specific comparative statics results.

4.1 Analytical Expressions for the Aggregates

Given N risky contracts, the measure eligible for risky contracts is $\frac{1-\underline{\sigma}_N}{1-\underline{a}}$. Since some households with $\rho > \sigma$ may not accept the risky contract they are offered, the measure that accepts risky loans is:

$$\text{Borrowers} = \alpha\frac{1-\underline{\sigma}_N}{1-\underline{a}} + \frac{1-\alpha}{1-\underline{a}}\sum_{j=1}^{N}(\underline{\sigma}_{j-1}-\underline{\sigma}_j)\frac{\hat{\rho}_j-\underline{a}}{1-\underline{a}},$$

where the first term captures correctly labelled borrowers (with $\sigma = \rho$) and the second term keeps track of the mislabelled borrowers who choose to accept the contract (with $(1-\alpha)\frac{\underline{\sigma}_{j-1}-\underline{\sigma}_j}{1-\underline{a}}$ being the measure of the mislabelled individuals and $\frac{\hat{\rho}_j-\underline{a}}{1-\underline{a}}$ being the fraction choosing to participate). Using the results from Section 4 in the paper, we can rewrite this as

$$\text{Borrowers} = \alpha\frac{N\theta}{1-\underline{a}} + \frac{(1-\alpha)\theta}{1-\underline{a}}\sum_{j=1}^{N}\frac{\hat{\rho}_j-\underline{a}}{1-\underline{a}},$$

where θ is the size of the interval of public types served by an individual risky contract (see equation (4.7)). Note that if the participation constraint of types with lower public signals than their true type never binds (so $\hat{\rho}_j = 1$ for all j), this collapses to $\frac{1-\underline{\sigma}_N}{1-\underline{a}} = \frac{N\theta}{1-\underline{a}}$.

Total Defaults equals the number of households who borrowed using the risky contract and experienced low income (y_l) in the second period of life:

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

Total Risky Borrowing in units of the period 1 good is given by[6]

$$\text{Debt} = \sum_{j=1}^{N}\frac{\underline{\sigma}_{j-1}-\underline{\sigma}_j}{1-\underline{a}}q_jL\left(\alpha+(1-\alpha)\frac{\hat{\rho}_j-\underline{a}}{1-\underline{a}}\right) = \theta\gamma y_h\sum_{j=1}^{N}\frac{q_j}{1-\underline{a}}\left(\alpha+(1-\alpha)\frac{\hat{\rho}_j-\underline{a}}{1-\underline{a}}\right).$$

These expressions can be further simplified for the symmetric information version of the model.

4.1.1 Symmetric Information Environment

Key formulae that will be used to establish the comparative statics results are:

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

- The size of the interval covered by an individual contract is

$$\theta = \sqrt{\frac{2\chi(1-\underline{a})}{\gamma y_h \overline{q}}} \tag{4.1}$$

- Pricing of the contracts:

$$q_n = \overline{q}\underline{\sigma}_n \tag{4.2}$$

- Upper bound of the measure of types served by risky contracts:

$$U = \frac{(y_h - y_l)[\bar{q} - \beta(1 + \sqrt{\frac{2\chi(1-\underline{a})}{\gamma y_h \bar{q}}})]}{\bar{q} y_h - \beta(y_h - y_l)} \tag{4.3}$$

- Lower bound of the measure of types served by risky contracts:

$$L = U - \theta = \frac{(y_h - y_l)(\bar{q} - \beta) - \bar{q} y_h \sqrt{\frac{2\chi(1-\underline{a})}{\gamma y_h \bar{q}}}}{\bar{q} y_h - \beta(y_h - y_l)} \tag{4.4}$$

- Default rate in the economy:

$$\text{BankruptcyRate} = \frac{1-\underline{\sigma}_N}{2}\frac{1-\underline{\sigma}_N}{1-\underline{a}} = \frac{(1-\underline{\sigma}_N)^2}{2(1-\underline{a})} \tag{4.5}$$

- Total debt in the economy:

$$\text{Debt} = \frac{1-\underline{\sigma}_N}{1-\underline{a}}\gamma y_h \frac{q_1 + \bar{q}\underline{\sigma}_N}{2} \tag{4.6}$$

4.1.2 Asymmetric Information Environment

Key formulae in the asymmetric information setting are:

- The size of the interval (of public signals) covered by an individual contract is

$$\theta = \sqrt{\frac{2\chi(1-\underline{a})}{\alpha\gamma y_h \overline{q}}} \tag{4.7}$$

- Pricing of the contracts is pinned down by

$$\bar{q}\left(\alpha\underline{\sigma}_n + (1-\alpha)\frac{\hat{\rho}_n^2 - \underline{a}^2}{2(1-\underline{a})}\right) = q_n\left(\alpha + (1-\alpha)\frac{\hat{\rho}_n - \underline{a}}{1-\underline{a}}\right), \tag{4.8}$$

where $\hat{\rho}_n$ satisfies

$$\hat{\rho}_n = \frac{q_n y_h - \overline{q} y_l}{\beta(y_h - y_l)}. \tag{4.9}$$

- The condition that pins down the last contract offered is simply

$$\hat{\rho}_N = \underline{\sigma}_{N-1}, \tag{4.10}$$

or to be more precise, the largest n such that $\hat{\rho}_n \geqslant \underline{\sigma}_{n-1}$.

4.2 Fixed costs in the Model with Symmetric Info

Claim 4.1. *Precision of risk-based pricing (which is simply the inverse of the size of the interval of types served by a single risky contract) is decreasing in χ.*

Proof. This follows directly from equation (4.1). □

Claim 4.2. *A sufficiently large fall in the fixed cost χ of offering a contract leads to an increase in the number of contracts in equilibrium.*

Proof. Equation (4.1) implies that, if χ falls by a factor of 4, the number of contracts increases by a factor of 2 or more, as it now takes twice as many contracts to cover the same set of customers, and since the set of customers served will not shrink, as will be established in Claim 4.4.

One condition on proportional decrease in χ sufficient to guarantee an increase in the number of equilibrium contracts is that it shrinks by a factor $\left(\frac{N}{N+1}\right)^2$. That guarantees that θ shrinks by a factor $\frac{N}{N+1}$, thus making room for an additional contract. □

Corollary 4.3. *The proportional change in aggregate overhead cost is smaller than the underlying proportional change in χ.*

Claim 4.4. *Both the Upper and the Lower bounds on the measure of the borrowers served by risky contracts are decreasing in χ.*

Proof. This follows directly from the equations (4.3) and (4.4), as the coefficient in front of χ is negative. □

Corollary 4.5. *Both the Upper and the Lower bounds on*

- *the risk type of the riskiest borrower served by a risky contract*
- *the overall bankruptcy rate*

are decreasing in χ.

Claim 4.6. *Dispersion of interest rates is decreasing in χ. More specifically, the lowest interest rate is increasing in chi, while both the upper and the lower bounds on the highest interest rate are decreasing in χ.*

Proof. The first claim follows directly from equations (4.1) (which establishes that θ is increasing in χ) and (4.2) (which establishes that the lowest interest rate is decreasing in θ). The second claim follows from Corollary 4.5 and equation (4.2). □

Claim 4.7. *The upper bound of the average price of risky bonds (approximately corresponding to the inverse of the average interest rate) is increasing in χ.*

Proof. The average price of risky bonds in this economy can be expressed simply as

$$\frac{q_1 + q_N}{2} = \frac{\sigma_1 + \underline{\sigma}_N}{2}\overline{q}.$$

The upper bound of the lowest bond price q_N can thus be derived by plugging in the upper bound of $\underline{\sigma}_N$, which is simply $(1 - L)$, where L is defined by equation (4.4). Thus, the upper bound of the average price of risky bonds is

$$\frac{1 - \theta + 1 - L}{2}\overline{q} = \overline{q}\left(1 - \frac{L + \theta}{2}\right) = \overline{q}\left(1 - \frac{U}{2}\right)$$

The claim then follows from the fact that U is decreasing in χ. □

Note: The result in claim 4.7 does not extend to the lower bound of the average price of risky of bonds. The sign of the derivative of the average risky price with respect to χ is the same as the sign of $(2\beta(y_h - y_l) - \overline{q}y_h)$. To see that, simply plug U instead of L into the above equation and rearrange to get

$$\frac{1-\theta+1-U}{2}\overline{q} = \frac{\overline{q}}{2}\left(1-\theta+\frac{\overline{q}y_l+\beta(y_h-y_l)\theta}{\overline{q}y_h-\beta(y_h-y_l)}\right).$$

The coefficient in front of θ, which is the only term containing χ, is then $\frac{\overline{q}(2\beta(y_h-y_l)-\overline{q}y_h)}{2(\overline{q}y_h-\beta(y_h-y_l))}$.

4.3 Risk-free Rate in the Model with Symmetric Info

Claim 4.8. *Precision of risk-based pricing (which is simply the inverse of the size of the interval of types served by a single risky contract) is increasing in* $\overline{q}$.

Proof. This follows directly from equation (4.1). □

Claim 4.9. *A sufficiently large increase in* $\overline{q}$ *leads to an increase in the number of contracts in equilibrium.*

Proof. Equation (4.1) implies that, if $\overline{q}$ increases by a factor of 4, the number of contracts increases by a factor of 2 or more, as it now takes twice as many contracts to cover the same set of customers, and since the set of customers served will not shrink, as will be established in Claim 4.10.

One condition on proportional increase in $\overline{q}$ sufficient to guarantee an increase in the number of equilibrium contracts is that it grows by a factor $\left(\frac{N}{N+1}\right)^2$. That guarantees that θ shrinks by a factor $\frac{N}{N+1}$, thus making room for an additional contract. □

Claim 4.10. *Both the Upper and the Lower bounds on the measure of the borrowers served by risky contracts are increasing in* $\overline{q}$.

Proof. Begin by rewriting the expression (4.3) for the upper bound as

$$U = 1 - \frac{\bar{q}y_l + \beta(y_h - y_l)\sqrt{\frac{2\chi(1-\underline{a})}{\gamma y_h \bar{q}}}}{\bar{q}y_h - \beta(y_h - y_l)}. \tag{4.11}$$

Differentiating with respect to $\overline{q}$ yields

$$\frac{\partial U}{\partial \overline{q}} = -\frac{\left(y_l - \frac{\beta(y_h-y_l)}{\bar{q}}\sqrt{\frac{\chi(1-\underline{a})}{2\gamma y_h \bar{q}}}\right)(\bar{q}y_h - \beta(y_h-y_l)) - \left(\bar{q}y_l + \beta(y_h-y_l)\sqrt{\frac{2\chi(1-\underline{a})}{\gamma y_h \bar{q}}}\right)y_h}{(\bar{q}y_h - \beta(y_h-y_l))^2},$$

which reduces to

$$\frac{\partial U}{\partial \bar{q}} = \frac{\beta(y_h - y_l)}{(\bar{q}y_h - \beta(y_h - y_l))^2}\left[\frac{3}{2}y_h\sqrt{\frac{\chi(1-\underline{a})}{2\gamma y_h \bar{q}}} - \frac{\beta}{\bar{q}}(y_h - y_l)\sqrt{\frac{\chi(1-\underline{a})}{2\gamma y_h \bar{q}}} + y_l\right].$$

Since $\frac{\beta}{\bar{q}} < 1 < \frac{3}{2}$, we get the first result that $\frac{\partial U}{\partial \bar{q}} > 0$.

Since $L = U - \theta$, and since θ is decreasing in $\overline{q}$, the lower bound is also increasing in $\overline{q}$. □

Corollary 4.11. *Both the Upper and the Lower bounds on*

- *the risk type of the riskiest borrower served by a risky contract*
- *the overall bankruptcy rate*

are increasing in $\overline{q}$.

4.4 Signal Precision in the Model with Asymmetric Info

Claim 4.12. *Precision of risk-based pricing is increasing in the precision α of the public signal.*

Proof. First, the size of the interval of observable types served by a single risky contract in decreasing in α, as can be seen from equation (4.7). Second, there are fewer misclassified individuals (purely mechanically). The only qualifier is that there may be fewer "opt-outs," which would work against one of the definitions of the precision of the pricing. □

A key observation regarding these comparative statics:

Lemma 4.13. *Consider contracts $(q_A, [\underline{\sigma}_A, \bar{\sigma}))$ and $(q_B, [\underline{\sigma}_B, \bar{\sigma}))$ obtained in respective equilibria under different parameter values that differ only in α, with $\alpha_A > \alpha_B$. (Note that the two intervals share the top boundary.) As long as the average misclassified borrower accepting the contract is riskier than an average targeted borrower, $\underline{\sigma}_A > \underline{\sigma}_B$, $q_A > q_B$, and $\hat{\rho}_A \geqslant \hat{\rho}_B$.*

Proof. First, note that $\theta_A < \theta_B$, which immediately implies $\underline{\sigma}_A > \underline{\sigma}_B$. Second, equation (4.8) together with the restriction that correctly classified borrowers are less risky than the misclassified ones, implies that, if $\hat{\rho}$ were the same across the contracts, then the price would be higher in the A contract. Lastly, this implies that $\hat{\rho}_A > \hat{\rho}_B$ (see equation (4.9)), which further reinforces the second point, i.e., further raises q_A relative to q_B. □

The restriction that the average misclassified borrower accepting the contract is riskier than an average targeted borrower is always satisfied for both the top contract and the last contract offered. There is a possibility that it is not satisfied for intermediate contracts. The problem could be that the pool of mislabeled customers is better than the pool of the target customers, which would create a downwards pressure on the price in response to an increase in α. This problem does not affect the following proofs, as they characterize the riskiest contract offered.

Claim 4.14. *A sufficiently large increase in the precision α of the public signal leads to an increase in the number of contracts in equilibrium.*

Proof. Consider an proportional increase in α by a factor $\left(\frac{N-1}{N}\right)^2$, from α_0 to α'. This guarantees that the top N contracts now cover the interval of public types $[\underline{\sigma}_{N-1}, 1]$. The rest of this proof simply establishes that an additional contract will be offered at that point. That is, we have to establish that the borrower with public type $\underline{\sigma}_{N-1}$ would be willing to accept that additional contract. Note that this borrower was willing to accept the original Nth contract with price q_N^0, given by equations (4.8) and (4.9) with $\alpha = \alpha_0$. Lemma 4.13 establishes that this borrower is also willing to accept the new $(N+1)$th contract under α'. □

Claim 4.15. *The Lower bound on the measure of the public signals served by risky contracts is increasing in α.*
To be specific, comparing the right ends of the newly introduced bottom contracts as α gradually increases, the later the contract is introduced, the lower is the right end of the interval (loosely corresponding to $1 - L$ in the symmetric info case).

Proof. This can be proven by contradiction: Suppose that the statement does not hold, namely that the right end of the interval covered by the Nth contract ($\underline{\sigma}_{N-1}$) when it was first introduced (at the point when $\alpha = \alpha_N$) is lower then the right end of the interval covered by the Mth contract ($\underline{\sigma}_{M-1}$) when it was first introduced (at the point when $\alpha = \alpha_M$), where $M > N$ (and $\alpha_M > \alpha_N$).
To derive the contradiction, consider the level of α' smaller than α_M, but larger than α_N, such that the left end of the last contract is exactly equal to $\underline{\sigma}_{N-1}$. At that point, a new

contract would already have been introduced as entry would occur before α reached α_M. □

Note: The proof does not work for the lower edge of the last interval.

4.5 Social Planner's Problem

Section 5.4 of the paper briefly discusses *ex-ante* constrained Pareto optimal allocation. There are two key points to keep in mind regarding that optimal allocation. First, optimality is from "behind the veil of ignorance," that is, taking ex-ante expectation over all possible ex-post realization of individuals' types (ρ and σ). Second, we maintain the assumption that *contracts are costly* (which is the key constraint added to the usual participation and incentive constraints). The constrained optimal allocation is the solution to the following Constrained Social Planner's Problem, which has one unusual feature — it contains "prices":[7]

$$\begin{aligned} \max_{N^*,(q_n^*,L_n^*,\underline{\sigma}_n^*),n^*(\rho,\sigma)} \quad & E_{(\rho,\sigma)}\left[q^*_{n^*(\rho,\sigma)}L^*_{n^*(\rho,\sigma)} + \beta\left(\rho\left(y_h - L^*_{n^*(\rho,\sigma)}\right) + (1-\rho)(1-\gamma)y_l\right)\right] \\ \text{s.t.} \quad & \bar{q}E_{(\rho,\sigma)}\left[\rho\, L^*_{n^*(\rho,\sigma)}\right] \geqslant E_{(\rho,\sigma)}\left[q^*_{n^*(\rho,\sigma)}L^*_{n^*(\rho,\sigma)}\right] + N^*\chi \\ & n^*(\rho,\sigma) \in \text{argmax}_{n\in n^*(.,\sigma)}\left[q_n^* L_n^* + \beta\left(\rho\left(y_h - L_n^*\right) + (1-\rho)(1-\gamma)y_l\right)\right] \\ & L_n^* \in (\gamma y_l, \gamma y_h] \quad \forall n \end{aligned}$$

where $n^*(\rho,\sigma)$ is the assignment rule of borrowers to contracts; the first constraint is the resource constraint and the second is the incentive constraint. The statement of the social planner's problem incorporates some basic results: 1) the planner does not grant loans in excess of γy_h, 2) the risk-free loan of size γy_l at price $\bar{q}$ is offered to everyone.

5 Data

This section provides further details and discussion of the data discussed in Sections 6 and 7 of Livshits, MacGee, and Tertilt (2014). Unless otherwise noted, the date we use is

[7] We restrict the social planner to use the same type of contracts as those available to private lenders. In our environment, each contract specifies promised repayment L (which does not depend on a borrower's income realization), transfer to the borrower in the first period qL, and a set of observable types of borrowers that are eligible for the contract.

Table 1: Number of Households with Balance and Non-Imputed Rate, SCF

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	4305	279	2386	1029
2001	4442	265	2523	1085
2004	4519	440	2458	1185

from the Survey of Consumer Finances (SCF).

5.1 Increased Number of Consumer Credit Contracts

The interest rate data in Table 2 in the paper use the SCF's questions on the credit card interest rate of respondents. For 1995 - 2004, the question asked for the card with the largest balance, while the 1983 survey asked for the best guess of the average annualized interest on the bank or store card uses most often if the full amount was not paid. One issue that affects the number of different rates reported is that in recent 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 (see Table 1).

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

5.2 Increased Access to Credit Card Borrowing by Riskier Borrowers

5.2.1 Fraction of Households with Access to Credit Cards

In Livshits, MacGee, and Tertilt (2014) we report the fraction of households with a bank credit card by income quintile (reproduced as Table 2 below). In Figure 8(c), earned income is Wages + Salaries + Professional Practice, Business, Limited Partnership, Farm + Unemployment or Worker's Compensation.

We briefly summarize some alternative cuts that indicate that credit card borrowing by lower income households increased, and that the rise in credit card borrowing did not merely reflect a shift from borrowing via other forms of unsecured credit such as lines of credit.

Table 2: Percent of Households who Own a Bank Credit Card, by Income Quintile

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

Source: Survey of Consumer Finances, Bankcards only.

To show that increased access to bank cards was accompanied by use of the cards to borrow, we report the fraction of households with a bank credit card that have a negative balance (Table 3) and the fraction with a balance greater than $500 (in 1989 dollars, Table 4). While as expected, the fraction of households that carry a balance is lower than the fraction with a card, the overall trend is similar to the fraction with a card.

Table 3: Percent of Households with negative balance on a Bank Credit Card, by Income Quintile

Quintile	1983	1989	1992	1995	1998	2001	2004
1	0.04	0.08	0.11	0.16	0.17	0.22	0.23
2	0.13	0.18	0.29	0.32	0.33	0.40	0.38
3	0.24	0.37	0.39	0.41	0.42	0.49	0.49
4	0.32	0.45	0.47	0.51	0.52	0.47	0.50
5	0.37	0.41	0.38	0.46	0.42	0.37	0.43
All	0.22	0.29	0.33	0.46	0.42	0.37	0.43

Source: Survey of Consumer Finances, Bankcards only.

Table 4: Percent of Households with balance of at least $500 on a Bank Credit Card, by Income Quintile

Quintile	1983	1989	1992	1995	1998	2001	2004
1	0.03	0.04	0.07	0.09	0.10	0.12	0.14
2	0.07	0.14	0.20	0.23	0.21	0.24	0.26
3	0.14	0.25	0.25	0.30	0.29	0.33	0.35
4	0.20	0.33	0.34	0.37	0.40	0.35	0.38
5	0.26	0.32	0.28	0.35	0.33	0.29	0.35
All	0.14	0.21	0.23	0.27	0.26	0.27	0.30

Source: Survey of Consumer Finances, Bankcards only.

One concern may be that the rise in credit card borrowing may simply reflect substitution away from other forms of unsecured borrowing. The closest product to a credit card is an unsecured line of credit, which also offers a borrower a revolving credit facility. While the fraction of households with an unsecured line of credit does decline as access to bank credit cards rise, the level change is small compared to the rise in the fraction of households with a bank credit card (see Table 5). It is also worth noting that the fraction of households with a secured line of credit rises between 1989 and 2004, with the rise driven mainly by the top three deciles.[8]

[8]This likely reflects the fact that home ownership rates are much higher for higher income households, and that home ownership is a necessary prerequisite for s secured line of credit.

Table 5: Percent of Households with Unsecured Line of Credit, by Income Quintile

Quintile	1989	1992	1995	1998	2001	2004
1	0.02	0.01	0.01	0.02	0.02	0.01
2	0.05	0.04	0.03	0.04	0.03	0.04
3	0.04	0.05	0.05	0.05	0.04	0.03
4	0.10	0.08	0.07	0.05	0.05	0.03
5	0.14	0.10	0.10	0.07	0.05	0.05
All	0.07	0.06	0.05	0.04	0.03	0.04

Source: Survey of Consumer Finances, non home equity secured only.

5.2.2 New Cardholders

The discussion in Livshits, MacGee, and Tertilt (2014) of changes in access to credit cards by borrowers with (observably) riskier characteristics focused on a comparison of credit card holders in 1989 and 1998. We focused on 1989 and 1998 for three reasons. First, since 1989 the SCF asks whether households were at least 60 days late on a bill payment, which we use as a proxy for households at higher risk of bankruptcy. Second, the largest rise in bankruptcy filings occurred during the 1990s, with the filing rate per adult doubling between 1989 and 1998. Finally, both years correspond to similar points in the business cycle (i.e. well into expansions and roughly 2 years before recessions) which controls for cyclical trends.

In this section, we also report key statistics when we replicate our analysis for 1995 and 2001 to demonstrate that the conclusions we draw from the comparison of 1989 with 1998 are robust. In addition, we outline some additional details on our procedure.

Given our focus on consumer delinquency, we restrict attention to working age households (i.e., households with a head who age is 65 or less), with a net worth less than five million (and financial assets less than five million) in 1989.[9] To control for inflation, we scale our net worth (and financial assets and income) cut-off for late years by inflation (e.g., for 1998 the cut-off is 6.55 million).

Since the SCF data for the years we are interested in lacks a panel dimension, we require a procedure to identify "new" from "existing" cardholders. We follow Johnson

[9]We also drop households with a DSR greater than 100, which results in the dropping of 1 observations in each year. This was done to avoid biasing the reported DSR (FOR) values reported for non-cardholders, as it otherwise has a minimal impact on the results.

(2007), and assume that of the 69.5% of households with a card in 1998, 57% (the fraction with a card in 1989, see Table 7) are "existing" and the other 12.5% "new."[10] To identify the existing cardholders, we first run a probit regression of bank card ownership on households' characteristics in 1989 (see Table 6). Using the coefficients from this regression and household characteristics in 1998 (1995, 2001) we compute the probability that each household would have had a card in 1989. We order households by their imputed probability of card ownership, and assign the first 57% to the existing group and the remaining 12.5% to the new cardholder category.

To compute the contribution of the new cardholders to the rise in credit debt between 1989 and 1998, we sum the total (bank) credit card balances in 1989 and 1998 for our sample (using the household weights), as well as the total credit debt of new and existing households in 1998. The contribution of the new cardholders is their total balances outstanding divided by the change in total credit card balances (in constant 1998 dollars). This calculation implies that the new cardholders account for roughly 27% of the rise in total credit card balances. As a check that our sample restriction is not likely to bias our calculation we also compute the fraction of total credit balances that our sample accounts for in each year. We find a similar share, at just under 81 % in 1989, and just over 81% in 1998.

We repeated this exercise to identify new and existing cardholders for 1995 and 2001. In each year, we use the regression coefficients in Table 6 to compute the likelihood of card ownership. We label the 57% of households with the highest probabilities "existing cardholders", and the remaining as "new cardholders."[11] We then compute the means for a number of relevant variables for each category (the entire sample population, all bank cardholders, existing cardholders, new cardholders and non-cardholders) using the population weights.

To facilitate comparison with the results reported in the paper, Table 7 replicates Table 4 of Livshits, MacGee, and Tertilt (2014). Table 7 also reports the financial obligation ratio (FOR), which augments the DSR to include rent, property tax and auto leases as well as home owner expenses.[12] As can be seen from the Table, the mean value of FOR for non-cardholders is higher than that of cardholders (the opposite of the DSR). This reflects

[10]We differ from Johnson (2007) in our focus on bank-issued cards (she includes other cards such as store and gasoline cards) and the explanatory variables in the probits.

[11]The fraction of households with a bank card in our sample (under 65 and net worth less than five million) in 1989 is 57%.

[12]SPecifcally, FOR is DSR plus (1) Rent "x521 x602 x612 x619 x703 x708"; (2) Real estates tax "x721" and (3) Auto lease "x2105 x2112 x2117".

the fact that most non-cardholders are renters, while most cardholders are home-owners whose mortgage payments account for a large fraction of their DSR.[13]

Table 8 reports the same data for the 1989 vs 1995 comparison. Overall, the 1995 data provides a similar picture to the 1989-1998 comparison discussed in the paper. The "new" bank cardholders identified by our procedure more closely resemble non-cardholders than cardholders. They are less likely to be married, have less education, lower income, and lower net worth than the typical cardholder.

Table 9 reports similar estimates for 2001. If anything, the comparison of 2001 with 1989 is stronger evidence than that discussed in the paper. Similar to 1998, the "new" bank cardholders in 2001 are riskier along a number of observable dimensions: they are less likely to be married, have less education, lower income, and lower net worth than cardholders in 1989 (or those we identify as "existing" cardholders" in 2001). The 2001 data suggests that the extensive margin of riskier borrowers played an even larger role in accounting for the rise in delinquency. Since the average delinquency rate of existing borrowers in 2001 is nearly the same as that of all cardholders in 1989, our estimates imply that the rise in average delinquency rates for bankcard 1989 and 2001 can be attributed almost entirely to new cardholders.

5.2.3 Expected Delinquency Rates Based on 1989

An alternative approach to identify the contribution of new cardholders to changes in delinquency is by examining changes in the predicted delinquency of cardholders. Specifically, we ask what the expected delinquency rate for cardholders (new and existing) would be if one used the estimated relationship between observable household characteristics and delinquency in 1989 and observed household characteristics in 1998. To do this, we estimate a probit of delinquency status on household demographics, income, assets and debt measures using the 1989 SCF (see Table 10). Using the coefficients from 1989, we compute the predicted delinquency rates for the following years for new and existing cardholders, as well as for the counterfactuals where we set the credit card debt of new cardholders to zero or reduced the credit card debt of existing cardholders by a factor of 1.31. We then compute the mean delinquency rate for various groups (all

[13]We experimented with replacing the DSR in our bankcard regressions with FOR, and found similar results.

households, bank cardholdes, new cardholders, existing cardholders).[14]

As a check on our findings for 1998, we repeated these calculations for 1995 and 2001 (see Tables 11 - 13 below). We find broadly similar patterns (as discussed in the paper) for 1998. For all of the years, the new cardholders characteristics support the view that their expected delinquency rate was much higher (roughly 10 percentage points) than existing cardholders. Similar to our more direct accounting exercise above, the predicted delinquency rates also suggest that existing cardholders were less risky in 2001 than cardholders in 1989, while new cardholders characteristics suggested a much higher expected delinquency rate. For all years, we find that the counterfactual where we lower the credit card debt of existing cardholders (as a proxy for the intensive margin effect of increased credit card borrowing by these households) results in little change in the expected delinquency rate.

In these exercises, we set *all* credit card debt of new cardholders to zero. As a further check, for the new cardholders in 1998 we also computed the expected delinquency for: (i) setting just their holdings of *bank card* debt to zero; and (ii) setting bank card debt to zero and lowering their non-bank credit cards by the mean ratio of non-bank card balances in 1989 compared to 1998. The predicted delinquency rate is slightly higher than when we set all credit card debt to zero. For case 1, the expected delinquency rate is 11.9 and for case 2 it is 11.7 (versus 11.5 when we drop all credit card debt). This implies a contribution to the rise in delinquency slightly lower than that reported in the paper, of roughly one sixth instead of one fifth.

[14]We continue to focus on the same subset of the SCF, namely households with a head less or equal to 65 years of age with net worth (and financial assets) of less than 5 million (1989 dollars).

Table 6: Probit Estimates for Bank Cardholder, 1989

Explanatory Variable	Coefficient	standard error
Age	-0.119	(0.000575)
Age Squared	0.00227	(0.000014)
Age Cubed	-1.26e-05	(0.000000)
Education (years)	0.123	(0.000086)
Married	0.256	(0.000453)
Own Home	0.152	(0.000842)
Years at Address	0.0121	(0.000028)
Years at Job	0.00630	(0.000029)
Occupation (Sales/Admin Support)	0.368	(0.000611)
Occupation (Service)	-0.253	(0.000817)
Occupation (Production/Repairs)	-0.00455	(0.000663)
Occupation (Laborers)	-0.120	(0.000721)
Occupation (Farmers)	-0.750	(0.001290)
Occupation (Retired)	-0.135	(0.001100)
Occupation (Not Working)	0.134	(0.000823)
Denied Credit	-0.564	(0.000462)
Self-employed	-0.214	(0.000631)
Consumer Debt (pc Income)	0.236	(0.000471)
Secured Debt (pc Income)	0.145	(0.000308)
Networth	0.0172	(0.000094)
Income	1.390	(0.001660)
Income*Ownhome	-0.762	(0.001680)
DSR * $I_{DSR\ category}$		
1 = Under median DS	3.601	(0.006830)
2 = Median to 80th percentile DSR	1.142	(0.007930)
3 = Above 80th percentile DSR	-0.477	(0.001180)
Liquid Assets (LA) * $I_{LA\ category}$		
1 = Under 1.5% mean income	87.50	(0.138000)
2 = 1.5% to 4.5% mean income	68.90	(0.103000)
3 = Above 4.5% mean income	-0.119	(0.000305)
I_{DSR} * I_{LA}		
1 and 2	0.194	(0.001550)
1 and 3	1.096	(0.000791)
2 and 1	0.492	(0.001710)
2 and 2	-0.0946	(0.002220)
2 and 3	1.492	(0.001690)
3 and 1	0.761	(0.001050)
3 and 2	0.867	(0.001860)
3 and 3	1.633	(0.001120)
Black	-0.387	(0.000616)
Hispanic	-0.180	(0.000686)
Other Races	-0.188	(0.000860)
Constant	-1.359	(0.007420)
Observations	2262	
Correctly Predicted	79.79%	

All reported coefficients are significant at 1% level. DSR = debt service ratio

Table 7: Characteristics of Bank Card Holders 1989 vs 1998, SCF

Characteristics	1989 All cardholders	1989 Non cardholders	1998 All cardholders	1998 "Existing"	1998 "New"	1998 Non cardholders
Fraction HH	57.0	43.0	69.5	56.9	12.5	30.5
Income	68,019.8	26,403.9	65,309.8	72,425.7	33,053.1	23,420.9
Net Worth	262,001.5	66,885.6	260,780.0	302,589.5	71,256.0	45,282.4
DSR*	0.19	0.14	0.22	0.22	0.19	0.17
FOR*	0.28	0.40	0.36	0.35	0.38	0.53
Debt	57,540.7	14,687.4	69,508.0	79,099.5	26,029.0	17,990.8
CC Balance*	1,920.0	132.7	2,932.8	3,087.9	2,229.6	191.0
Bank CC Bal*	1,449.7	0	2,494.7	2,664.4	1,725.2	0
Store CC Bal.*	470.3	132.7	438.1	423.4	504.5	191.0
Own Home	75.5	42.0	74.0	78.1	55.4	37.0
Age (HH head)	42.4	39.7	43.2	43.9	40.3	38.9
No HS Degree*	8.8	30.8	6.0	3.4	17.9	29.0
College Degree	44.3	12.6	45.9	50.2	26.0	12.1
Married	71.1	47.9	68.2	73.3	44.9	46.6
Minority*	16.1	41.2	17.4	13.7	33.9	41.6
Self-Employ	13.5	9.7	13.7	14.4	10.2	8.1
CC IR*	NA	-	14.4	14.1	15.4	-
Delinquent	2.7	11.4	5.5	3.8	13.3	11.4

*DSR = Debt Service Ratio, FOR = Financial Obligations Ratio, CC = credit card (bank & store),

$quad$ IR = interest rate,HS = high school, Minority = sum of Black, Hispanic and Other Race

Source: Authors' calculations based on Survey of Consumer Finances. Values for 1989 are expressed in 1998 dollars using the CPI. Figures are averages using population weights, and rates are as a fraction of the sample: households whose head is between 20 and 65 with a net worth of less than 5 million.

Table 8: Characteristics of Bank Card Holders, 1989 vs 1995 SCF

Characteristics	1989 All cardholders	1989 Non cardholders	1995 All cardholders	1995 "Existing"	1995 "New"	1995 Non cardholders
Fraction HH	57.0	43.0	67.5	56.9	10.6	32.5
Income	68,019.8	26,403.9	58,934.2	64,287.0	30,105.2	22,083.5
Net Worth	262,001.5	66,885.6	215311.8	241615.0	73648.4	43006.2
DSR*	0.19	0.14	0.22	0.22	0.20	0.18
FOR*	0.28	0.40	0.34	0.32	0.42	0.55
Debt	57,540.7	14,687.4	59,263.0	66,128.0	22,289.5	14,668.1
CC Balance*	1,920.0	132.7	2494.2	2553.7	2173.4	312.3
Bank CC Bal*	1,449.7	0	2064.8	2118.6	1775.0	0.0
Store CC Bal.*	470.3	132.7	429.4	435.1	398.4	312.3
Own Home	75.5	42.0	73.3	77.7	49.5	37.6
Age (HH head)	42.4	39.7	42.69	43.10	40.50	39.31
No HS Degree*	8.8	30.8	6.6	5.1	14.6	27.7
College Degree	44.3	12.6	43.0	46.8	22.5	13.0
Married	71.1	47.9	68.4	71.7	50.1	46.4
Minority*	16.1	41.2	17.3	13.8	36.0	40.6
Self-Employ	13.5	9.7	12.1	12.3	11.2	9.2
CC IR*	NA	-	14.4	14.3	14.9	-
Delinquent	2.7	11.4	3.9	3.3	7.3	11.9

*DSR = Debt Service Ratio, FOR = Financial Obligations Ratio, CC = credit card (bank & store), IR = interest rate,HS = high school, Minority = sum of Black, Hispanic and Other Race

Source: Authors' calculations based on Survey of Consumer Finances. Values for 1989 are expressed in 1998 dollars using the CPI. Figures are averages using population weights, and rates are as a fraction of the sample: households whose head is between 20 and 65 with a net worth of less than 5 million.

Table 9: Characteristics of Bank Card Holders, 1989 vs 2001 SCF

Characteristics	1989 All cardholders	1989 Non cardholders	2001 All cardholders	2001 "Existing"	2001 "New"	2001 Non cardholders
Fraction HH	57.0	43.0	73.7	56.9	16.8	26.3
Income	68,019.8	26,403.9	70,879.0	82,263.7	32,191.7	26,156.7
Net Worth	262,001.5	66,885.6	306,274.8	370,076.0	89,467.5	53,110.3
DSR*	0.19	0.14	0.21	0.22	0.16	0.14
FOR*	0.28	0.40	0.32	0.30	0.37	0.47
Debt	57,540.7	14,687.4	70,068.7	83,781.0	23,471.9	19,603.6
CC Balance*	1,920.0	132.7	2,498.8	2,664.6	1,935.4	201.9
Bank CC Bal*	1,449.7	0	2,106.8	2,269.5	1,554.1	0.0
Store CC Bal.*	470.3	132.7	392.0	395.1	381.4	201.9
Own Home	75.5	42.0	74.3	81.3	50.6	37.0
Age (HH head)	42.4	39.7	43.2	43.8	40.9	39.8
No HS Degree*	8.8	30.8	6.2	3.2	16.5	30.0
College Degree	44.3	12.6	44.0	51.3	19.0	13.7
Married	71.1	47.9	67.7	74.4	44.8	47.3
Minority*	16.1	41.2	19.6	14.6	36.8	45.6
Self-Employ	13.5	9.7	14.3	14.7	13.2	6.6
CC IR*	NA	-	14.3	14.0	15.4	-
Delinquent	2.7	11.4	4.2	2.8	9.0	13.0

*DSR = Debt Service Ratio, FOR = Financial Obligations Ratio, CC = credit card,
IR = interest rate,HS = high school, Minority = sum of Black, Hispanic and Other Race

Source: Authors' calculations based on Survey of Consumer Finances. Values for 1989 are expressed in 1998 dollars using the CPI. Figures are averages using population weights, and rates are as a fraction of the sample: households whose head is between 20 and 65 with a net worth of less than 5 million.

Table 10: Probit Estimates for Delinquents, 1989

Explanatory Variable	Coefficient	standard error
Age	0.0876	(0.000873)
Age Squared	-0.00201	(0.000022)
Age Cubed	1.36e-05	(0.000000)
Education (years)	-0.00840	(0.000125)
Married	0.0946	(0.000683)
Own Home	-0.0545	(0.000890)
Years at Address	0.00705	(0.000047)
Years at Job	-0.0340	(0.000061)
Occupation (Sales/Admin Support)	0.0632	(0.000985)
Occupation (Service)	-0.171	(0.001290)
Occupation (Production/Repairs)	0.0131	(0.001080)
Occupation (Laborers)	0.179	(0.001100)
Occupation (Farmers)	-0.921	(0.002700)
Occupation (Retired)	-0.596	(0.002620)
Occupation (Not Working)	-0.109	(0.001180)
Denied Credit	0.452	(0.000584)
Self-employed	0.578	(0.000918)
Consumer Debt (pc Income)	0.224	(0.000477)
Secured Debt (pc Income)	-0.0443	(0.000543)
Networth	-0.0488	(0.000247)
Income	0.0586	(0.000500)
DSR * $I_{\text{DSR category}}$		
1 = Under median DS	5.101	(0.010200)
2 = Median to 80th percentile DSR	-1.915	(0.011500)
3 = Above 80th percentile DSR	-0.0307	(0.001200)
Liquid Assets (LA) * $I_{\text{LA category}}$		
1 = Under 1.5% mean income	-68.66	(0.180000)
2 = 1.5% to 4.5% mean income	-47.97	(0.173000)
3 = Above 4.5% mean income	0.0184	(0.001770)
I_{DSR} * I_{LA}		
1 and 2	-0.187	(0.002440)
1 and 3	-1.135	(0.001560)
2 and 1	0.783	(0.002370)
2 and 2	1.161	(0.003330)
2 and 3	-0.320	(0.002480)
3 and 1	0.473	(0.001280)
3 and 2	-0.191	(0.003210)
3 and 3	-0.499	(0.001670)
Black	0.516	(0.000735)
Hispanic	0.334	(0.000855)
Other Races	0.251	(0.001170)
Constant	-2.653	(0.011000)
Observations	2261	
Correctly Predicted	93.70%	

All reported coefficients are significant at 1% level. DSR = debt service ratio

Table 11: Predicted Mean Delinquency Rates, 1995

	New	Existing	All Holders	No Card	Pop.
Case 1	0.1347451	0.0331629	0.0459558	0.1106892	0.0670882
Case 2	0.12024	0.0331629	0.0441291	0.1106892	0.0658578
Case 3	0.1347451	0.0330626	0.0458681	0.1106892	0.0670291
Observations	293	2017	2310	835	3145

Case 1: baseline

Case 2: new cardholders debt set to 0

Case 3: existing cardholders CC debt reduced by factor of 1.24

Table 12: Predicted Mean Delinquency Rates, 1998

	New	Existing	All Holders	No Card	Pop.
Case 1	0.129730	0.030001	0.044507	0.109817	0.064368
Case 2	0.115037	0.030001	0.042369	0.109817	0.062880
Case 3	0.129730	0.029715	0.044263	0.109817	0.064198
Observations	350	1948	2298	830	3128

Case 1: baseline

Case 2: new cardholders debt set to 0

Case 3: existing cardholders CC debt reduced by factor of 1.31

Table 13: Predicted Mean Delinquency Rates, 2001

	New	Existing	All Holders	No Card	Pop.
Case 1	0.123108	0.025704	0.045177	0.100447	0.059690
Case 2	0.108181	0.025704	0.042192	0.100447	0.057490
Case 3	0.123108	0.025453	0.044976	0.100447	0.059542
Observations	502	1921	2423	742	3165

Case 1: baseline

Case 2: new cardholders debt set to 0

Case 3: existing cardholders CC debt reduced by factor of 1.42

References

Clemons, Eric K., and Matt E. Thatcher. 1998. "Capital One: Exploiting an Information-Based Strategy." *Proceedings 31st Annual Hawaii International Conference on System Sciences* 6:311–320.

———. 2008. "Capital One Financial and a Decade of Experience with Newly Vulnerable Markets: Some Propositions Concerning the Competitive Advantage of New Entrants." *Journal of Strategic Information Systems* 17:179–189.

Federal Reserve Board. 2007, August. Report to the Congress on Credit Scoring and Its Effects on the Availability and Affordability of Credit. http://www.federalreserve.gov/Pubs/reports_other.htm.

Frame, W. Scott, and Lawrence J. White. 2004. "Empricial Studies of Financial Innovation: Lots of Talk, Little Action?" *Journal of Economic Literature* 42 (1): 116–144 (March).

Hunt, Robert M. 2006. "The Development and Regulation of Consumer Credit Reporting in America." In *The Economics of Consumer Credit*, edited by Giuseppe Bertola, Richard Disney, and Charles Grant, 301–346. Boston: MIT Press.

Johnson, Kathleen. 2007. "Household Credit Usage: Personal Debt and Mortgages." In *Recent Developments in the Credit Card Market and the Financial Obligations Ratio*, edited by Sumit Agarwal and Brent Ambrose, 13–35. Palgrave Macmillan.

Livshits, Igor, James MacGee, and Michèle Tertilt. 2014. "The Democratization of Credit and the Rise in Consumer Bankruptcies." *mimeo*.

Mays, Elizabeth, ed. 2004. *Credit Scoring for Risk Managers – The Handbook for Lenders*. Thomson – South Western.

Nocera, Joseph. 1994. *A Piece of the Action: How the Middle Class Joined the Money Class*. Simon & Schuster.

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

Rothshild, M., and J. Stiglitz. 1976. "Equilibrium in Competitive Insurance Markets: An Essay on the Economics of Imperfect Information." *Quarterly Journal of Economics* 90:629–649.

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

Wilson, C. 1977. "A Model of Insurance Markets with Incomplete Information." *Journal of Economic Theory* 16 (2): 167–207.