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MODELING THE REVOLVING REVOLUTION:
THE DEBT COLLECTION CHANNEL**

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Modeling the Revolving Revolution:
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ABSTRACT

We investigate the role of information technology (IT) in the collection of delinquent consumer debt. We argue that the widespread adoption of IT by the debt collection industry in the 1990s contributed to the observed expansion of unsecured risky lending such as credit cards. Our model stresses the importance of delinquency and private information about borrower solvency. The prevalence of delinquency implies that the costs of debt collection must be borne by lenders to sustain incentives to repay debt. IT mitigates informational asymmetries, allowing lenders to concentrate collection efforts on delinquent borrowers who are more likely to repay.

Keywords: debt collection, credit cards, consumer credit, unsecured credit, revolving credit, moral hazard, costly state verification, informal bankruptcy, information technology

JEL Codes: E21, D91, G20

The consumer credit industry is one of the most information technology (IT)-intensive.[1] Few if any aspects of consumer lending that do not involve IT use (Berger, 2003). Yet, its transformative effect on consumer lending is still difficult to gauge, resulting in a growing body of research in consumer finance. Our paper contributes to this research agenda by highlighting a novel channel of technological progress in consumer credit markets: the use of IT in the collection of delinquent consumer debt. We argue that the widespread adoption of IT by the debt collection industry in the 1990s contributed to the observed expansion of risky lending to consumers, such as unsecured credit card lending.

Our focus on debt collection stems from the fact that the adoption of IT by the consumer lending industry has been mirrored by similar developments in the debt collection industry. In particular, the 1990s brought the emergence of IT-enabled statistical modeling of the evolution of delinquent debt, resulting in an extensive use of large databases to predict the outcome of debt collections. According to the industry, the use of IT-based collection platforms brought a major reduction in collection costs and improved collection efficiency.[2] Other notable improvements included predictive dialers, speech analytics software, Internet-based skiptracing, and the provision of collection scores by the credit bureaus.

To explore the link between IT improvements in debt collection and the supply of (unsecured) consumer credit, we develop a new model of consumer default in which debt collection plays an essential role in sustaining risky lending. The novelty of our model—relative to the standard theory of unsecured consumer lending (Athreya, 2002; Livshits et al., 2007, 2010; Chatterjee et al., 2007)— is that consumer default takes the form of persistent delinquency rather than a formal bankruptcy that automatically terminates the debt obligation. This feature implies that lenders face the choice of whether to collect unpaid debt from delinquent borrowers, which is

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[1]Depository and nondepository financial institutions are the most IT-intensive industry in the U.S. as measured by the ratio of computer equipment and software to value added. See Table 2 in Triplett and Bosworth (2006).
[2]Section II (fact 4) describes the evidence.

costly and involves asymmetric information about their ability to repay. IT aids this process by providing a noisy signal of the borrowers' financial state.

Our major points of departure from existing models of consumer credit accord well with the available evidence. While some consumers do file for personal bankruptcy protection, most delinquent consumers do not (see Dawsey and Ausubel (2004) and Section II), giving rise to a large debt collection industry.[3] Crucially, as described by Makuch et al. (1992) and Chin and Kotak (2006), IT has indeed been used to identify consumers who are more likely to repay their debt.

The main prediction of our model is that IT-driven improvements in debt collection—which in our model take the form of improved signal precision—lead to a more prevalent use of risky loans (i.e., loans exposed to the risk of default) and hence result in a higher default rate. As signals become more precise, lenders adopt them to target delinquent consumers who are more likely to pay back their debt. This lowers the cost of sustaining risky loans, making such loans more prevalent in equilibrium.

To highlight the quantitative strength of our new channel, we relate it to the observed expansion of risky credit card lending in the U.S. As we discuss in Section II, the last few decades have witnessed a major increase in the default risk on credit card loans outstanding—as implied by an upward trend in the net charge-off rate on credit card loans (fraction of loans written off due to consumer delinquency, net of the flow of recoveries). We calibrate the parameters of the model by matching the key moments characterizing the U.S. credit card market in 2004. We choose year 2004 to avoid the confounding forces associated with the 2005 bankruptcy reform and the 2008 financial crisis. We set credit market parameters to match the 2004 trend values

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[3] The debt collection industry in the U.S. (NAICS 56144), which excludes internal collection departments, employs about 150,000 according to the Bureau of Labor Statistics. Altogether, bill and account collectors as a profession held about 434,000 jobs in 2006, according to Bureau of Labor Statistics (2006). ACA International (2007) reports that about two-thirds of debt placed in collection is consumer debt. To put these numbers in perspective, the total number of officers across all law enforcement agencies is about 700,000.

of gross credit card debt to median household income of 15.1 percent and the charge-off rate on credit card loans of 5.2 percent. We also set debt collection parameters to account for the estimated aggregate costs of collecting credit card debt in 2004, which we estimate to be equal to about 4 percent of net charge-offs. Finally, to quantify the effect of IT, we re-create the pre-adoption market by reducing the signal precision below the *IT adoption threshold* at which signals become used by lenders to segment delinquent consumers.

We find that a reduction in signal precision below the IT adoption threshold reduces the charge-off rate from the calibrated value of 5.2 percent to at least 3.3 percent, which is similar to the change observed in the data. This result contrasts with the effect of a decline in a simple reduced-form wedge between the borrowing rate and the lending rate, which has the opposite effect. This property was first noted by Livshits et al. (2010), who showed that a decline in a reduced-form lending wedge raises indebtedness more than default losses.

The change in collection efficiency implied by our model is broadly consistent with the available micro-level evidence. Makuch et al. (1992) describe one of the industry's first large-scale implementations of a statistical platform to collect unpaid credit card debt by a large retail card servicer, GE Capital. Prior to the adoption, which took place in the early 1990s, the company faced an annual flow of $1 billion in delinquent credit card debt and $400 million in annual charge-offs on a $12 billion portfolio. Pre-adoption collection costs accounted for 1.25 percent of outstanding debt and about 37 percent of its charge-offs. In a controlled rollout of the new system, its implementation reportedly reduced these costs by 31 basis points relative to the outstanding debt and by 9 percent relative to the pre-adoption charge-offs. Our model implies a similar efficiency gain, despite using lower pre-adoption costs of collecting debt than those reported in the study. The model is also consistent with larger efficiency gains, as the more recent industry evidence suggests.[4]

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[4]See data evidence discussion in Section II.

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The fact that the mechanism we highlight is quantitatively powerful requires comment. Similarly to the standard theory that we build on, the insurance gains from risky loans (brought by the default option) are fairly modest in our setup. As a result, the default rate predicted by the model is sensitive to the cost of providing risky loans. Interestingly, the presence of debt collection technology — which results in a targeted enforcement of credit contracts — implies that our model does not suffer from the usual difficulties of sustaining the high level of indebtedness and the high default rate seen in the U.S. data. This is because selective debt collection naturally imposes higher default penalties on non-distressed borrowers than on distressed borrowers.

Finally, our theory is consistent with the basic observation that today's debt collection technology relies *less* on litigation and more on the use of information. Using credit bureau data, we find that the average number of legal collections per delinquent borrower fell 16 percent from 2000 to 2006.[5] At the same time, the use of credit bureau information on delinquent borrowers by debt collectors — directly related to the use of signals in our model — rose 30 percent. While our data do not go back to the 1990s, using court data on wage garnishments from Virginia, Hynes (2006) documents a related pattern in the 1990s.

The rest of this paper is organized as follows. Section I reviews the literature. Section II discusses the stylized facts on which we rely. Section III lays out our theory and discusses the basic mechanism of the model. We present the main theoretical result in Section IV. Section V describes our quantitative model and results. Section VI concludes.

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[5]Our data source is described in Section II (fact 2).

I Related literature

The extensive use of IT in consumer credit markets raises questions about its effect on the availability of credit. Most of the existing literature has focused on its effect on informational asymmetries at the lending stage. To the best of our knowledge, our paper is the first to explore the effects of IT progress on debt collection.

The use of IT to mitigate adverse selection in lending and its effect on the provision of risky unsecured credit has been analyzed by Athreya et al. (2012), Narajabad (2012), Sanchez (2012) and Livshits et al. (forthcoming). They look at a similar set of facts to the ones that we examine here. Our analysis is complementary to their work by exploring a novel and qualitatively different channel of IT progress in credit markets. In addition, two important studies, by Athreya (2004) and Livshits et al. (2010), evaluate a set of alternative explanations for the rise in bankruptcies and expansion of credit card lending. Both papers stress the importance of lending technology rather than other factors as the driving force behind the expansion. Drozd and Nosal (2007) examine the fall in the fixed cost incurred by the lender to solicit potential borrowers and the effect of changing competitiveness in the marketplace.

Our paper's focus on persistent delinquency is closely related to the literature on the connection between delinquency and formal bankruptcy, such as White (1998), Chatterjee (2010), Benjamin and Mateos-Planas (2013), and Athreya et al. (2016). These papers lay theoretical foundations for the prevalent use of persistent delinquency as a form of default. On the empirical side, our model builds on the evidence documented by Dawsey and Ausubel (2004) and Agarwal et al. (2003), which we extend in Section II.

Our paper is also related to a small body of literature focusing on various aspects of the debt collection industry. Two notable studies that are relevant for our analysis are Fedaseyeu (2015) and Fedaseyeu and Hunt (2015). Fedaseyeu (2015) investigates the empirical link between debt

collection regulations and the supply of consumer credit; Fedaseyeu and Hunt (2015) focus on the phenomenon of delegation within the debt collection industry.

II Stylized Facts

We begin with a discussion of the four stylized facts that underpin our analysis. The first fact shows that the expansion of credit card lending has been associated with a secular rise in the average default risk. The second and third facts show that persistent delinquency is a prevalent form of default in the data and that it gives rise to a large debt collection industry. Finally, the fourth fact discusses the role of IT in enhancing debt collection efficiency in recent years.

Fact 1: The expansion of credit card borrowing in the 1990s has been associated with an increase in the charge-off rate on credit card debt.

Figure 1 illustrates one of the hallmarks of the "revolving revolution:" the rise in the charge-off rate on credit card debt, which measures the average net default rate on a statistical dollar of outstanding credit card debt.[6] The main result of our paper will be to show that a plausible progress in debt collection can result in a change that is similar in magnitude to the change in the data.

Fact 2: Persistent delinquency rather than formal bankruptcy is the prevalent form of consumer default on credit card debt.

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[6] The charge-off rate is measured as a percentage of outstanding loans and net of recoveries. We use the charge-off rate reported by the Board of Governors of the Federal Reserve System (BOG, hereafter). Federal regulations require creditors to charge off revolving credit accounts after 180 days of payment delinquency. See the Uniform Retail Credit Classification and Account Management Policy, 65 FR 36903-01 (June 12, 2000). Credit card loans consist mostly of revolving consumer credit. The BOG defines consumer credit as outstanding credit extended to individuals for household, family, and other personal expenditures, excluding loans secured by real estate. With the exception of total unsecured lending, all series in the figure come from the G.19 Statistical Release by the BOG. Total unsecured lending is an estimate taken from Livshits et al. (2010).
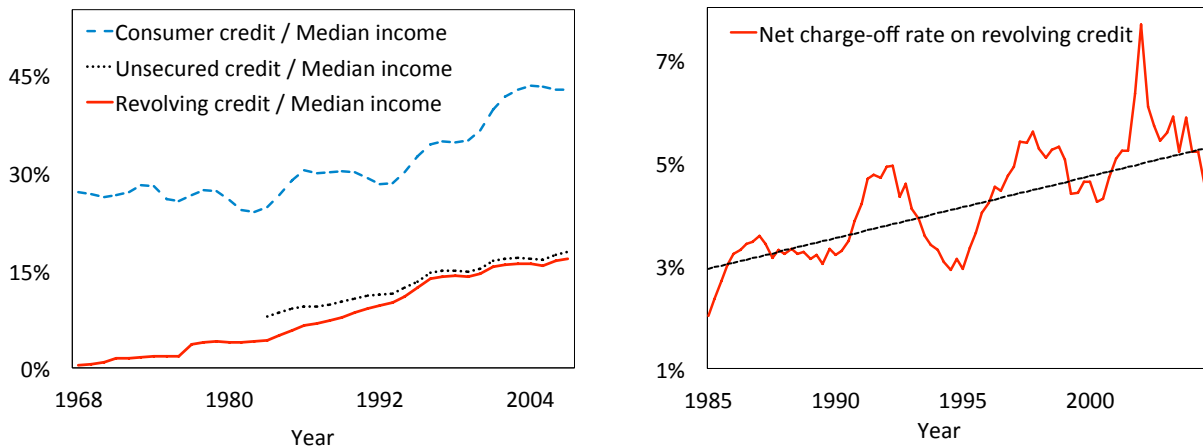
Figure 1: The Expansion of Risky Credit Card Lending in the U.S.

In the majority of defaults on credit card debt borrowers simply stop debt payments rather than filing for personal bankruptcy protection. Hence, a typical default on credit card debt does not readily terminate the debt obligation, giving rise to debt collection. This feature of the data is important because it is often up to lenders to decide how to handle delinquent debt, which is costly and informationally challenging.

To illustrate it we use a representative biennial panel of over 150,000 individuals from the Experian credit bureau database, which is one of the three major credit bureaus in the U.S. In July 2001, 2003 and 2005, we identify all borrowers who opened a credit card account within the last 24 months and which was 90+ days overdue at that time. We then follow each of these borrowers for up to four years and check how many of them filed for bankruptcy and how many showed signs of improvement.[7]

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[7]Delinquent borrowers are those who have at least one bank card opened within the past two years that is 90+ days overdue. This definition is similar to the one used by Agarwal et al. (2003). While a fraction of delinquent borrowers show improvement, this by no means implies full repayment. Our definition of "improvement" is fairly broad and indicates repayment of any credit account in the portfolio of a delinquent borrower. Hence, it is plausible that many borrowers who we flag as nondelinquent are still delinquent. The statistics are similar if we restrict our sample to delinquent borrowers with no prior history of bankruptcy. We thus do not impose such a restriction. See the Online Appendix for a detailed description of the data and our definitions.

Our findings confirm the results reported in the literature and based on account-level data (Agarwal et al., 2003; Dawsey and Ausubel, 2004). As is clear from Table 1, persistent delinquency is the most prevalent form of consumer default. On average, we find that the initial delinquency rate in the 2001, 2003 and 2005 waves is 31 per 1000 individuals. After two years, 20 still remain delinquent and only 5.5 filed for bankruptcy by that time. The conclusion is qualitatively the same even after four years.

Table 1: Delinquency on Credit Card Debt in the U.S. Credit Bureau Data

	31 per 1,000 Newly Delinquent Borrowers[a]	
	Show no sign of improvement[b]	File for bankruptcy
2 years after	66 percent (20 per 1000)	17 percent (5.5 per 1000)
4 years after	52 percent (16 per 1000)	20 percent (6.3 per 1000)

[a]Has at least one bank card opened within the past two years that is 90+ days overdue, charged off, or in collection.
[b]Paid in full or settled on any previously delinquent account, regardless of type (e.g. credit card, auto loan).

While our data does not go back to the early 1990s, the evidence reported by Makuch et al. (1992) suggests that delinquency had been an equally important consideration in the 1990s.

Fact 3: Credit card debt is a major contributor to debt placed in collection.

In 2014, as many as 35 percent of adults had on average $5,178 in nonmortgage debt in collection.[8] According to ACA International (2007)—the earliest survey conducted by the trade association of debt collectors—credit card debt accounted for about one-quarter of all debt placed in collection between 2003 and 2006. In 2006, the average credit card debt in collection was about $2,500 per account and the median was about $1,000. Importantly, ACA International consistently ranks fees earned on credit card debt as one of the highest among debt categories. For example, the mean commission rate on hospital and health-care debt, which is the main

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[8]According to the report by the Consumer Financial Protection Bureau (2015) available at files.consumerfinance.gov/f/201503_cfpb-fair-debt-collection-practices-act.pdf Similar results have been reported earlier by Avery et al. (2003).

contributor to debt placed in collection according to ACA International, was 40 percent in 2006, while it was 60 percent on credit cards.

We use these numbers to obtain an estimated cost of collecting credit card debt. Assuming that the yield per resource spent on collections is the same across different debt categories, the total cost of collecting credit card debt must have been at least $1.5 billion in 2004 (4 percent of the annual charge-offs).[9] While historic costs of debt collections are difficult to come by, Makuch et al. (1992) report much higher costs (37 percent of charge-offs).

Fact 4: The widespread adoption of IT collection systems in the 1990s enhanced collection efficiency.

Finally, our last fact points to major advancements in debt collection methods brought about by the advent of IT-enabled debt collection platforms in the early 1990s. The main hypothesis of our paper is that this progress has had a significant effect on credit markets.

The primary objective of the modern approach to debt collection systems is to avoid the costs of collecting debt from borrowers who have no means to pay back their debt. Modern systems rely on Markov models of the evolution of delinquency to perform a statistical cost-benefit analysis of collecting debt in a particular manner and at a particular point in time, giving rise to what the industry terms as "segmentation and prioritization." While IT had traditionally been used in some capacity, the emergence of comprehensive systems of this kind took place in the late 1980s and diffused throughout the industry in the 1990s.[10]

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[9]Under the equalized yield assumption, the contribution of credit card debt to costs of debt collection should be at least as high as its share in debt placed in collection. We use this share to compute credit card debt collection costs using the gross output of the debt collection industry as the lowest bound estimate of total collection costs in the economy, which according to IBISWorld (2005) was $6.2 billion in 2004. Note that the IBISWorld report focus on the debt collection industry NAICS 56144, and thus excludes in-house collection departments of lenders. To calculate charge-offs, we multiply the charge-off rate on credit card debt by the total revolving debt outstanding.

[10]See Chin and Kotak (2006); Hopper and Lewis (1992); Till and Hand (2003) for an additional description of this approach and Rosenberg and Gleit (1994) for a survey of different methods such as decision trees, neural networks and Markov chains.

The use of IT in debt collection has been associated with major savings and large gains in efficiency. For example, Makuch et al. (1992) report that the new system adopted by GE Capital in the early 1990s saved the company $37 million annually on a $150 million collection budget, amounting to 9 percent of the $400 million in annual charge-offs. Similar claims have been made in studies describing the implementation of similar systems by other banks (e.g., Chin (2006)).

Nowadays IT companies offering debt collection management software to the industry advertise gains that are at least as high. For example, FICO—a leading provider of credit scores—claims gains of 50 percent or more across its clients.[11] A major provider of IT systems, First Data, reports efficiency gains of 48 percent, while specifically attributing them to improved precision of information (Davey, 2009). Portfolio Recovery Associates, one of the largest debt collection agencies that handles credit card debt, boasted that its debt collection efficiency per resource spent increased by 120 percent from 1998 to 2005 primarily due to its proprietary debt collection system.[12]

Moreover, since the mid-1990s all three credit bureaus (Experian, Equifax and TransUnion) have offered collection scores and other collection services to the industry, such as real-time monitoring of flagged accounts and skiptracing.[13] The direct involvement of credit bureaus has made these tools ubiquitous. According to IBISWorld (2013), the revenue share of credit bureaus and rating agencies accounted for by debt collection and risk management services was 7.5 percent in 2013. To put this number in perspective, about 37 percent of the total revenue came from banks and other financial institutions (excluding mortgage originators).

Finally, the success of segmentation and prioritization in collection of credit card debt has led other industries to adopt a similar approach, which further underscores its effectiveness.

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[11] Fair Isaac Corporation (2012).

[12] Portfolio Recovery Associates (2005).

[13] Experian introduced RecoveryScore for charged-off accounts in 1995 (personal communication), while TransUnion has been offering collection scores since at least 1996 (Pincetich and Rubadue, 1997). As an example of collection scores, Section 3, Table 4 in the online Appendix shows that Experian's Bankcard RecoveryScore is correlated with future repayment by currently delinquent consumers.

Examples include Fannie May and Freddie Mac in 1997 for managing delinquent mortgages (Cordell et al., 1998), and New York State in 2009 for collecting unpaid taxes (Miller, 2012). In particular, New York State increased its collections from delinquent taxpayers by \$83 million (an 8 percent increase) using the same amount of collection resources. (For an extended discussion of the debt collection industry and its evolution, see our online Appendix.)

III Theoretical framework

We first propose a simple two-period model to convey most of the economic intuition. In our quantitative analysis we generalize it to a multi-period life-cycle environment so as to better relate it to the data. The novel features of our model build on the costly state verification framework (Townsend, 1979).

The economy is populated by a large number of lenders and a continuum of consumers. Lenders have deep pockets and extend competitively priced credit lines to consumers. They commit to contract terms.

Consumers borrow from lenders to smooth consumption. They face an exogenous income stream $Y > 0$ in each period and begin their life with a stock of pre-existing debt B. With probability $p < 1/2$ they suffer from an idiosyncratic financial distress shock that reduces their second-period income by some fixed amount $E > 0$ (e.g., job loss, divorce, medical bills). The random variable denoting the shock is $d = 0, 1$ and its realization is private information of the borrowers. Lenders only observe an imperfect public signal $\hat{d}$ of the shock. The precision of the signal is denoted by $\pi \in [0, 1]$. The signal reveals d with probability π and is uninformative with probability $1 - \pi$.

Credit is unsecured and consumers can renege on repayment at a pecuniary dead-weight cost θY, where $0 < \theta < 1$. After defaulting, lenders can resort to *debt collection* (state verification

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technology) to recover unpaid debt, which is assumed to be effective only in the case of nondistressed consumers. The (sunk) cost of debt collection per borrower is denoted by $\lambda > 0$ and is borne regardless of the outcome of debt collection.

The sequence of events is as follows: 1) the credit market opens and lenders extend competitively priced credit to consumers; 2) consumers privately observe the shock and the signal is revealed; 3) consumers choose consumption and decide whether to repay or default; 4) debt collection takes place. We assume that the shock precedes consumption choices to gain analytic tractability.

We next describe each of the model's actors, their optimization problems, and analyze the resulting equilibrium to highlight the key mechanism of the model. For ease of exposition, all proofs are relegated to the Appendix.

III.A   Lenders

Credit contracts are flexibly specified as an option to borrow up to a specified credit limit L and finance charges are assumed non-distortionary. That is, for access to a credit line of a size L, the borrower pays a fixed cost I charged in the second period (at repayment).[14] Lenders commit to a debt collection strategy, which is specified as a probability $P(\hat{d})$ that debt collection will take place following default and signal realization $\hat{d}$. Bertrand competition between lenders implies that the equilibrium contract maximizes the consumer's expected utility subject to a zero profit condition. For simplicity, we normalize the cost of funds to zero.

Let $\Pi(S, I, L, P)$ be the profit earned on a fixed contract (I, L, P) and let $\delta(S, I, L, P)$ be the consumer's default decision, where $S := (\hat{d}, d)$ describes consumer's exogenous state. We assume the following as far as the payments are concerned: i) if the consumer does not default ($\delta = 0$),

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[14]In an earlier version of the paper credit lines were characterized by interest rates (i.e., finance charges were proportional to borrowing rather than fixed). Having a fixed finance charge simplifies the consumer problem by eliminating the intertemporal distortion of consumption caused by interest rates. For robustness purposes, in the online Appendix, we quantitatively analyze a model with interest rates and obtain similar results.

the lender collects interest I and the principal; ii) if the consumer does default ($\delta = 1$), and additionally suffers from a distress shock ($d = 1$) or is not subject to debt collection, the lender loses L because the consumer maxes out on the credit line; iii) if the consumer is nondistressed ($d = 0$), and debt collection does take place, the lender recovers the principal and the borrower pays an exogenous penalty interest $\bar{I} > 0$. Together these assumptions imply

$$
\Pi(S, I, L, P) := \begin{cases} I & \text{if } \delta(S, I, L, P) = 0 \\ -L + (1-d)P(\hat{d})(L + \bar{I}) & \text{if } \delta(S, I, L, P) = 1. \end{cases} \tag{1}
$$

Let Λ denote the cost of collecting debt on a normalized portfolio of accounts of measure one. This cost depends on the unit cost λ of each collection as well as the measure of consumers subject to debt collection ex post, $\delta(S, I, L, P)P(\hat{d})$. Hence,

$$
\Lambda(S, I, L, P) := \lambda\delta(S, I, L, P)P(\hat{d}). \tag{2}
$$

Given the ex-ante expected indirect utility function of consumers, denoted by $V(I, L, P)$ — defined in the next section — the lender problem can be summarized as follows:

$$
\max_{I, L, P} V(I, L, P) \tag{3}
$$

subject to

$$
\sum_S [\Pi(S, I, L, P) - \Lambda(S, I, L, P)]Pr(S) \geq 0,
$$

where $Pr(S)$ denotes the probability distribution of the exogenous state $S = (\hat{d}, d)$.[15]

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[15] $Pr(S) := Pr(\hat{d}, d)$ is given by $Pr(0,0) = (\pi + (1-\pi)(1-p))(1-p)$, $Pr(1,0) = Pr(0,1) = (1-\pi)(1-p)^2$, and $Pr(1,1) = (\pi + (1-\pi)p)p$.

III.B   Consumers

Consumers borrow from lenders to maximize their utility. The utility function is $U(c, c') = u(c) + u(c')$, where c is consumption in the first period and c' is consumption in the second period. We assume that u is strictly increasing, strictly concave and differentiable.

Consumers' decision to default δ maximizes their utility. Hence, δ solves:

$$\delta(S, I, L, P) := \begin{cases} 1 & \text{if } D(S, I, L, P) > N(S, I, L, P), \\ 0 & \text{otherwise} \end{cases} \tag{4}$$

where $N(\cdot)$ is the indirect utility function conditional on repayment and $D(\cdot)$ is the indirect utility conditional on default.[16]

The indirect utility conditional on repayment is

$$N(S, I, L, P) := \max_{c, c', b} U(c, c'), \tag{5}$$

subject to

$$0 \leq c = Y - B + b,$$

$$0 \leq c' = Y - b - I - dE,$$

and the borrowing constraint given by

$$b \leq L. \tag{6}$$

To define the indirect utility from defaulting, we introduce more notation. Let $m = 0, 1$ be the random variable indicating debt collection and recall that its probability distribution is

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[16] We assume that, when a consumer is indifferent between defaulting or not, she does not default.

determined by P.[17] $D(S,I,L,P)$ is then defined as follows:

$$D(S,I,L,P) := \max_{c,c',b} \sum_m U(c,c')Pr(m), \tag{7}$$

subject to

$$0 \leq c = Y - B + b,$$

$$0 \leq c' = (1-\theta)Y - b + L - dE - m(1-d)(L+\bar{I}),$$

and (6).

Finally, the ex-ante expected indirect utility that determines the choice of contracts is given by

$$V(I,L,P) := \sum_S \left(\delta(S,I,L,P)D(S,I,L,P) + (1-\delta(S,I,L,P))N(S,I,L,P)\right)Pr(S). \tag{8}$$

Since the contract on hand is an endogenous object, we set the utility of the consumer to negative infinity whenever positive consumption is not feasible.

III.B.1   Default set

Before we proceed, it is instructive to characterize consumer's decision to default. To ensure V is a well-defined object, we assume that the budget constraint is non-empty when the consumer defaults, which is guaranteed by the following assumption.

Assumption 1. $\bar{I} < (2-\theta)Y - B$.

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[17]We assume that the lender's information set is fully summarized by the signal. In particular, no additional information can be extracted by observing how much the consumer borrows. This could be justified by the presence of a savings technology that allows consumers to initially borrow L and allocate resources across periods as a function of the shock.

Lemma 1. *1) If $I > \theta Y + \bar{I}$ the consumer always defaults. 2) If $I \leq \theta Y + \bar{I}$ then i) if $L \leq \theta Y - I$, the consumer always repays; and ii) if $L > \theta Y - I$, the distressed consumer ($d = 1$) defaults but the nondistressed consumer repays if and only if $P(\hat{d}) \geq \bar{P}(I, L)$, where $\bar{P}(I, L) \in (0, 1]$ is a continuous and increasing function of I, independent of π.*

Intuitively, consumers never default on credit lines with $L \leq \theta Y - I$. We refer to such credit lines as *risk-free*. Note that Bertrand competition implies $I = 0$ on the equilibrium risk-free lines. Since the ex-ante utility function is weakly increasing in L, there is no loss in assuming that when a risk-free credit line is offered in equilibrium it features $I = 0$ and $L = \theta Y$. Conversely, all profit feasible credit lines with $L > \theta Y$ are exposed to a positive probability of default, implying $I > 0$. We refer to such credit lines as *risky*.

III.C   Equilibrium

The equilibrium comprises strategies δ, b, I, L, and P, and the corresponding indirect utility functions such that they satisfy (3), (5), (7), and (8).

Lemma 2. *If Assumption 1 holds, an equilibrium exists.*

In what follows, we ensure that in equilibrium risky contracts are feasible and the default rate is less than one. That is, lenders set $P(\hat{d}) = \bar{P}(I, L)$ following at least one signal realization, as opposed to letting everyone default and collecting debt ex-post to break even.[18]

Assumption 2. $p\lambda \leq (1 - p)\theta Y$.

Intuitively, the left-hand side of Assumption 2 is the cost of collecting debt from all defaulting consumers who are distressed. The right-hand side is the deadweight loss from defaulting suffered by nondistressed consumers when $P(\hat{d}) < \bar{P}(L, I)$ for all $\hat{d}$. In short, the assumption guarantees

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[18]Low collection costs and low pecuniary costs of defaulting may give rise to an equilibrium in which everyone defaults.

that, *for some* $\hat{d}$, the costs of collecting from distressed delinquent consumers so as to prevent nondistressed consumers from strategically defaulting are lower than the deadweight cost of strategic default.

Lemma 3. *If Assumption 2 holds, then: i) the set of profit-feasible risky contracts is non-empty, and ii) equilibrium risky contracts feature default prevention for at least one signal realization (i.e., $P(\hat{d}) \geq \bar{P}(I, L)$ for some $\hat{d}$).*

IV Comparative statics

We next characterize how IT progress (improved signal precision π) affects the equilibrium of our model. We derive two key results. The first result shows that the use of signals in debt collection takes place only after signal precision reaches a certain critical level. The second result shows that the use of signals is associated with a more prevalent use of risky loans and leads to both a higher default rate and higher discharged debt per default. In the next section, we show that in a calibrated model these effects can result in a change in the charge-off rate similar to the one in the data (see fact one in Section II).

IV.A IT progress and the evolution of debt collection technology

Our first result shows that, contingent on issuing risky credit, there is a threshold on π above which lenders adopt a collection strategy that involves different collection probabilities depending on the realization of the signal $\hat{d}$. We refer to this threshold as the *IT adoption threshold.*

Lemma 4. *There exists $0 < \pi^* < 1$ such that if $L > \theta Y$ in equilibrium, then:*

(i) *(indiscriminate collection) $P(\hat{d}) = \bar{P}(I, L)$ for all $\hat{d}$ and all $\pi < \pi^*$;*

(ii) *(selective collection) $P(0) = \bar{P}(I, L)$ and $P(1) < \bar{P}(I, L)$ for all $\pi > \pi^*$.*

The presence of an IT adoption threshold is brought about by the inherent trade-off between the deadweight cost of strategic default and the lower cost of collecting debt under selective collection. On the one hand, having $P(1) = \bar{P}$ is costly because with probability $\bar{P}$ all distressed borrowers under the signal of distress are subjected to debt collection, which costs $\bar{P}\lambda$ per distressed borrower. On the other hand, if $P(1) < \bar{P}$ all nondistressed borrowers under $\hat{d} = 1$ default. When the signal precision is low, there are proportionally more of these agents, making the deadweight loss of strategic default under $\hat{d} = 1$ large relative to $\bar{P}\lambda$.

More formally, we prove the existence of an adoption threshold π^* by showing that the utility from the preferred credit line using selective collection is strictly increasing in signal precision, due to the aforementioned reduction in both deadweight losses and collection costs. In contrast, the utility from the best line sustained by indiscriminate collection is constant in π. The crossing point is necessarily interior because, first, perfect signal precision eliminates strategic default under selective collection and collection costs are zero; and, second, when $\pi = 0$ Assumption 2 guarantees that prevention of strategic default for all $\hat{d}$ is optimal.

IV.B   IT progress and the risk composition of debt

We next turn to our main result showing that IT progress can lead to an increase in both debt discharged per default and the default rate. To demonstrate this, we show that an increase in signal precision can lead to a switch from a risk-free or a risky credit line sustained by indiscriminate collection to a risky credit line sustained by selective collection. In either case, this leads to the rise in both the default rate as well as the amount of debt discharged in equilibrium. The switch from a risk-free to a risky contract with selective collection arises when the cost of collecting debt λ is sufficiently high, while the switch from indiscriminate to selective-collection happens when unit collection costs are low. As we will see in the next section, both forces are at play in the quantitative model.

The condition for the switch, formally stated in the next lemma, is fairly intuitive. First, the pecuniary dead-weight cost of defaulting, θY, must be low enough to be offset by the consumption smoothing benefit from defaulting. If it is not, there is no default in equilibrium. In addition, the increase in signal precision must be large enough to result in the use of signals in debt collection (adoption of selective collection to sustain risky lending).

Lemma 5. *There exists $\theta^* > 0$, independent of λ, such that for all $\theta < \theta^*$ there is a threshold $\pi^{**}(\theta) < 1$ such that $L > \theta Y$ in equilibrium for all $\pi > \pi^{**}(\theta)$, and it is sustained by selective collection.*

We are now ready to present the main result, which summarizes the model's key comparative statics: IT progress leads to an increase in credit but also to an increase in its exposure to default risk through the use of signals in debt collection. These predictions are qualitatively consistent with the stylized facts laid out in Section II.

Proposition 1. *If $\theta < \theta^*$ there exists $\underline{\pi}, \bar{\pi}$ satisfying $0 < \underline{\pi} \leq \bar{\pi} < 1$ such that an increase in precision from $\pi_0 < \underline{\pi}$ to $\pi_1 > \bar{\pi}$ induces, in equilibrium,*

(i) the adoption of selective collection;

(ii) an increase in credit limits;

(iii) an increase in the probability of default;

(iv) an increase in the amount of debt discharged in default.

In addition, there exists $\bar{\lambda} > 0$ such that $L = \theta Y$ at π_0 for all $\lambda > \bar{\lambda}$, and $L > \theta Y$ with indiscriminate collection at π_0 for all $\lambda < \bar{\lambda}$.

Figure 2 illustrates the premise behind the proof of Proposition 1. The figure plots the indirect utility V associated with each of the three contracts that are candidate to equilibrium:

the best risky contracts sustained using selective collection and indiscriminate collection, and the risk-free contract. The risky contract sustained by selective collection is the only one that is affected by the technology (π on horizontal axis), while the other two are invariant to signal precision. The intersection between them determines the level of technology at which a switch occurs. The position of the utility function from the risk-free contract determines whether the switch is from the risky-free contract or from a risky contract sustained by indiscriminate collection. Our results establish the conditions on θ and λ so that technology has an impact on the type of contract that is extended to the consumer.
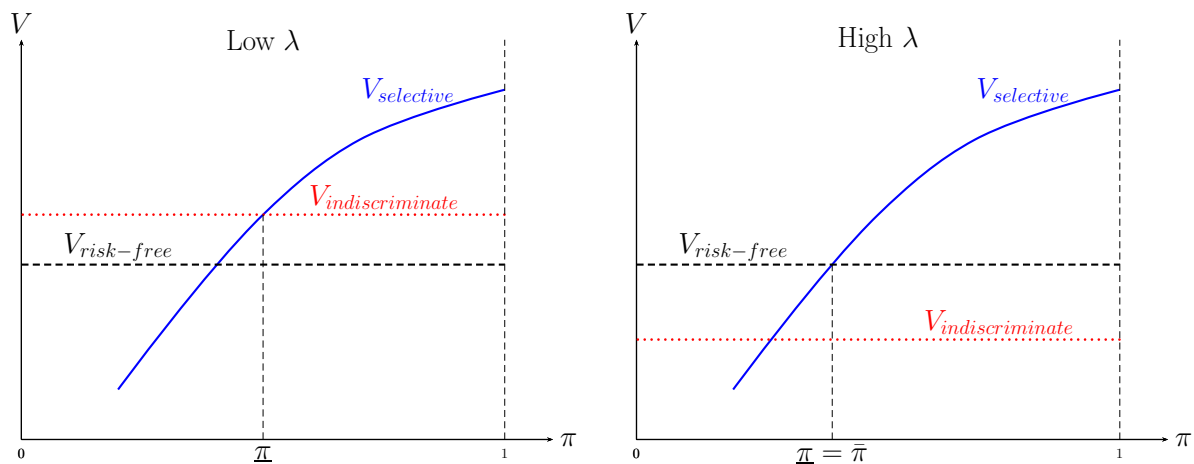
Figure 2: Effect of IT Progress the Choice of Contracts.

Having established that our model can *qualitatively* deliver our stylized facts, it remains to be shown that the described effect is *quantitatively* significant. The main finding in the next section is that this is the case for the following intuitive reason. Similar to the standard theory that we build on, the welfare gains associated with the default option are fairly modest in our setup as long as p is small. As a result, the default rate predicted by the model turns out to be fairly sensitive to the cost of providing risky loans, which debt collection technology

affects. Interestingly, the presence of debt collection technology — which also results in a targeted enforcement of credit contracts — implies that the model does not suffer from the usual difficulties of sustaining the high level of indebtedness and the high default rate seen in the data. This is because selective debt collection imposes high default penalties on most non-distressed borrowers without disincentivizing default by distressed borrowers.

V Quantitative analysis

We now generalize our model to quantitatively relate it to the data. We do so by embedding our basic two-period setup in a more standard life-cycle environment à la Livshits et al. (2010) and Chatterjee et al. (2007). Our extended setup adds multiple periods, endogenous debt accumulation across the periods, income uncertainty, and partially defaultable expense shocks. In what follows, we describe the key modifications of the model, its parameterization, and then present our quantitative results.

V.A Extended model setup

We assume that consumers live for T periods. In each period, their state is summarized by age $t = 1, ..., T$, income realization $z = 1, ..., n$, the distress shock $d = 0, 1$, the public signal of the distress shock $\hat{d} = 0, 1$, and debt carried into the period B (savings if negative).

Let $S = (t, z, d, \hat{d})$ be period t exogenous state and let $S' = (t+1, z', d', \hat{d}')$ be the $t+1$ generic state. Let (I, L, P) be the equilibrium contract extended in state (B, S) and let (I', L', P') be the equilibrium contract extended in state (B', S').[19]

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[19]P is allowed to depend only on $\hat{d}$, as in the two-period model.

The consumer's default decision δ in the extended model solves

$$V(B, S; I, L, P) := \max_{\delta \in \{0,1\}} \{(1 - \delta)N(B, S; I, L, P) + \delta D(B, S; I, L, P)\},$$

where $N(\cdot)$ and $D(\cdot)$ are the value functions associated with repayment and default, respectively. The decision function δ is as defined in (4). The value function conditional on repayment, N, is given by

$$N(B, S; I, L, P) := \max_{C, B'} \{u(C) + \beta \mathbb{E}_S V(B', S'; I', L', P')\},$$

subject to the budget constraint

$$0 \leq C \leq Y(z, t) - B + B' - I - dE(z), \tag{9}$$

and the borrowing constraint

$$B' \leq L. \tag{10}$$

The income of the agent $Y(z, t)$ is stochastic and depends on both the age of the agent (t) and the income state (z), which follows a Markov process. The size of the distress shock $E(z)$ and its probability $p(z)$ also depend on the income state. We define these functions in the next section. $\mathbb{E}_S$ denotes the expectation operator conditional on state S.

The value function associated with defaulting is

$$D(B, S; I, L, P) := \max_{C, B'} \mathbb{E}_S \{u(C) + \beta \mathbb{E}_S V(0, S'; 0, 0, 0)\},$$

and its formulation reflects the standard assumptions that consumers are excluded from the credit markets in the period following default.[20] In addition, we allow defaulting consumers

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[20]Jagtiani and Li (2015) find that consumers filing for bankruptcy in the U.S. have much lower access to credit (lower credit limits) in the years after filing, even if their credit scores improve substantially. In addition, the

to discharge a fraction $1 - \phi(z)$ of the distress shock (e.g. medical bills). Accordingly, if debt collection does not take place ($m = 0$), the budget constraint following default is given by

$$0 \leq C \leq (1 - \theta)Y(z,t) - B + B' - \phi(z)dE(z), \tag{11}$$

and when debt collection does take place ($m = 1$), it is given by

$$0 \leq C \leq (1 - \theta)Y(z,t) - B + B' - \phi(z)dE(z) - X, \tag{12}$$

where $X = B' + I$ as long as

$$C \geq C_{\min} - \theta Y(z,t), \tag{13}$$

and otherwise $0 \leq X < B' + I$ so as to ensure (13) holds with equality. If this is not possible, it is assumed that debt collection is ineffective and $X = 0$. Borrowing B' is similarly restricted by (10). The minimum consumption restriction imposed by equation (13) generalizes our earlier assumption that no debt can be collected from distressed consumers. Such a generalization is necessary given multiple income states and endogenous debt accumulation across the periods.

As in our two-period model, lenders offer competitively priced one-period credit lines after observing $z, \hat{d}$, and B (they also know the consumer's age). Their cost of funds is assumed to be positive and given by τ. The cost of funds lowers the stream of profits earned on a contract by an amount proportional to actual borrowing, $\tau \mathbb{E}_z B'$. In addition, as explained above, debt collection is assumed to be effective to the extent that the minimum consumption constraint (13) holds. Apart from these modifications, the lender problem is analogous to (3).

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one-period exclusion from the credit market has little impact on the results in the context of our model, given that our calibration procedure will simply yield a different value of θ without such exclusion.

V.B   Parameterization

We assume that a single model period corresponds to two years in the data. The total number of periods in the model is chosen to match the life expectancy conditional upon reaching 18 years old, which implies $T = 31$. It is assumed that the last 6 periods are retirement periods and the first 25 are working age periods.

During the working age income $Y(z,t)$ is stochastic and during retirement it is deterministic. The utility function u exhibits constant relative risk aversion with a risk aversion parameter of 2. Consumption is age adjusted as in Livshits et al. (2007) so as to reflect the variations in household size over the life cycle.[21]

V.B.1   Independently selected parameters

During working age consumer's income is given by $Y(z,t) = A(t)Z(z)$, where $z = 1, 2, ..., 6$ follows a Markov switching process and $A(t)$ denotes a deterministic trend. The initial value of income is drawn from the ergodic distribution of the process and is stochastic across individuals. The transition matrix $P(z|z_{-1})$ of the Markov process is age-invariant until retirement.

To choose the parameters of the income process during the working age and the distress shock process, we start with the process for log earnings used by Livshits et al. (2010) as well as their reported estimates of major life-cycle shocks (referred to as *expense shocks* in their paper). These additional shocks include divorce, unwanted pregnancy, and medical bills. We estimate $(A(t), Z(z), P(z|z_{-1}))$ and $(E(z), p(z), \phi(z))$ by assuming that the distress shock absorbs all life-cycle shocks as well as any drops in earnings that are larger than 50 percent of the mean value of the process.[22] We assume that only medical bills can be directly discharged by defaulting,

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[21]Consumption that enters the utility function is C_t/ν_t, where ν_t is extrapolated from the values assumed by Livshits et al. (2007) due to a different period length in their model.

[22]Since Livshits et al. (2010) use a triennial model, we scale the probability of the life-cycle shocks reported by them. That is, we assume that the small expense shock is -0.26 and that it occurs with probability $0.071 \times (2/3)$ (per our model period); we assume that the large expense shock is -0.264 and that it occurs with probability

which determines the value of ϕ. The distress shock is $(E, p, \phi) = (0.24, 0.15, 0.9)$ for the lowest realization of z and $(E, p, \phi) = (0.33, 0.05, 0.5)$ otherwise. The transition matrix and income brackets are reported in the online Appendix.

We assume that throughout retirement income is constant and equal to the average of the consumer's realized income in the period before retirement and the average income in the economy, appropriately scaled down to imply a 70 percent median replacement rate (Munnell and Soto, 2005).

To account for the difference between interest earned on savings (normalized to zero) and interest paid on debt, we assume lenders' cost of funds is $\tau = 0.0816$ (4 percent per annum).[23]

To set the value of $C_{\min}$, we use Title 3 of the Consumer Credit Protection Act (CCPA) and relate it to our model using equations (9) and (11). Title 3 bans wage garnishments when disposable weekly income falls below the minimum threshold of 30 times the federal hourly minimum wage. We interpret this clause as an implicit target to preserve minimum consumption of a median debtor in the economy and back out $C_{\min}$ accordingly.[24]

$0.0046 \times (2/3)$. The continuous state process for earnings is also taken from Livshits et al. (2010) and it is given by $y = a_t \eta_t \zeta_t$, where a_t is a deterministic time trend, ζ is the persistent component, and η is the transitory component. The persistent component follows an AR(1) process in logs, $\log(\zeta) = .95 \log(\zeta_{-1}) + \epsilon$, where $\epsilon \sim N(\mu = 0, \sigma^2 = 0.025)$. The transitory component is log-normally distributed, $\log(\eta) \sim N(\mu = 0, \sigma^2 = 0.05)$. We convert the joint stationary process $\eta \zeta$ to a biannual process by averaging two consecutive annual realizations. We assume that the single distress shock absorbs all distress shocks reported by Livshits et al. (2010), as well as any realizations of the stationary component that falls 50 percent below the mean value of the process. We use the residual to estimate the Markov process (Z, P). $Y(z, t)$ is the product of the Markov process and the deterministic trend $A(t)$, where the deterministic trend is interpolated from a polynomial approximation of a_t's reported by Livshits et al. (2010) to adjust for the different period length in our model.

[23] To set the value of τ we calculate the annual interest rate on credit card debt reported by Federal Reserve Board of Governors, net of the charge off rate on credit card debt and the yield on five years to maturity government bonds. Consistent with the way we treat other credit market related calibration targets, we estimate a trend line between 1993 and 2004 and target the trend value rather than the actual value of the series in 2004.

[24] $C_{\min} = 0.2\bar{Y}$ in our model, where $\bar{Y}$ is the median income in the economy. To calculate it, we proceeded as follows. First, we noted that, when (13) binds, by (11) and (13), the consumer's budget constraint can be rewritten as: $C + B = \mathcal{Y} - \mathcal{R}$, where $\mathcal{Y} := Y - \phi dE$ denotes consumer's disposable income and $\mathcal{R} = L - X$ is the amount recovered in debt collection when (13) binds. We then define $\underline{\mathcal{Y}}$ as the income of a person whose weekly earnings are 30 times the minimum hourly wage. The restriction given by Title 3 of CCPA implies that $\mathcal{R} = 0$ when $\mathcal{Y} = \underline{\mathcal{Y}}$, and we assume that the minimum consumption implicit to Title 3 restriction is the level of consumption of a median debtor with disposable income $\underline{\mathcal{Y}}$ (from whom nothing is collected). Consequently, $\frac{C_{\min}}{\bar{Y}} = \frac{\underline{\mathcal{Y}}}{\bar{Y}} - \frac{\bar{B}}{\bar{Y}}$, where $\frac{\bar{B}}{\bar{Y}}$ corresponds to the debt-to-median-income ratio assumed in our calibration. To arrive at the final number, we used the following values: 1) $\underline{\mathcal{Y}} = 30 \times \$5.3 \times 52$ weeks, where $\$5.3$ corresponds

V.B.2 Jointly calibrated parameters

We calibrate β, λ, θ, and π jointly by targeting the following moments in the U.S. data: 1) the 2004 trend value of debt-to-median-income ratio of 15.1 percent, 2) the 2004 trend value of net charge-off rate on credit card debt of 5.2 percent, and 3) the 2004 estimated aggregate costs of collecting credit card debt of 4 percent relative to charge-offs, as reported at the end of Section II (fact 2). In addition, consistent with the evidence of the widespread adoption of IT by 2000s, as our fourth target, we restrict attention to the parameter values that are consistent with the fact that most lenders already used selective collection by 2004. Specifically, we impose a requirement that at least 90 percent of risky contracts in the model are sustained using selective collection. This qualitative restriction allows us to distinguish between the state of IT in debt collection as described by π and the cost of collecting debt λ. Without this restriction the numeric targets 1-3 are insufficient to identify the parameters of the model.[25]

Using a global search over the entire parameter space, we have verified that signal precision must be $\pi = 0.76$ or higher to match the targets given the values of the independently calibrated parameters. We have also verified that the above four conditions uniquely pin down parameter values up to the level of initial precision π. To cover a range of possible cases for the initial value of π, we report our results for three initial levels of signal precision: $\pi = 0.76$, $\pi = 0.78$ and $\pi = 0.8$. The values of the parameters are reported in Table 2.

V.B.3 Interpretation of the calibrated value of λ

The implied value of λ in our benchmark calibration ($\pi = 0.78$) is about \$5,091 (in 2004 dollars). The Consumer Financial Protection Bureau (2016) reports an estimated range of

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to the average minimum hourly wage across the U.S. states in 2004; 2) $\bar{Y} = \$23,355$ corresponds to the net compensation in 2004 according to the Social Security Administration, https://www.ssa.gov/oact/cola/central. html; 3) $\frac{\bar{B}}{\bar{Y}} = 15.1$ percent is one of our calibration targets.

[25]See the online Appendix for more details.

Table 2: Calibration of Jointly Selected Parameters

	Data*	Model $\pi = 0.76$	$\pi = 0.78$	$\pi = 0.80$
Targeted moments (all in percent)				
Debt/income	15.1	15.1	15.1	15.1
Net charge-off rate	5.2	5.2	5.2	5.2
Collection costs/debt	0.21	0.21	0.21	0.21
Collection costs/charge-offs	4.0	4.0	4.0	4.0
Use of IT in collections	> 90	100	100	100
Calibrated parameter values				
Discount factor β		0.7296	0.7306	0.7339
Cost of defaulting $1 - \theta$		0.0774	0.0777	0.079
Collection cost λ		0.0930	0.1015	0.1090

*Reported data values for debt-to-income ratio and charge-off rate pertain to trend values for 2004 and 1990, respectively. We estimated the trend using the time series from 1985 to 2004. Section II (fact 3) describes how we estimated the costs of collecting credit card debt.

average litigation costs reported by debt collectors. If a case goes to trial, the average litigation cost reported by the agencies is between $500 and $2500 (in 2016 dollars).

To interpret properly our model vis-à-vis the data, it is important to take into account the fact that in the data debt collection costs are often borne by multiple lenders and litigation represents only a fraction of the overall costs, as the borrowers may have multiple credit card accounts in default. Hence λ should be interpreted as the cumulative costs of collecting debt borne over a period of two years (model period length). Most importantly, however, what makes the comparison challenging is the fact that the cost λ is borne in the model with a low probability, which may be different than what it is in the data. Specifically, the average collection probability is $P = 0.1$ in our benchmark calibration, implying that the expected cost of collecting debt, $P\lambda$, is as low as $500 (in 2004 dollars).

Table 3: Effect of IT Progress on Credit Markets and Debt Collection

Statistics	Model			Data
Signal precision π	**0.760**	**0.780**	**0.800**	
Use of IT in collections (in percent of total collections)	100	100	100	
	0	0	0	

A. Use of Credit (in percent per annum, unless noted otherwise)

Debt/income	15.1	15.1	15.1	15.1^a
	14.7	14.6	14.2	8.5^a
Charge-off rate	5.2	5.2	5.2	5.2^b
	3.3	3.2	2.9	3.4^b
Defaults per 1,000	18	18	17	19^c
	13	13	12	
Strategic defaults per 1,000	2.1	1.9	1.8	
	0	0	0	
Utilization rate	63	63	62	47^d
	65	65	65	46

B. Debt Collection (in percent per annum)

Efficiency gain from using IT/debt	0.11	0.23	0.37	0.31^e
Efficiency gain from using IT/charge-offs	3.4	7.3	12.9	9^e
Efficiency gain from using IT/charge-offs (myopic)	31	33	35	
Frequency of collections	10	9	9	9.2^f
	47	43	40	
Collection costs/debt	0.21	0.21	0.21	0.21
	0.71	0.71	0.67	1.25^g
Collection costs/charge-offs	4	4	4	4^h
	22	22	23	37^g

^{a,b}Trend values for 2004 and 1989. Linear trends estimated using time series from 1985 to 2004. ^{c}As reported in Section II (fact 2), Table 1. The measure focuses on delinquency rate on newly opened accounts within past 24 months, which after two years are still delinquent with no bankruptcy on record. Given newly opened accounts are 12 months old on average, the rate approximately captures persistent delinquency rate per annum. ^{d}Pulled from the 1989 and 2004 waves of the Survey of Consumer Finance. ^{e}Source: Makuch et al. (1992). See also Section II (fact 4). ^{f}Average number of lawsuits, judgments or wage garnishments filed per delinquent borrower. Computed using credit bureau data described in Section II (fact 2). ^{g}Source: Makuch et al. (1992). ^{h}Assumed calibration target. See also Section II (fact 3).

V.C Quantitative comparative statics results

The goal is to show that IT progress in debt collection is consistent with the stylized facts discussed in Section II. Specifically, we ask here to what extent by making our model consistent with stylized facts three and four we can deliver on stylized fact one.

Table 3 reports our results. The results pertain to the effect of reducing signal precision from the calibrated level in year 2004 so as to undo IT adoption in debt collection (i.e. induce a switch to indiscriminate debt collection). Each row of Table 3 contains two numbers: the top row pertains to the calibrated precision level so as to match the targets for year 2004, and the bottom row corresponds to zero precision to illustrate the impact of IT adoption. The first three columns of Table 3 contain three admissible calibrations of our model, as listed in Table 2. The last column of Table 3 report the values in the data whenever possible. Recall that the first case, $\pi = 0.76$, is the lowest precision level that is consistent with our calibration targets for 2004.

V.C.1 Credit markets

Panel A of Table 3 focuses on the use of credit. Our main finding is that the model predicts a quantitatively sizable change in the charge-off rate as a result of IT progress in debt collection. The charge-off rate in the model goes down from the calibrated value of 5.2 percent to less than 3.3 percent, which is similar to the observed change in the data. In terms of the overall growth of borrowing, the model does not do as well and accounts for only a small fraction of the observed change in the data. This indicates that, while the use of risky debt is fairly sensitive to the wedge introduced by debt collection, borrowing is not.

To see more clearly what drives these changes in the model, Figure 3 presents the breakdown of loan types in our comparative statics exercise. As is clear from the figure, the main change is the emergence of risky loans sustained by selective collection (third column) at the expense of

both risk-free loans (first column) and risky loans sustained by indiscriminate collection (second column).[26]
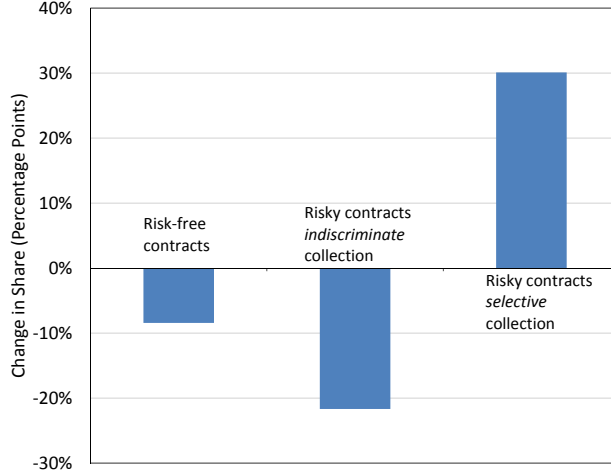

Figure 3: Change in the Share of Each Loan Type ($\pi = 0 \rightarrow \pi = 0.78$)

To shed more light on how these changes contribute to the change in the charge-off rate in the model, it is instructive to consider a simple decomposition of the change in the net charge-off rate into the extensive margin (default rate) and the intensive margin (amount defaulted on per delinquent borrower):

$$\text{Charge-off Rate} = \underbrace{\text{Default Rate}}_{\text{contributes 72 percent}} \times \underbrace{\frac{\text{Average Discharge per Delinquency}}{\text{Average Debt per Consumer}}}_{\text{contributes 28 percent}} \qquad (14)$$

The extensive margin is more important, contributing 72 percent to the change in the charge-off rate between the $\pi = 0$ economy and the $\pi = 0.78$ economy. This increase is driven by both

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[26]Our quantitative model, in contrast to the two-period model, gives rise to a second type of indiscriminate risky loans: risky loans sustained by no threat of debt collection. These contracts are characterized by tight credit limits to ensure that nondistressed agents do not default when $P = 0$, and their quantitative effect is negligible. In Figure 3, we pool those loans under the label of risky indiscriminate loans since sustaining such loans does not involve the use of signals. The reason why such contracts arise here and not in our two-period model is because the two-period model assumes that distress shocks are not defaultable, whereas in the quantitative model a fraction $\phi > 0$ of the shock is assumed defaultable.

the decrease in risk-free and risky contracts sustained by indiscriminate collection in favor of risky contracts sustained by selective collection, which additionally involve strategic default. As Table 3 shows, the rise in strategic default accounts for about a third of the overall change in the default rate in the model.

The fact that the intensive margin plays a role in our exercise may raise a concern that our model may have counterfactual implications for the utilization rate of credit lines (determined by the relation between B' and L). This is not the case. The change in the average utilization is small, which is consistent with the data.

V.C.2   Debt collection

Our model is consistent with industry evidence regarding the effect of IT progress in debt collection on collection efficiency. The first three rows of panel B of Table 3 focus on the efficiency gains from IT adoption, which have been calculated to closely mimic the approach used by Makuch et al. (1992).

Our measure of efficiency gains considers a hypothetical lender who holds a large portfolio of equilibrium accounts in the $\pi = 0$ economy (before IT was adopted). We assume that, after extending the loans, the lender unexpectedly receives a more precise signal (generated by the new IT system). For simplicity, we assume that the new signal precision level is equal to the 2004 calibrated precision levels. We then allow the lender to adjust its collection strategy to maximize profits, keeping I and L unchanged. As far as consumers expectations go, we consider the case of *rational expectations* and *myopic expectations*. Under rational expectations consumers decide to default after they become fully aware of the new signal precision. Under myopic expectations consumers are unaware of the new signal precision. In all cases, we report gains in profitability relative to debt and charge-offs prior to the observation of the signal.

We find that the model falls within a plausible range of the estimated gains from IT adoption

reported by Makuch et al. (1992). In particular, under rational expectations, the model can be consistent with low gains and it can also match higher gains by assuming higher levels of initial signal precision in 2004. Under myopic expectations, the model implies gains that are about three times higher than the ones reported in Makuch et al. (1992). Since borrowers over a longer period of time are likely to become aware of the new technology and delinquency in practice allows them to "test the waters," our preferred measure is the one that assumes rational expectations.[27]

The next two items in Panel B of Table 3 compare the total collection costs to the collection costs reported by Makuch et al. (1992)—a measure of the impact of IT that is somewhat easier to interpret than efficiency gains. We find that our model underpredicts the costs of collecting delinquent debt back in the 1990s, consistent with our focus on the lower bound of collection costs targeted in the calibration. We also verified that it is possible to calibrate our model to higher collection costs. In such a case, the effect of IT progress on the charge-off rate is even more pronounced. See the online Appendix (Section 1.3) for more details.

Finally, Figure 4 considers our comparative statics exercise over the entire range of signal precision (for the parameters associated with the $\pi = 0.78$ calibration). The figure shows that the effect of IT progress on credit market variables is highly nonlinear. As expected, IT progress has very little impact until it reaches a certain level above which the adoption of selective collection grows rapidly with precision. This is consistent with the fact that the adoption of IT in debt collection generally lagged behind the use of IT by the lending industry. For instance, in their survey paper Rosenberg and Gleit (1994) report that, while the 1980s had already witnessed the widespread use of credit scoring as well as an increase automation of credit card account management, the use of segmentation and prioritization in collections was still in its infancy.

[27]The gains from IT adoption are lower under rational expectations because consumers default strategically.
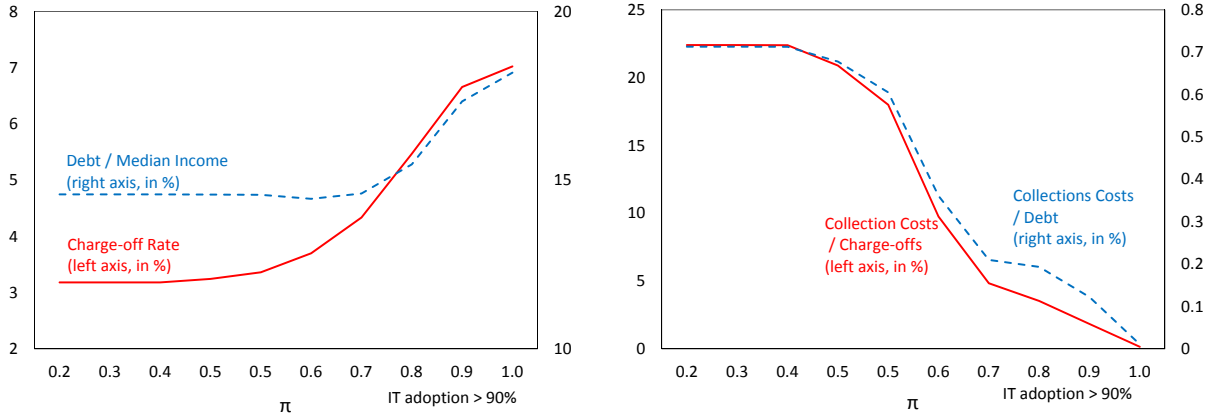
Figure 4: Effect of IT Progress: Lending and Debt Collection ($\pi = 0.78$ calibration)

V.D   Sensitivity and robustness

We finish our analysis by reporting the sensitivity of our results to changes in the parameter values. We also verify the robustness of our results to several qualitative modifications of the setup. In the interest of space, we discuss here the conclusions and report the details in the online Appendix.

1. We studied a version of our model in which the finance charge I is assessed in proportion to borrowing. We found similar results.

2. We analyzed the effect of IT progress captured in a reduced-form fashion as the fall in the transaction cost of lending, both modeled as a wedge between the lending rate and the borrowing rate and as a drop in the fixed cost per contract. We found that, while a decline in such wedges increases the debt-to-income ratio more than in the benchmark model, it leads to a counterfactual behavior of the charge-off rate. This result does not depend on the presence of asymmetric information, which is consistent with a similar finding reported

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Myopic expectations result in no change in strategic default behavior of consumers.

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by Livshits et al. (2010).

3. We looked at a calibration that directly targets the reported historic collection costs by Makuch et al. (1992). Specifically, as reported by this study, we calibrated λ, β, θ to target a charge-off rate of 3.3 percent, costs of collections/debt of 1.25 percent, and costs of collections/discharged debt of 37 percent. We dropped the debt-to-income ratio as a calibration target, given we do not have such information for this particular lender. Since the study pertains to the pre-IT adoption period, we assumed $\pi = 0$ for simplicity. The calibrated model matched the targeted charge-off rate as well as the two measures of collection costs. In terms of comparative statics, the effect of IT progress on the charge-off rate was even more pronounced: an increase in precision from $\pi = 0$ to $\pi = 0.5$ led to an increase in the charge-off rate from 3.3 percent to about 6.5 percent.

4. Finally, we studied the effect of removing debt collection technology from the model.

   We found that without debt collection we cannot match the targeted value of the debt-to-income ratio and the charge-off rate by varying β and θ. The presence of debt collection technology in our model thus crucially enhances our model's ability to match the 2004 levels of gross indebtedness and default statistics on credit card loans.

VI   Limitations and concluding remarks

We conclude the paper by discussing several limitations of our analysis and how they may impact our results.

1. *Formal bankruptcy.* We have not modeled the choice between formal bankruptcy and (persistent) delinquency as two distinct forms of consumer default. This is a potential

limitation of our analysis.[28] However, we do not expect our results to be significantly affected by including formal default. First, our approach is supported by the fact that delinquency is what gives rise to debt collection costs in the data. Second, by calibrating our model to aggregate collection costs, we implicitly take into account any reduction in debt collection costs resulting from bankruptcy filings. One may nonetheless be concerned that the absence of a formal bankruptcy option may interfere with our comparative statics exercise. For this to happen, however, the nature of consumer default would have have to have qualitative changed over the 1990s. Available evidence suggests this was not the case (Dawsey and Ausubel, 2004; Makuch et al., 1992).

2. *Screening.* Our model does not allow for ex-post renegotiation of contracted terms between the lender and the borrower. Both debt forgiveness and the option of filing for bankruptcy can be useful for screening consumers and thus reducing the costs of debt collection.[29] For instance, Kovrijnykh and Livshits (forthcoming) show how the use of partial debt forgiveness can help lenders separate consumers by propensity/ability to repay their debts. While the inclusion of debt forgiveness as a screening device, along the lines of Kovrijnykh and Livshits (forthcoming), may affect our results, it is important to stress that debt forgiveness is still costly for lenders. Hence, as signals become more precise, the use of this tool becomes less attractive than simply preventing agents with non-distress signals from defaulting through the use of selective collection with little or no debt forgiveness. In a reduced-form way, our approach of calibrating model parameters to the aggregate costs of collecting debt takes into account any other collection cost-reducing measures employed in practice, including debt renegotiation.

Likewise, lenders may use the choice between formal and informal default to identify dis-

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[28]For some recent work in this area, see Athreya et al. (2016).

[29]We thank an anonymous referee for pointing this out.

tressed borrowers. Specifically, lenders may offer to subsidize defaulting borrowers' costs of filing for bankruptcy, this way separating distressed from nondistressed delinquent borrowers who may not be eligible for bankruptcy protection. Such a possibility would invalidate our channel if collection costs were substantially higher than formal bankruptcy costs. However, to implement such a strategy, all delinquent borrowers would have to be offered such a deal. Since the average collection cost per delinquent borrower in our calibrated model amounts to just a few several hundred dollars (see Section V.B), lenders would be on very a tight budget to implement such a strategy. Costs of filing for bankruptcy are estimated to be at least several hundred dollars.[30]

3. *Other manifestations of IT progress.* We do not consider improvements in debt collection that imply lower unit collection cost λ, even though such a change would have a similar effect in our model. The reason why we focus on precision of information is twofold. First, while other costs might have decreased, legal collection costs have actually increased. Consumer protection from debt collectors was also on the rise in the 1990s. Second, a fall in λ produces a counterfactual prediction of a more intensive use of debt collection, which we do not see in the data. Specifically, using our credit bureau dataset, we find that the average number of legal collections per delinquent borrower—such as judgments and wage garnishments filed in court—decreased by about 16 percent relative to debt from 2000 to 2006. At the same time, the use of credit bureau information on delinquent borrowers by debt collectors—a close counterpart to the notion of signals in our model—went up by 30 percent. This is consistent with improved precision of information in our model and inconsistent with the effect of a major decline in unit collection costs λ.[31]

4. *Other credit instruments.* Our model restricts attention to a single credit instrument,

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[30]For example, Hynes (2008) reports filing fee of \$299 plus \$1,000-2,000 in lawyer fees in 2007.

[31]While our data do not go back to the 1990s, using court data on wage garnishments from Virginia, Hynes (2006) documents that the growth of debt-related garnishment orders was also negative.

which is a potentially serious limitation. However, there is no immediate reason to think that multiplicity of contractual arrangements or strategic interdependence among (simultaneous) lenders interferes with our particular mechanism. As far as calibration goes, we assumed that the parameter λ represents the total cost of collecting delinquent debt from a given consumer by all lenders over the period of two years.

5. *Other channels of IT progress in credit markets.* Finally, it is important to stress that while our analysis shows that improvements in debt collection technology can have a substantial impact on the risk composition of consumer debt, it does not tell us how large the contribution of our channel is *relative* to other channels that might have been operational in the data. Answering such a question would call for a more complex model and a tighter link between the model and the data, which is beyond the scope of the current paper.

A   Omitted Proofs

Proof of Lemma 1. We denote consumption in each period by $c_\delta(d, m; b)$ and $c'_\delta(d, m; b)$, respectively, and omit their dependence on contract (I, L, P) to ease notation.

1) $I > \theta Y + \bar{I}$ implies $c_1(d, m; b) = c_0(d, m; b)$ and $c'_1(d, m; b) > c'_0(d, m; b)$ for all d, m and b. Hence, $D > N$ since the utility function is strictly increasing in consumption.

2i) Assume $I \leq \theta Y + \bar{I}$ and note that $L \leq \theta Y - I$ implies $c_1(d, m; b) = c_0(d, m; b)$ and $c'_1(d, m; b) < c'_0(d, m; b)$ for all d, m, and b. Hence, $D < N$.

2ii) Assume $I \leq \theta Y + \bar{I}$ and let $L > \theta Y - I$. Observe that $c_1(1, m; b) = c_0(1, m; b)$ and $c'_1(1, m; b) > c'_0(1, m; b)$ for all b and m. Hence, $D > N$ for $d = 1$ and all P. When $d = 0$, we have that $c_1(0, m; b) = c_0(0, m; b)$ and $c'_1(0, 1; b) < c'_0(0, 1; b)$ for all b, and hence $N > D$ for $P = 1$. In addition, $c'_1(0, 0; b) > c'_0(0, 0; b)$ for all b. By continuity of D w.r.t. P (Berge's maximum

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theorem), and the fact that N is independent of P, there must exist $\bar{P} \leq 1$, contingent on contract terms (I, L), such that a nondistressed consumer defaults iff $P(\hat{d}) < \bar{P}$.

Under Assumption 1, $I \leq \theta Y + \bar{I}$ implies $I < 2Y - B$, and thus N is well defined for $d = 0$. D is always well defined by Assumption 1. Continuity of $\bar{P}$ w.r.t. I and L follows from Berge's maximum theorem applied to D and N. N is strictly decreasing in I because I shrinks the budget set of the consumer. Since D is independent of I, P is increasing in I. $\bar{P}(I, L)$ is independent of π because expressions for (5) and (7) are independent of π. $\qquad\square$

Proof of Lemma 2. Without loss of generality, the set of contracts can be restricted to a bounded set $L \in [0, \bar{L}]$, where $\bar{L}$ is some sufficiently high credit limit and $I \in [0, \theta Y + \bar{I} - \varepsilon]$, for some sufficiently small $\varepsilon > 0$. The upper bound on I is implied by the fact that all consumers default when $I > \theta Y + \bar{I}$ (nobody pays I if everyone defaults). Because debt collection is only effective when consumers are nondistressed, default losses are unbounded as a function of L. Since interest revenue is bounded, there exists $\bar{L}$ such that any $L > \bar{L}$ is not profit-feasible. The set of profit-feasible contracts is also non-empty because it contains at least a null contract with $L = 0$ and $I = 0$.

To establish existence, we divide the space of profit-feasible contracts into three subsets and show that the indirect utility V is continuous in (I, L, P) within each subset.

1) Let $I < 2Y - B - E$, and let L and P be arbitrary. The constraint sets underlying (7) (D, hereafter) and (5) (N, hereafter) are nonempty for any $d, \hat{d}$ and L.[32] Since the definitions of D and N involve the maximization of a continuous function over a non-empty compact set, Berge's maximum theorem applies. Hence, D and N are continuous with respect to contract terms I, L, P, implying V (max of two continuous functions) is continuous.

2) Let $I \geq 2Y - B$. The constraint set underlying N (any $d, \hat{d}$) is empty and the consumer always defaults, implying $V = D$.

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[32]Recall that assumption 1 implies $(1 - \theta)Y + Y - B - dE - \bar{I} > 0$.

3) Finally, let $I \geq 2Y - B - E$ and $I < 2Y - B$. The constraint set underlying N is empty following $d = 1$, in which case $V = D$. This holds for any signal realization and for any L, P. For $d = 0$, the constraint sets underlying N and D are both non-empty, and so V is the maximum of the two indirect utility functions as in 1). For a sufficiently low $\varepsilon > 0$, as above, we can wlog restrict attention to values of I in the interval $[2Y - B - E, 2Y - B - \varepsilon]$. N can be made arbitrarily low for I close enough to $2Y - B$ (by making ε smaller), and D is always finite and independent of I. We can thus make sure that the agent always defaults for a sufficiently low ε. Hence, V is continuous in (I, L, P) on the restricted set.

Concluding, contracts that are profit feasible can be effectively represented as a union of three closed and bounded sets on which V is continuous. The existence of equilibrium then directly follows from the Weierstrass extreme value theorem applied to (3) split into three disjoint maximization problems and a max operator over the three resulting values. $\qquad\square$

Proof of Lemma 3. We prove part (i) by showing that there is a non-empty interval of credit limits above $L = \theta Y$ that can yield zero profits under collection strategy $P(\hat{d}) = 1$ for all $\hat{d}$. Consider a nondistressed consumer who expects debt collection with probability $P = 1$. As in the proof of Lemma 1, such a consumer defaults iff $I > I_{\max} := \theta Y + \bar{I}$. Hence, if a risky contract can be sustained through default prevention (by setting $P \geq \bar{P}(I, L)$), it must be that $L > \theta Y$ breaks even at an interest rate that does not exceed $I_{\max}$. Assuming default prevention is successful when $P = 1$, the costs of collecting debt are $p\lambda$ and the losses associated with defaults are pL. This implies that the break-even interest charge is $I_0(L) = pL + p\lambda$. Hence, in order to ensure $I_0(L) \leq I_{\max}$, we must have $L \leq L_{\max} := (\theta Y + \bar{I} - p\lambda)/p$. Accordingly, a credit limit in the interval $(\theta Y, L_{max}]$ can break even if

$$p\lambda \leq (1 - p)\theta Y + \bar{I}, \tag{15}$$

which holds by Assumption 2. Finally, note that $L_{max} > \theta Y$ by Assumption 2, and so the interval $(\theta Y, L_{max}]$ is indeed non-empty.

To prove part (ii), we show that $L > L_{\max}$ — in which case default prevention would not be possible — is infeasible for lenders under Assumption 2. To see why, note that default losses on such a credit line are at least $pL_{\max}$, and even if lenders are able to collect unpaid debt from all nondistressed consumers, the total (penalty) interest revenue is only $(1-p)\bar{I}$. Hence, $L > L_{\max}$ is infeasible if $pL_{\max} > (1-p)\bar{I}$ or

$$p\lambda < \theta Y + p\bar{I}, \tag{16}$$

which holds by Assumption 2.

We next show that for any $L \in (\theta Y, L_{\max})$ default prevention is optimal following at least one signal realization. Compare a break-even contract (I_1, L, P_1) that features default prevention for all signals (i.e., $P_1(\hat{d}) \geq \bar{P}(I_1, L)$) to a break-even contract (I_2, L, P_2) that features no default prevention at all (i.e., $P_2(\hat{d}) < \bar{P}(I_2, L)$ for all $\hat{d}$). We prove that (I_1, L, P_1) attains a higher value in the lender's program (3).

Observe that the indirect utility of distressed consumers is the same in the two cases because credit limits are identical. Hence, the value of the program is solely determined by the utility of nondistressed consumers. In the case of default prevention (first case), the second period consumption of nondistressed consumers is $c_0'(0, m; b) = Y - b - I_1$. In the case of no default prevention, given b, the second period consumption is $c_1'(0, 0; b) = (1-\theta)Y - b + L$ with probability $1 - P_2(\hat{d})$ and $c_1'(0, 1; b) = (1-\theta)Y - b + \bar{I}$ with probability $P_2(\hat{d})$. Since the formula for the first period consumption is identical between the two cases ($c = Y - B + b$ and L are the same), we need to show that the second period consumption when $d = 0$ under (I_1, L, P_1) is higher than the *expected* second period consumption under (I_2, L, P_2). The utility function is strictly concave, hence the fact that c' is a random variable under the latter contract only lowers $V(I_2, L, P_2)$

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relative to the utility from *expected consumption*. Therefore, if we show that consumption under (I_1, L, P_1) is greater than expected consumption under (I_2, L, P_2), we would have proven that $V(I_1, L, P_1) > V(I_2, L, P_2)$. The expected consumption is given by $(1 - \theta)Y - b - P_2(\hat{d})\bar{I}$ under (I_2, L, P_2), which can be expressed as $Y - b - (P_2(\hat{d})\bar{I} + \theta Y)$. Hence, $V(I_1, L, P_1) > V(I_2, L, P_2)$ if

$$(1 - p)I_1 < (1 - p)P_2(\hat{d})\bar{I} + (1 - p)\theta Y. \tag{17}$$

Now, the zero profit condition implies that I_1 has to cover default losses and collection costs. Accordingly, $(1 - p)I_1 = pL + pP_1(\hat{d})\lambda$. Likewise, in the case of no default prevention, $(1 - p)P_2(\hat{d})\bar{I}$ has to similarly cover default losses and collection costs, implying $(1 - p)P_2(\hat{d})\bar{I} = (1 - p)(1 - P_2(\hat{d}))L + pL + P_2(\hat{d})\lambda$. Since the last equation implies $pL < (1 - p)P_2(\hat{d})\bar{I}$, (17) holds under Assumption 2 by the following evaluation:

$$(1 - p)I_1 = pL + pP_1(\hat{d})\lambda < (1 - p)P_2(\hat{d})\bar{I} + p\lambda < (1 - p)P_2(\hat{d})\bar{I} + (1 - p)\theta Y.$$

$\square$

Proof of Lemma 4. In what follows, we drop the dependence of $\bar{P}$ on (I, L) to ease notation. We first show that, while a deviation from full default prevention $P(\hat{d}) \geq \bar{P}$ for all $\hat{d}$ to no default prevention $P(\hat{d}) < \bar{P}$ for all $\hat{d}$ is not possible by Lemma 3, it may nonetheless be optimal to set $P(\hat{d} = 0) = \bar{P}$ and $P(\hat{d} = 1) < \bar{P}$. To see why, consider the argument used in Lemma 3. There we have demonstrated that default prevention is optimal because

$$(1 - p)\theta Y - p\lambda\bar{P} > 0. \tag{18}$$

Rewriting the above condition as

$$(1-p)(Pr(0|0)\theta Y - Pr(1|0)\lambda \bar{P})+$$

$$p(Pr(0|1)\theta Y - Pr(1|1)\lambda \bar{P}) > 0, \tag{19}$$

where $Pr(x|z)$ denotes $Pr(d = x|\hat{d} = z)$, it is clear that either one or both terms on the left-hand side of (19) must be positive. Now, because $Pr(0|0) > Pr(0|1)$ and $Pr(1|0) < Pr(1|1)$, if only one of these two terms is positive, it must be the first one. Accordingly, by an argument analogous to the one made in Lemma 3, but applied separately to each signal realization, $Pr(0|0)\theta Y - Pr(1|0)\lambda \bar{P} > 0$ implies $P(0) = \bar{P}$, while $Pr(0|1)\theta Y - Pr(1|1)\lambda \bar{P} < 0$ may still imply $P(1) < \bar{P}$. If both expressions are positive, it is optimal to set $P \geq \bar{P}$ regardless of the signal. Note also that it is suboptimal to set $P > \bar{P}$ because debt collection is costly and there are no gains from collecting debt above the default prevention threshold $\bar{P}$.

Denote the indirect utility function associated with the risky contract under indiscriminate collection by $V^*_{P(1)=\bar{P}}$. We have shown in the proof of the Lemma 3 that $V^*_{P(1)=\bar{P}}$ is well defined. (There we prove that when $P(\hat{d}) = 1$ for all $\hat{d}$ the set of profit-feasible risky contracts is nonempty.) In addition, $V^*_{P(1)=\bar{P}}$ is constant in π since $\bar{P}$ is independent of π (Lemma 1).

Consider now the problem of choosing the best profit-feasible risky contract under selective collection. Denote the resulting indirect utility function by $V^*_{P(1)<\bar{P}}$. It is clear that for $\pi = 1$ collection costs are zero and there is no strategic default in this case since $Pr(0|1) = 0$. Note that wlog we can restrict credit limits to be $L > \theta Y + \varepsilon$ for $\varepsilon > 0$ small enough since otherwise the risk-free contract $(I = 0, L = \theta Y)$ would be strictly preferred to any feasible risky contract with L arbitrarily close to θY. By an argument analogous to the one used in the proof of Lemma 3, we can express the maximization problem in (3), additionally restricted to the use of risky loans sustained by selective collection, as a maximization of a continuous function on a compact

set.[33] This implies that $V^*_{P(1)<\bar{P}}$ is well defined for $\pi = 1$, and by the continuity of $\bar{P}(I, L)$ with respect to (I, L), established in Lemma 1, the zero profit interest charge I is continuous with respect to π for any fixed L as long as $P(1) < \bar{P}$. Accordingly, there exists $0 \leq \hat{\pi} < 1$ so that $V^*_{P(1)<\bar{P}}$ is well defined for all $\pi \geq \hat{\pi}$ and $V^*_{P(1)<\bar{P}}$ is negative infinity otherwise. (Note that if it is negative infinity for some level of signal precision because consumption is negative, it is also negative infinity for any lower level of signal precision. This is because given any contract (I, L, P) collection costs and strategic default losses are higher when signal precision is lower.)

To prove the existence of adoption threshold π^*, we show that: i) $V^*_{P(1)<\bar{P}}$ is strictly increasing in the interval $[\hat{\pi}, 1]$; ii) $V^*_{P(1)=\bar{P}} < V^*_{P(1)<\bar{P}}$ at $\pi = 1$; and iii) $V^*_{P(1)=\bar{P}} > V^*_{P(1)<\bar{P}}$ at $\pi = 0$.

Since a higher precision level under selective collection strictly reduces the collection costs for any fixed selective collection strategy P, and since $V^*_{P(1)<\bar{P}}$ is strictly decreasing in I, $V^*_{P(1)<\bar{P}}$ is strictly increasing in π for any $\pi \geq \hat{\pi}$. To see why, note that lower collection costs imply I can be lowered by the zero profit condition and that higher signal precision implies that for any fixed selective P debt is collected from fewer agents. Recall also that $\bar{P}(I, L)$ is decreasing in I, implying that default is still prevented under the signal realization $\hat{d} = 0$. Furthermore, by continuity of $\bar{P}$ with respect to I, note that a sufficiently small change will preserve selective debt collection (i.e., it ensures $P(\hat{d} = 1) < \bar{P}$).

When $\pi = 1$, for any $L > \theta Y$, selective collection attains a higher utility than indiscriminate collection because collection costs under the former are zero and only distressed consumers default in both cases.

Finally, if $\pi = 0$, note that the proof of part (ii) of Lemma 3 — which shows that default prevention is optimal — applies to each signal realization separately when signals are uninformative. Hence, $V^*_{P(1)=\bar{P}} > V^*_{P(1)<\bar{P}}$ when $\pi = 0$. $\qquad\square$

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[33]To ensure that the constraint set is compact we can restrict attention wlog to contracts such that $P(1) \leq \bar{P}(I, L) - \xi$ for $\xi > 0$ small enough. This is because if $P(1)$ is arbitrarily close to $\bar{P}$ switching to indiscriminate monitoring lowers both the deadweight loss from default and collection costs by preventing strategic default.

Proof of Lemma 5. We prove the lemma by showing that the indirect utility under the preferred risky contract is strictly higher than the utility associated with the risk-free contract when π is close to one and θ is close to zero. When $\pi = 1$, the preferred risky contract must involve selective collection by Lemma 4. If the credit limit is L, zero profits imply $I = \frac{p}{1-p}L$, since there is no strategic default and no collection costs are borne at $\pi = 1$. We can find a lower bound on the utility associated with such contract by imposing that $b = 0$ for all d. Accordingly, when $\pi = 1$ and $\theta = 0$, we know that indirect utility is bounded from below by

$$(1 - p)\left[u(Y - B) + u(Y - \frac{p}{1-p}L)\right] + p\left[u(Y - B) + u(Y - E + L)\right]. \tag{20}$$

The utility from the risk-free contract ($L = \theta Y = 0$ and $I = 0$ in this case) is

$$(1 - p)\left[u(Y - B) + u(Y)\right] + p\left[u(Y - B) + u(Y - E)\right]. \tag{21}$$

Hence, (20) is higher than (21) if

$$(1 - p)u(Y - \frac{p}{1-p}L) + pu(Y - E + L) > (1 - p)u(Y) + pu(Y - E).$$

Note that both sides of the inequality correspond to expected utility. Moreover, expected consumption on the left-hand side (LHS) is the same as on the right-hand side (RHS), since $(1 - p)\left(-\frac{p}{1-p}L\right) + pL = 0$. Finally, note that when L is small but positive, consumption on the RHS is a mean-preserving spread of consumption on the LHS. Accordingly, by the strict concavity of u, and given that $E > 0$, we can find $L > 0$ such that the above inequality holds. Since the inequality is strict, THE same argument applies when θ is positive but small and for π sufficiently close to one. The reason is that, although for $\pi < 1$ expected utility also includes the utility from strategic default, the probability of strategic default is very small at π close to

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one, leading to a lower bound on utility very close to the one established above, and to second-period consumption under selective collection that is close enough to a mean-preserving spread of consumption under the risk-free contract. □

Proof of Proposition 1. By lemmas 4 and 5, we know that if precision increases from a sufficiently low to a sufficiently high level there is a switch to a risky contract sustained by selective collection either from a risk-free contract or from a risky contract sustained by indiscriminate collection. The former switch trivially implies an increase in L, the default rate and the amount of discharged debt. In addition, selective collection involves a higher default rate than indiscriminate collection due to the presence of strategic default. Hence, we only need to prove that, if π_1 is sufficiently high, the switch from indiscriminate to selective collection necessarily leads to a higher L and hence to higher discharged debt.

We prove it by showing that the equilibrium credit limit at $\pi = 1$ (which involves selective collection in equilibrium) must be strictly higher than the credit limit under indiscriminate collection. To do so, we note that neither contract involves strategic default. Hence, utility under either contract can be expressed as

$$(1-p)\left[u(Y - B + b_0) + u(Y - I - b_0)\right] + p\left[u(Y - B + b_1) + u((1 - \theta)Y - E + L - b_1)\right],$$

where b_0 and b_1, respectively, represent borrowing for $d = 0$ and $d = 1$. The only difference in resources available for consumption between the two contracts is that $I = \frac{p}{1-p}L$ when $\pi = 1$ under selective collection and $I = \frac{p}{1-p}(L + \lambda)$ under indiscriminate collection. Hence, what we need to show is that the extra resources when $\pi = 1$ lead to a higher L (as opposed to only a lower I). To see why this must be the case, consider two cases that can arise: 1) the optimal risky contract under selective collection has a borrowing constraint that is non-binding for all d; and 2) the borrowing constraint is binding for some d.

Let $\hat{I}$ and $\hat{L}$ be the credit terms of the optimal risky contract sustained by selective collection and I', L' the terms under indiscriminate collection. Assume by contradiction that $L' \geq \hat{L}$.

Case 1) If $\hat{L}$ is not binding, then note several things. First, as long as $\hat{L}$ does not bind there is consumption smoothing for each d across periods by concavity of u. Second, the zero profit condition implies that $\hat{I} = \dfrac{p}{1-p}\hat{L}$. Hence, the transfer of second-period consumption resources across shock realizations ($Y - \hat{I}$ for $d = 0$ and $(1-\theta)Y + \hat{L} - E$ for $d = 1$) through zero-profit changes in I and L is actuarially fair, $\dfrac{\Delta L}{\Delta I} = \dfrac{p}{1-p}$. Third, given the concavity of u and the fact that first-period consumption resources ($Y - B$) are independent of d, we must have that the second-period consumption resources are equalized in equilibrium, i.e., $Y - \hat{I} = (1-\theta)Y + \hat{L} - E$. Hence consumption must be equal across periods and realizations of d. Now, if L' is weakly higher than $\hat{L}$, then $I' > \hat{I}$ since $I' = \frac{p}{1-p}(L + \lambda)$. This implies that L' is also not binding. But, since the transfer rate $\dfrac{\Delta L}{\Delta I}$ is also actuarially fair under indiscriminate collection, the above argument applies and consumption is also equalized across dates and states. This contradicts that $L' \geq \hat{L}$ because

$$(1 - \theta)Y + \hat{L} - E = Y - \hat{I} > Y - I' = (1 - \theta)Y + L' - E.$$

Case 2) Now consider the case in which $\hat{L}$ is binding. Note that it must be so for $d = 0$ or for all d, because if it is only binding for $d = 1$ it would imply that $(1 - \theta)Y + \hat{L} - E > Y - \hat{I}$ and in such a case it would be optimal to lower both $\hat{L}$ and $\hat{I}$ by the concavity of u (recall that first-period resources $Y - B$ are identical for all d). In addition, if $L' \geq \hat{L}$ and thus $I' > \hat{I}$, the following is true:

(a) The second-period marginal utility for $d = 0$ under the selective collection contract is lower than under the indiscriminate collection contract because second-period consumption is higher in the former case. This is because the present value of resources under the selective collection contract ($2Y - \hat{I} - B$) are higher than the present value of resources under indiscriminate

collection $(2Y - I' - B)$ and the borrowing constraint is tighter under selective collection.

(b) The first-period marginal utility is higher than the second-period marginal utility for $d = 0$ under selective collection since $\hat{L}$ is binding. Moreover, if L' is also binding the first-period marginal utility for $d = 0$ is higher under selective collection than under indiscriminate collection since $Y - B + \hat{L} \leq Y - B + L'$.

(c) The first- and second-period marginal utilities for $d = 1$ are (weakly) higher under selective collection than under indiscriminate because $\hat{L} \leq L'$.

We next show that (a)-(c) imply that we can find actuarially fair $\Delta L > 0$ and $\Delta I > 0$ that lead to an increase consumer's utility under selective collection, contradicting the optimality of $\hat{L}$. First, by (a), the utility loss from ΔI is strictly lower at $\hat{L}$ than at L' for ΔL small enough. Second, (a) and (b) imply that ΔL raises utility for $d = 0$ more under the selective collection contract. To see why we need to consider two cases, depending on whether L' is binding. If L' is not binding utility does not change under indiscriminate collection while it goes up under selective collection since marginal utility is higher in the first period than in the second period by (b) (the first-period gain from borrowing an extra ΔL is higher than the second-period loss from $-\Delta L$). If L' is binding, first-period marginal utility is higher under selective collection by (b) while the utility loss in the second period from ΔL is lower by (a). Third, (c) implies that the first- and second-period utility gains from ΔL for $d = 1$ are weakly higher at $\hat{L}$ than at L'. Given these facts, since the optimality of L' under indiscriminate collection implied raising the credit limit up to $L' \geq \hat{L}$, it must be the case that raising the credit limit above $\hat{L}$ by a sufficiently small ΔL under selective collection is also optimal.

It only remains to show that the above arguments are not invalidated by the fact that there is an upper bound on the set of feasible credit limits that prevents $\hat{L}$ to be above L'. From the proof of Lemma 3, we already know that the upper bound is given by the condition that the zero profit interest charge is less than or equal to $\theta Y + \bar{I}$. Since $\hat{I} = \frac{p}{1-p}\hat{L} < \frac{p}{1-p}(\hat{L} + \lambda)$, the upper

bound on profit feasible credit limits is strictly higher under selective than under indiscriminate collection.

Finally, since utility strictly goes up at $\pi = 1$ by setting credit limits above L', it also must be the case at π close to one.[34]

To prove the last part of the proposition, note that the indirect utility function from a risk-free contract is independent of λ. In contrast, it is strictly decreasing under the preferred profit-feasible risky contract sustained by indiscriminate collection and unbounded from below. Hence, it must be the case that for sufficiently high λ the risk-free contract strictly dominates all profit-feasible risky credit lines sustained using indiscriminate collection. On the other hand, if $\lambda = 0$ then the indirect utility under indiscriminate collection coincides with that of a selective collection contract when $\pi = 1$, which by Lemma 5 is higher than under the preferred risk-free contract as long as $\theta < \theta^*$. □

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[34] At $\pi < 1$ expected utility also includes the utility from strategic default. Since the probability of strategic default is very small at π close to one, the above argument is still valid since the above transfer of resources is roughly the same.

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