Modeling the Revolving Revolution: The Role of IT Reconsidered

Lukasz A. Drozd and Ricardo Serrano-Padial[*]

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ABSTRACT

Credit card default losses increased dramatically in the 80s and 90s, from 3% to over 5% of outstanding debt. We explore whether technological progress in debt collection is behind this change by developing a new theory featuring costly state verification with signals. We motivate our approach by the predominance of informal bankruptcy in the credit card market, which necessitates the costly involvement of the lending industry to enforce repayment. We show that the presence of enforcement costs, when combined with the rate of technological progress suggested by the available evidence, rationalizes the observed shift in the risk composition of debt.

JEL: E21, D91, G20
Keywords: credit cards, consumer credit, unsecured credit, revolving credit, informal bankruptcy, debt collection, moral hazard, state verification, default risk

1 Introduction

There is a widespread consensus in the economic literature that the expansion of unsecured borrowing over the last 30 year has been fueled by IT progress (see, for instance, White, 2007). This transformation is largely associated with the development of centralized of consumer scoring, which allowed lenders to assess default risk quickly, inexpensively and more precisely. The intensive use of IT is particularly visible in the credit card market, which has become a predominant source of unsecured consumer credit in the U.S., and more generally a major form of credit for U.S. households.

Alongside the aforementioned expansion, the credit card market has also experienced a puzzling shift in the risk composition of debt. Figure 1 illustrates this phenomenon. As we can see, the fraction of unsecured revolving debt defaulted on has steadily been rising, far outpacing the expansion of the market itself. However, theoretically attributing this particular development to IT progress has been quite elusive.
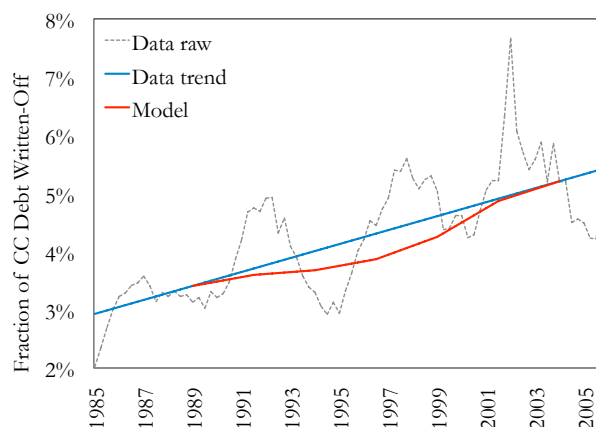

Figure 1: The Rise of Credit Card Debt Written-Off in the US.

Here we argue that the observed shift in the risk composition of debt can be well understood by taking into account the important role that IT has played in the collection of debt and the enforcement of credit contracts. This channel has been thus far neglected in the economic

literature, despite the fact that recent evidence suggests that this margin potentially plays an important role in the workings of the credit markets. This evidence motivates our study, as it shows that, first, defaults on credit card debt are predominately informal, necessitating the costly involvement of the lending industry to collect unpaid debt.[1] Second, consistent with the predominance of informal default, the lending industry actually devotes significant resources to enforcement and debt collection.[2]

Our reading of this evidence is that existing theories potentially miss out on a crucial aspect of credit markets, namely the costs that must be assumed by the lending industry to sustain repayment. In light of a well documented IT-based revolution that has transformed how debt is collected in the U.S., we postulate that the presence of such costs can have important ramifications for the pricing of risk. Showing that this channel can explain the aforementioned shift in the risk composition of debt is the central goal of our paper.

To develop this theme, we explicitly model the enforcement of credit contracts as a costly state verification process, similarly to Townsend (1979). We enrich this framework by introducing a signal extraction technology, which lenders can adopt to better target their verification efforts. IT progress in our framework is captured by improvements in signal informativeness.

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[1] Persistent delinquency implies debt forgiveness, as the statue of limitations on unpaid debt renders debt uncollectable after about 3-7 years (depending on the state). Micro-level studies, which carefully track the life-cycle of unpaid unsecured consumer debt, consistently show that at least half of the defaulted debt in the U.S. is discharged in such an 'informal' way. For example, using a panel of 50,831 credit card borrowers, Dawsey and Ausubel (2004) show that as much as half of discharged credit card debt during 1997-98 is not attributable to formal bankruptcy filings thereafter. Similarly, Agarwal, Liu and Mielnicki (2003) study a panel of over 1.5 million credit cards and report that informal defaults represent between 64% and 78% of defaults in 1998-2000. Similar figures are reported in industry studies (e.g. 1999 Annual Bankruptcy Survey by Visa U.S.A. Inc.). In Section 2, we analyze a panel of credit records of a representative sample of Americans and also find that 73% of borrowers who default, do so informally.

[2] According to the BLS, employment in the third-party debt collection industry is about 150,000 people. PricewaterhouseCoopers estimates that the industry as a whole directly or indirectly supports employment between 300,000 and 420,000 jobs (see "Value of Third-Part Debt Collection to the US Economy in 2004: Survey and Analysis," by PricewatehouseCoopers, prepared for ACA International). IBISWorld (2013b) reports that credit card receivables are the largest sector serviced by the debt collection industry, representing approximately a third of its $13-billion expected revenue in 2013. This suggests that about 1/3rd of these resources might be devoted to collection of credit card debt. To put these numbers in perspective, the size of the U.S. police force is about 700,000 officers across all agencies. See our online appendix for further details about this industry.

As in Townsend (1979), the rationale behind our modeling approach is the presence of asymmetric information about true solvency status of the borrower – here brought about by the phenomenon of informal default.[3] Since lenders can only obtain repayment from solvent consumers, state verification in our model is necessary as, in the absence of it, solvent consumers would also be tempted to default. State verification costs thus partly determine the price of credit contracts.

The key implication of our theory is that improvement in the informativeness of signals can crucially affect the equilibrium risk composition of debt. In particular, our model implies two enforcement regimes, with a cutoff rule on information precision governing the switching between regimes: *full monitoring* and *selective monitoring.* Under *full monitoring*, which arises when IT is underdeveloped, lenders do not adopt the signal extraction technology and thus engage in state verification of all delinquent borrowers. In contrast, as signal precision improves, our model predicts a switch to *selective monitoring*, which involves the use of signals to target only a subset of defaulters, i.e., those more likely to be solvent. Such switch lowers the price of contracts exposed to default risk, and thus crucially alters the relative attractiveness of such contracts to consumers. In the presence of riskless contracts characterized by tight credit limits, this is sufficient to alter the risk composition of debt, as risky contracts become more prevalent. In addition, the switch to selective monitoring, by implying strategic default among non-verified consumers, further reinforces the result.

Under plausible assumptions on enforcement costs and technological progress, our mechanism can fully account for the rise of the charge-off rate in the data, as Figure 1 illustrates.[4] Importantly, this result is achieved by, first, setting monitoring costs to match the resources

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[3]Informal bankruptcy is critical. Formal bankruptcy renders such considerations irrelevant by definition since it grants borrowers full legal protection from lenders.

[4]We could extend our model to early 1980s. However, we do not focus on earlier periods due to binding usury laws, which have been gradually eliminated in the US by the 1978 Supreme Court ruling, Marquette National Bank of Minneapolis vs. First of Omaha Service Corp. The increase in credit card lending in the early 80s was likely affected by this decision and our analysis may not apply to this time period. Due to a major bankruptcy reform in 2005, and later financial crisis, we do not look at the data after 2004.

devoted to the collection of unsecured debt in the data and, second, by increasing the precision of signal in line with industry evidence about the impact of IT-progress in debt collection.

In plain words, our model explains the recent changes in the US unsecured credit market in the following way. In the late 80s, the enforcement technology employed by the lending industry was not ready to deal with a vast pool of risky accounts; this shortcoming made enforcement of repayment from moral hazard-prone borrowers costly. Consequently, such contracts were rarely offered in the market; instead, lenders relied on safe contracts and/or extended credit mostly to segments of the market posing little or no default risk. However, while improving the ability to estimate credit risk – e.g., through the use of credit scoring models – in the late 1980s and over the 1990s, the industry has also learned how to better assess delinquent borrowers' ability to repay. Such knowledge helped to optimize on collection effort and led the industry to assume greater credit risk. This could have happened both along the intensive margin of offering more generous and thus more risky credit contracts to existing customers, or by expanding to riskier segments of the market.

Our story is broadly consistent with the evidence on the recent evolution of debt collection practices. Throughout the 1990s, the lending industry embraced the use of *collection scoring* and engaged in a much more selective use of resources,[5] an approach known in the industry lingo as *segmentation* of delinquent accounts based on collection scores, and *prioritization* of collection resources. For example, credit bureaus started to provide comprehensive collection scores since the mid 90s. Interestingly, over 7.5% of the credit reporting industry's $10 billion annual revenue is coming from serving debt collectors (IBISWorld, 2013a). To put this number into perspective, 37% of this industry's revenue comes from banks and financial institutions. These figures forcefully underscore the widespread use of IT to facilitate the enforcement of debt contracts. The global presence of commercially available collection scores speaks directly to the

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[5]Similar to credit scores, collection scores are aimed at predicting the recovery rate from delinquent borrowers based on borrower characteristics and the nature of delinquency. For an overview of the different types of collection scores used by the industry see the online appendix.

use of signals and selective monitoring predicted by our model.[6] Furthermore, existing studies report large gains brought by IT-driven collections, typically leading to 20-40% productivity increases. These productivity gains came from the adoption of technologies that very much paralleled the ones used by lenders to extend initial credit to new consumers.

Our theory is qualitatively consistent with several other related phenomena. For example, the data reveals a secular decline in the use of legal actions to recover unpaid debt: from 2000 to 2006 the average number of suits, judgments and wage garnishments filled in court *per delinquent borrower* decreased by 16.3%.[7] At the same time, the use of credit bureau information on delinquent borrowers by debt collectors, including credit and collection scores, went up by 30%. We interpret these two trends as suggestive of a noticeable increase in the use of IT-driven, selective approaches to enforcement.

To the best of our knowledge, no other study on consumer credit markets systematically relates information technology to the effectiveness of debt collection. However, viewed more broadly, our paper is related to a number of recent contributions in this area. These include the adverse selection models of the IT-driven credit expansion by Narajabad (2012), Athreya, Tam and Young (2008), and Sanchez (2012); papers on informal bankruptcy by Chatterjee (2010), Athreya et al. (2012), Benjamin and Mateos-Planas (2012), and White (1998); and other work on the effects of technology on credit pricing, such as Drozd and Nosal (2007), and Livshits, MacGee and Tertilt (2010, 2011).

The paper is organized as follows. Section 2 reviews the existing evidence on informal default and collection technology. We analyze the theoretical model in Section 3, which includes our main comparative statics result and a discussion of possible extensions. Section 4 presents the quantitative model and results. Section 5 concludes.

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[6]As an example of collection scores, Table 5 in the Appendix shows how Experian's *Bankcard RecoveryScore* successfully predicts whether a delinquent credit card borrower in our dataset will default.

[7]Our data set only goes back to July 1999. However, using court data on wage garnishments from Virginia, Hynes (2006) finds that, while the number of personal bankruptcy filings were rapidly growing over the 90s, the growth of debt-related garnishment orders was negative.

2 Empirical Motivation

This section overviews the evidence that motivates our approach and our key modeling decisions. Specifically, we first describe the prevalence of informal default. We then document how IT is used to deal with the informational asymmetries brought by informal default. In particular, we discuss how collection methods have changed with the advent of IT-based solutions.

2.1 Informal Default

The existing evidence shows that informal default is the preferred channel for the discharge of credit card debt. Here we analyze the behavior of delinquent credit card borrowers using a panel of over 150,000 borrowers from Experian, one of the three major credit bureaus. Consistent with other studies that use account-level data, such as Dawsey and Ausubel (2004) and Agarwal, Liu and Mielnicki (2003), we find that informal default is by far the most prevalent form of default.[8] Our data contains credit history, delinquency and public record (bankruptcy, suits, judgments) information, allowing us to distinguish between informal and formal default. As in Agarwal, Liu and Mielnicki (2003), we define delinquency as being 90 days or more past due date in a credit card opened in the last two years. Of those we flag as delinquent, we consider them to be informal defaulters two and four years later if they did not filed for bankruptcy and they did not fully pay back any of their delinquent accounts. We find that 73% of delinquent credit card borrowers in the period 2001-05 that were still in default two years later did not file for bankruptcy (79% for those still in default two years later). These numbers are remarkable given that our notion of default uses long delinquency periods, compared to the typical 180 days past due used in the above studies, and thus highlights the sheer magnitude of informal default in the credit card market.[9]

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[8]The panel contains 150,000 randomly selected individuals in July 2001 (the earliest date for which data was accessible) and followed them every two years. It also contains, to partially account for attrition, another set of randomly selected 150,000 in July 2013 that were 'tracked back' every two years down to July, 2001.

[9]These statistics are similar if we restrict the sample to borrowers with no history of bankruptcy.

As Table 1 shows, those who default informally rarely turn to formally filing for bankruptcy protection down the road (about 4.4%). This implies that formal and informal bankruptcy represent quite disconnected paths, arguably appealing to distinct segments of borrowers. In this context, we find that, as in Dawsey and Ausubel (2004), the credit card balances of informal defaulters are 45% lower than those of formal filers. Such lower debt levels may explain why informal defaulters have a strong incentive not to file for bankruptcy protection: just the legal costs of doing so eat up a large fraction of their credit card debt discharged, typically around 13-25%.[10] This can also explain why even mode st collection costs can introduce substantial frictions in unsecured credit markets.

Finally, while a fraction of delinquent borrowers show some improvement in the data, this does not necessarily imply repayment of credit card debt. This is because our definition of 'improvement', due the lack of account level information, is fairly broad and indicates repayment of any credit account in the portfolio of a delinquent borrower.

2.2 Collection Technology and its Recent Evolution

In light of the predominance of informal default and the long life of charged-off debt before it runs its statute of limitation (3-10 years), typically transitioning from in-house to third-party collection agencies to being sold and re-sold to distressed debt-buyers, collection costs per account can be quite substantial. To optimize on these costs, over the 90s the lending industry developed a debt collection infrastructure centered around the use of IT. This transition paralleled similar developments on the evaluation of credit risk, such as automated and centralized credit scoring. We provide a brief overview of this technological switch below. For an extended review refer to the online appendix.

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[10]Hynes (2008) reports a filing fee of $299 plus $1000-2000 in lawyer fees in 2007. This represents a lower bound on legal and other costs associated to formal filing. Dawsey and Ausubel (2004) found that in 1997 credit card discharged per informal defaulter was about $9,648 in 2007 dollars.

Table 1: Delinquency Transitions

	Delinquent		
$t = 0$	3.10%		
	$\swarrow^{a}$	$\downarrow$	$\searrow$
	Bankruptcy	Inf. Default[b]	Improvement
$t = 2$ years	17.5%	65.7%	16.8%
	$\swarrow$	$\downarrow$	$\searrow$
	Bankruptcy	Inf. Default	Improvement
$t = 4$ years	4.4%	79.5%	16.1%
No. Observations[c]	483,732		

[a]The arrows indicate the transition rates from the corresponding state in the upper row to a particular state in the lower row.
[b]Delinquent borrowers that did not file for bankruptcy, and did not showed an increase in the number of paid accounts that were at least 90 days past due.
[c]Includes observations for the three waves prior to the financial crisis: 2001, 2003 and 2005.

Before the 90s, debt collection relied on heuristic and labor intensive methods (Makuch et al., 1992; Hunt, 2007). Under this 'traditional approach,' debt collectors would be physically looking into each case to decide what action to take, and analyzed data themselves. Occasionally, ad hoc in-house solutions were adopted to aid this heuristic approach (Rosenberg and Gleit, 1994). The pioneering development of an IT-based solution by GE Capital opened the door to more sophisticated methods (Makuch et al., 1992). With the advent of global scoring and credit history databases these methods gained in precision (Chin and Kotak, 2006; Till and Hand, 2003). The key difference between traditional methods and modern collection technologies is the systematic use of information and statistical modeling, combined with computer-based optimization methods to optimally allocate collection resources. For instance, the core idea behind PAYMENT, the credit card collections system adopted by GE Capital back in 1990, was to model their portfolio of delinquent accounts as a Markov matrix summarizing the transition probability from X to $X + y$ days of delinquency, with the probability being a function of a set of possible collection actions that can be undertaken in

a given state (Makuch et al., 1992). A computer algorithm then used this matrix to perform cost-benefit analysis and choose the best action for each delinquent account based on borrower and account characteristics. (See Hopper and Lewis (1992) for a description of the approach and Rosenberg and Gleit (1994) for a survey of the different methods such as decision trees, neural networks and Markov chains).

This early implementation led to major savings in its first months of operation, relative to the existing heuristic methods use by the company. Specifically, using a randomized controlled trial, Makuch et al. (1992) estimate that GE capital, at the time the largest provider of "private label" consumer credit in the US, experienced a 7-9% increase in average recoveries while targeting a smaller fraction of accounts. Overall, the adoption of PAYMENT led to at least $37-million annual savings, equivalent to 9% of write-offs in 1990. Using the same empirical approach, Banerjee (2001) analyzes the introduction of segmentation and prioritization in a large bank in eastern U.S. during 1998, with a particular emphasis on the selective use of costly arbitration/litigation. The estimated average savings were $217 per account, implying savings of $40 million or about 11% of total write-offs. Importantly, the study reports total collection costs incurred by the company, which were about 1.25% of outstanding debt. This number is actually much higher than what our model will later imply for the 1990s.

These savings are similar or even larger in industry studies that look at productivity gains in less tightly controlled environments. For example, in its 2005 annual report filed with the SEC, Portfolio Recovery Associates, one of the four largest debt collection agencies, and whose portfolio is primarily comprised of credit card receivables, documents a 120% increase in debt recovered per dollar spent on collection. The company argues that their IT-driven approach – which utilizes two large scale proprietary statistical models – is the main culprit of their successful operations and growth. In another study, a medium scale bank, Trustmark National Bank, reports that, after the adoption of an IT-based collection system, they increased the

recovery rate on charged-off consumer accounts from 35% to 58% over the period 1998-2004, while employing the same manpower in debt collection (Fair Isaac Corporation, 2006).[11]

Since the mid 90s access to these sophisticated methods has been greatly expanded with the offering of centralized collection scoring by the major credit bureaus, such as Experian and TransUnion.[12] Over 7.5% of the credit reporting industry's $10 billion annual revenue nowadays comes from debt collection services (IBISWorld, 2013a). To put this number into perspective, 37% of this industry's revenue comes from banks and financial institutions. These figures forcefully underscore the widespread use of IT-based collections. The global presence of commercially available collection scores speaks directly to the use of signals and selective monitoring that our model involves.

Finally, it is worth mentioning that the success of segmentation and prioritization in the collection of credit card debt has led other industries to adopt a similar approach. Examples include Fannie May and Freddie Mac in 1997 to manage delinquent mortgages (Cordell et al., 1998); and New York State in 2009 to collect unpaid taxes (Miller, 2012). After adoption, New York State increased its collections from delinquent taxpayers by $83 million (an 8% increase) using the same resources.

3   Model

We first analyze a stylized model that highlights the main theoretical mechanism. Later on we generalize it to a quantitative life-cycle environment to explore its ability to match the data.

The economy is populated by a continuum of consumers and a finite number of credit card lenders. Credit card lenders have deep pockets and extend credit to consumers at the beginning

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[11]Although these figures pertain to all receivables, given that about 1/3 of collected debt in the US by the debt collection industry comes from credit cards, this evidence suggests IT-driven, double digit gains in collection.

[12]Experian introduced RecoveryScore for charged-off accounts in 1995 (personal communication), while TransUnion have been offering collection scores since at least 1996 (Pincetich and Rubadue, 1997).

of the period. Consumers live for one period composed of two sub-periods. Their objective is to smooth consumption across the two sub-periods by borrowing from lenders, as they enter the period with some pre-existing exogenous stock of debt $B > 0$ – it is endogenous in our life-cycle model. Credit is unsecured and consumers can default. Specifically, in the second sub-period they are subject to a random realization of a binary distress shock $d \in \{0, 1\}$ of size $E > 0$ (e.g., job loss, divorce, or medical bills), which hits with probability $p < 1/2$. The option to default provides some insurance against distress.

The key point of departure from the literature is the presence of moral hazard brought by the fact that lenders do not observe d upon default. As a result, non-distressed borrowers may be tempted to default *strategically* in expectation of debt forgiveness by lenders. To deal with this problem, lenders in our model have access to a costly state verification technology that allows them to learn the shock and induce repayment from non-distressed consumers. Lenders also have access to a signal extraction technology that produces a noisy signal $\hat{d} \in \{0, 1\}$ of the distress shock.

The timing is as follows. At the beginning of the period, lenders compete to extend credit lines to consumers and commit to a verification strategy. After accepting a contract, each consumer privately learns whether she will be hit by the shock and all agents observe signal $\hat{d}$. With this information in hand the consumer decides how much to borrow and whether she will repay or default in the second sub-period. If the consumer defaults lenders decide whether to verify the shock given the signal realization and their monitoring strategy.

3.1 Lenders

Lenders are Bertrand competitors and offer credit lines to consumers. Credit lines are unsecured and committed to consumers prior to the realization of the the distress shock d. They are characterized by a credit limit L, a fixed finance charge I, and a state verification or *mon-*

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itoring strategy $P(\hat{d})$, which represents the probability that a defaulting consumer with signal $\hat{d}$ will be verified or monitored.[13]

Signals are characterized by exogenous precision $0 \leq \pi \leq 1$. That is, with probability π they reveal the true state and with probability $1 - \pi$ the are uninformative. This parameter embodies *the state of information technology* in the economy. Change in this parameter will later be the main focus of our analysis.

While monitoring results in repayment from non-distressed defaulters, for simplicity here we assume it is completely ineffective in the case of truly distressed consumers.[14] Formally, at the beginning of the period lenders choose a credit line contract (I, L, P) to maximize the ex-ante expected utility of consumers:

$$\max_{I,L,P} V(I, L, P) \tag{1}$$

subject to the ex-ante zero profit condition

$$\mathbb{E}\Pi(S, I, L, P) \geq \lambda \sum_{S} \delta(S, I, L, P) P(\hat{d}) Pr(\hat{d}).$$

In the above problem, $\mathbb{E}\Pi(S, I, L, P)$ denotes ex-ante profits (gross of monitoring costs) from a customer pool with normalized measure one, $S = (d, \hat{d})$ is the interim state of the consumer, λ represents verification or monitoring costs (per measure one of borrowers), and $\delta(S, I, L, P)$ describes the consumer's default decision (defined formally in the next section), which equals

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[13]While our approach is positive in nature, our restriction to these contracts is partly based on optimality grounds. First, credit lines allow for flexible borrowing levels, which are contingent on the shock realization given the model's timing. Second, fixed finance charges are superior to interest payments proportional to borrowing since they do not distort intertemporal smoothing. Finally, commitment parsimoniously implements efficient monitoring policies, and conveniently abstracts from any institutional characteristics of the debt collection industry. In his costly state verification model, Townsend (1979) shows that loan contracts with monitoring commitment are constrained efficient. Unlike here, there are no intertemporal smoothing considerations in his model since consumption only takes place after verification takes place.

[14]In our quantitative model we take a more general approach by assuming an enforcement constraint that applies uniformly to all consumer types.

one in case of default and zero otherwise. The interim profit function is given by

$$\Pi(S, I, L, P) = \begin{cases} I & \text{if } \delta(S, I, L, P) = 0, \\ -L + (L + \bar{I})(1 - d)P(\hat{d}) & \text{if } \delta(S, I, L, P) = 1, \end{cases} \qquad (2)$$

This expression incorporates the fact that, as we argue below, defaulting consumers discharge the full credit line L plus finance charges I, while I is collected whenever the consumer chooses not to default. Monitoring reverts any non-distressed defaulting consumer back to repayment by recouping $L + \bar{I}$, where $\bar{I}$ is an exogenous penalty charge.[15]

3.2 Consumers

Consumers are endowed with utility over consumption given by $u(c, c')$, where c and c' denote first and second sub-period consumption, respectively, and u is a strictly concave, differentiable and symmetric utility function. They choose c, c', borrowing within the period b, and default decision $\delta \in \{0, 1\}$. For simplicity, these choices are made at the interim stage, that is, after the signal $\hat{d}$ and the distress shocks d are observed. Such timing greatly simplifies the proof of our main comparative statics result, although most of our results do not depend on the specific timing of borrowing decisions. It also captures in an stylized way the borrowing flexibility that credit cards provide to consumers. Note that consumers potentially face the residual uncertainty associated with being monitored upon default, which is denoted by $m \in \{0, 1\}$. Formally, given I, L and P, the consumer chooses the default decision δ to solve

$$V(I, L, P) \equiv \mathbb{E} \max_{\delta \in \{0,1\}} [(1 - \delta)N(S, I, L, P) + \delta D(S, I, L, P)]. \qquad (3)$$

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[15]Although we think of $\bar{I}$ as non-negative, our model could incorporate the idea of partial debt forgiveness when $I < 0$.

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where $N(\cdot)$ and $D(\cdot)$ denote the interim indirect utility associated with repayment and default, respectively, that is, they are conditional on state S.

Under repayment, the consumer chooses b to solve

$$N(S, I, L, P) \equiv \max_{b \leq L} u(Y - B + b, Y - b - I - dE) \tag{4}$$

To define utility under default, we assume that defaulting *distressed* consumers incur a pecuniary cost of defaulting equal to θY, and they can always fully discharge their debt. *Non-distressed* defaulting consumers can discharge their debt only if they are not monitored, in which case they also suffer penalty θY. If they are monitored, they must pay back the amount defaulted on plus $\bar{I}$. In this context, defaulting consumers find optimal to cash out the entire credit line in the first sub-period. This is consistent with empirical evidence: credit card utilization rates of defaulters are very high, with a median utilization rate of 100% in our dataset (see also Herkenhoff (2012)). By doing so, distressed consumers mitigate the impact of the shock, and non-distressed agents maximize their utility when they are not monitored ($m = 0$) without affecting their utility under $m = 1$.[16] Accordingly,

$$D(S, I, L, P) \equiv \max_{b \leq 0} \mathbb{E}_S \, u(c, c'), \tag{5}$$

subject to

$$c = Y - B + b + L$$

$$c' = \begin{cases} m(Y - b - L - \bar{I}) + (1 - m)((1 - \theta)Y - b) & d = 0 \\ (1 - \theta)Y - b - E & d = 1, \end{cases}$$

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[16]By maxing out on L, non-distressed defaulters also avoid separation from distressed defaulters. Hence our assumption of monitoring being only a function of $\hat{d}$ is without loss.

where $\mathbb{E}_S$ denotes the expectation operator conditional on state S. Note that the above expressions already embed the decision to max out on L prior to default. Heretofore, we refer to default by a distressed consumer as *non-strategic*, and to default by a non-distressed consumer as *strategic*.

Finally, we introduce two assumptions. The first avoids equilibrium indeterminacy by having consumers choose to repay when indifferent between repayment and default.

Assumption 1. *If* $N(S, I, L, P) = D(S, I, L, P)$ *then* $\delta = 0$.

The second assumption rules out the uninteresting case in which everyone defaults in equilibrium under both signal realizations. This might happen if default penalties are very small compared to monitoring costs. In such context, if the monitoring intensity needed to deter strategic default is very high, lenders might allow everyone to default and recoup part of the lost revenue by reverting back a fraction of defaulters.

Assumption 2. $\lambda < \frac{(1-p)^2}{p}\theta Y$.

The condition implies that the monitoring costs of preventing default by non-distressed agents are smaller than the default penalties associated to allowing every non-distressed agent to default under signal $\hat{d} = 0$. The condition is quite slack for any reasonable choice of parameters.

Finally, by *equilibrium* in this economy we mean a collection of indirect utility functions $V(\cdot), N(\cdot), D(\cdot)$ and decisions $\delta(\cdot), b(\cdot), I, L, P(\cdot)$ that are consistent with the definitions and optimization problems stated above.

3.3 Characterization of Equilibrium

The goal of this section is to characterize the impact of information precision π on the risk composition of debt. To accomplish this task, we first characterize the optimal monitoring

strategies that can arise in equilibrium to sustain any risky contracts, and then discuss the pricing implications of our model. Before doing so, we state a preliminary result characterizing default decisions in our model as a function of contract terms. (Unless otherwise noted, all proofs are relegated to the Appendix.)

Proposition 1. *For any contract (I, L, P), the default decision satisfies:*

1. *There exists $L_{\min}(I) > 0$, continuous and decreasing in I, such that a borrower repays if $L \leq L_{\min}(I)$, for all S and P.*

2. *If $L > L_{\min}(I)$ then distressed borrowers default, regardless of P. In addition, there exists $\bar{P}(I, L) \in (0, 1]$, continuous and increasing in I, and independent of information precision π, such that a non-distressed borrower with signal $\hat{d}$ repays (defaults) if $P(\hat{d}) \geq (<) \bar{P}(I, L)$.*

If expected profits are zero at $L = L_{\min}(I)$ and $P(\hat{d}) = 0 \; \forall \hat{d}$, then $I = 0$ and $L = L_{\min} \equiv \theta Y$.

The last part comes from the fact that costs of funds are zero and no one defaults when $L = L_{\min}(I)$, implying that costs are zero and so are finance charges. The above result allows us to distinguish between the two classes of contracts that can arise in equilibrium, risky, i.e., exposed to default, and risk-free.

Definition 1. *We refer to a contract as a:*

i) *risk-free contract, if $L \leq L_{\min}$,*

iii) *risky contract, if $L > L_{\min}$.*

3.3.1 Optimal Monitoring

Our first result shows that lenders sustain risky contracts in equilibrium by using two types of monitoring strategies: i) *full monitoring*, and ii) *selective monitoring*. Under full monitoring, lenders simply ignore the signal, and uniformly monitor all defaulting borrowers up to the

point at which strategic default is fully prevented (i.e. non-distressed consumers are indifferent between defaulting and repaying). Under selective monitoring, lenders prevent strategic default only under $\hat{d} = 0$, while non-distressed consumers with a signal of distress are not monitored enough to prevent them from defaulting strategically. Selective monitoring might still involve some monitoring under $\hat{d} = 1$, as long as it yields enough revenue by reverting strategic defaulters back to repayment. Since the yield from monitoring in this case does depend on signal precision, we write $P_\pi(\cdot)$ instead of $P(\cdot)$ whenever the latter is affected by π.

Proposition 2. *Risky contracts are supported in equilibrium by one of the following strategies:*

   i) full monitoring: $P(\hat{d}) = \bar{P}(I, L)$, $\hat{d} = 0, 1$, or

   ii) selective monitoring: $P(0) = \bar{P}(I, L)$ and $0 \leq P_\pi(1) < \bar{P}(I, L)$,

Furthermore, if $\pi > \pi^* \equiv 1 - \frac{\lambda}{(L+\bar{I})(1-p)}$ then $P_\pi(1) = 0$.

Corollary 1. *Equilibrium risky contracts involve:*

   i) no strategic default in the case of full monitoring,

   ii) strategic default by borrowers with signal $\hat{d} = 1$ under selective monitoring.

Proposition 2 in essence rules out the possibility of having widespread default under $\hat{d} = 0$ by setting $P(0) < \bar{P}(I, L)$, which could be sustained by reverting a fraction of non-distressed agents back to repayment. Assumption 2 guarantees that, compared to the case of $P(0) = \bar{P}(I, L)$, such contracts involve excessive deadweight losses in the form of default penalties θY, as well as suboptimal consumption smoothing across states of the world. In particular, we show for any $L > L_{\min}$ that, compared to any zero profit contract with $P(0) < \bar{P}(I, L)$, the zero profit full monitoring contract provides the same utility under distress, while it provides both higher resources for consumption and lower consumption risk under no-distress. The former is due to the lower deadweight losses while the latter is caused by the randomness associated to having both strategic default and repayment states. These facts combined imply that lowering

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$P(0)$ below $\bar{P}(I, L)$ is akin to taking a gamble with negative expected value, something a risk averse agent would never be willing to do.

3.3.2 Pricing of Risky Contracts

We next characterize pricing of risky debt by decomposing finance charges into a *monitoring premium* and a *default premium*. Let I^{FM} and I^{SM} denote the finance charges associated to the best zero-profit full monitoring and selective monitoring contracts, respectively. The next proposition provides such decomposition for the class of full monitoring contracts. It is derived from the corresponding zero profit condition associated to a credit line of size L which, given Proposition 2 and Corollary 1, is given by

$$(1 - p)I - pL - p\bar{P}(I, L)\lambda = 0, \tag{6}$$

where the first term is the expected revenue, and the remaining terms respectively capture expected default losses and the overall cost of monitoring. The proof of the proposition directly follows from the equation above and is therefore omitted.

Proposition 3. *I^{FM} can be decomposed into a monitoring premium $\mathcal{M}$ and a default premium $\mathcal{D}$ as follows: $I^{FM} = (\mathcal{D} + \mathcal{M}) \times L$, where $\mathcal{D} = \frac{p}{1-p}$ and $\mathcal{M} = \frac{p}{1-p}\bar{P}(I, L)\frac{\lambda}{L}$. Furthermore, $\mathcal{M} = \mathcal{D} = 0$ for risk-free contracts.*

The above result is intuitive. First, under full monitoring, only distressed consumers default, and the probability of such occurrence is p. To break even, lenders must be compensated for bearing this default risk. Second, lenders must be also compensated for the expected cost of monitoring per dollar of credit granted, given by $p\bar{P}\lambda/L$. A key implication of Proposition 3 is that, finance charges in full monitoring contracts are independent of signal precision.

We next derive the pricing of *selective* monitoring contracts. Let $Pr(x, z)$ denote the joint probability that $\hat{d} = x$ and $d = z$, and recall that the probability that $\hat{d} = 1$ is equal to p.

Proposition 4. $I^{SM} = (\mathcal{D} + \mathcal{M}) \times L$, where

$$\mathcal{D} = \frac{p}{Pr(0,0)} + \underbrace{\frac{Pr(1,0)}{Pr(0,0)}}_{\text{“strategic” default}} \quad and$$

$$\mathcal{M} = \frac{Pr(0,1)\bar{P}(I,L) + pP_\pi(1)}{Pr(0,0)} \frac{\lambda}{L} - \frac{Pr(1,0)}{Pr(0,0)}P_\pi(1)\left(1 + \frac{\bar{I}}{L}\right).$$

Furthermore, as $\pi \to 1$, $\mathcal{D}$ and $\mathcal{M}$ converge to $p/(1-p)$ and 0, respectively.

The default premium involves an additional cost associated with the strategic default of non-distressed borrowers with signal $\hat{d} = 1$. That is, selective monitoring contracts are inherently riskier than full monitoring contracts. Thus, $\mathcal{D}$ is strictly higher than under full monitoring, and the difference depends on π. At the same time, a smaller mass of agents is monitored, and the monitoring premium is generally lower, although the difference again depends on π. Moreover, $\mathcal{M}$ is reduced by the expected recovery rate whenever $P_\pi(1) > 0$.

The left panel of Figure 2 shows the resulting pricing schedules. By Proposition 1, we know that contracts with low credit limits are risk-free. This makes the pricing schedule discontinuous: $I = 0$ for $L \leq L_{\min}$ and $I \geq \frac{p}{1-p} > 0$ and increasing for $L > L_{\min}$.
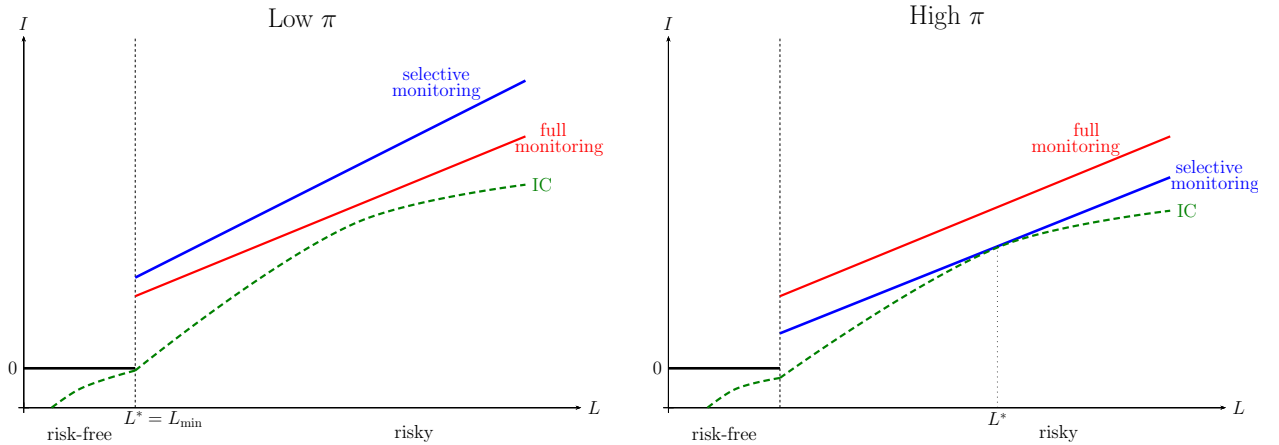

Figure 2: Effect of IT Progress on Equilibrium Price of Debt.

3.3.3 Linking IT Progress to Risk Composition of Debt

We next turn to the comparative statics exercise. Looking at the expression for $\mathcal{D}$ under selective monitoring, it is apparent that it goes down as signals become more informative, since $Pr(1,0)$ and $Pr(0,1)$ decrease with precision. However, to understand how I^{SM} evolves with precision, we need to determine the behavior of $P_\pi(1)$.

Proposition 5. *If $\bar{I} < \lambda$ and $P_\pi(1) > 0$ then $P_\pi(1)$ is strictly decreasing in π and $\lim_{\pi\uparrow\pi^*} P_\pi(1) = 0$, where π^* is defined in Proposition 2.*

Propositions 3 -5 imply that, as the precision of information improves, the optimal monitoring strategy that sustains any fixed credit line eventually switches from *full* to *selective* monitoring.

Proposition 6. *For each $L > L_{\min}$ there exists $0 < \underline{\pi}(L) \leq \bar{\pi}(L) < 1$ such that for all $\pi > \bar{\pi}(L)$ the best zero-profit selective monitoring contract yields a strictly higher utility than the zero profit full monitoring contract, while full monitoring yields higher utility when $\pi < \underline{\pi}(L)$.*

This result is driven by the fact that I^{SM} and $P_\pi(1)$ eventually go down with precision while I^{FM} is constant. In addition, Proposition 5 establishes that the drop in the price of selective monitoring contracts relative to full monitoring is even more pronounced when penalty charges are insufficient to cover monitoring costs, in which case, monitoring costs fall faster with precision since $P_\pi(1)$ is strictly decreasing in π.

Figure 2 illustrates the implications of Proposition 6 on the selection of contracts in equilibrium. This is the key mechanism behind our results. When signals are not very informative, consumers may opt for risk free contracts typically involving tight credit limits ($L = L_{\min}$) and no default (left panel). In contrast, at high precision, risky contracts with selective monitoring exhibit low prices, leading to higher credit limits ($L = L^*$) and positive default risk (right panel). That is, more precise information can lead to a larger share of risky contracts and also

to a higher prevalence of selective monitoring among risky contracts. Since selective monitoring involves strategic default and thus higher default rates than full monitoring, the pool of equilibrium contracts shifts towards riskier contracts after an increase in π. In our quantitative exercise, both phenomena are behind the increase in default and charge-off rates.

It is worth noting that I^{SM} will generally more sensitive to π for borrowers at a greater risk of distress, given that $Pr(0,1)$ and $Pr(1,0)$ are higher, and $Pr(0,0)$ lower, at higher p.[17] As a result, the model implies that the riskier a given segment of the consumer market is, as implied by p, the more the price of risky contracts declines as the precision of information improves. This result is consistent with the "democratization of credit" (Johnson, 2005; White, 2007). Indeed, Agarwal et al. (2013) shows that nowadays riskier borrowers, such as those with lower credit scores, are the most profitable segment for the credit card industry.

3.4   Discussion

Our model focuses on the effect of IT on informational asymmetries between borrowers and lenders at the enforcement stage. Accordingly, it abstracts from such important aspects of debt collection as renegotiation, the choice between formal and informal bankruptcy, and any other aspects of enforcement for that matter. Here we discuss some of these issues and argue that the mechanism we highlight would be at play in a more general framework.

Renegotiation and the option to default formally can serve as a tool for screening consumers and thus save on enforcement costs.[18] For instance, Kovrijnykh and Livshits (2013) show how the use of partial debt forgiveness can help lenders separate consumers by propensity/ability to repay their debts. In this context, our main comparative static result would nevertheless hold in the following sense: as information becomes more precise lenders will find renegotiation less attractive, compared to selective monitoring with little or no debt forgiveness. This is because,

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[17]Up to an ambiguous effect of p on $P_\pi(1)$, which matters only in the case of $\pi < \pi^*$.
[18]We thank an anonymous referee for raising this point.

as precision increases, both monitoring costs and strategic default losses go down relative to the losses associated with partial debt forgiveness.

Alternatively, if the costs (both pecuniary and non-pecuniary) of formal bankruptcy are small relative to monitoring costs, lenders could use the choice between formal and informal default to identify distressed borrowers. Specifically, they could offer defaulting borrowers a compensation in exchange for filing formally and, at the same time, monitor anyone who does not take the deal. By doing so they could drive monitoring costs to zero at the expense of compensating distressed borrowers for formally filing. While this solution is unlikely to practical, our mechanism would nevertheless still be operational. To see why, note that IT progress will lead to qualitatively the same outcome: as signals become more precise lenders can save on *formal filing* costs by engaging in selective monitoring. The associated savings can be substantial given that, as mentioned above, just the legal costs may account for about 13-25% of the average debt discharged by informal defaulters. In addition, given the expected monitoring costs per defaulter in our quantitative model for 2004, lenders would have about $800 to 'bribe' borrowers, well below the estimated pecuniary costs of filing for formal bankruptcy.

Furthermore, in our model, the only enforcement costs present are the state verification costs borne by lenders (λ). However, a significant enforcement costs likely lie on the consumer side. After all, delinquent borrowers may suffer disutility and even incur in pecuniary costs whenever they are pursued by lenders. Our main result would still hold if such costs are present. In fact, this would greatly reinforce our mechanism. Specifically, the enforcement costs of selective monitoring contracts, however broadly defined, go down as IT improves, given that the mass of defaulters who end up being monitored is decreasing in signal precision.[19]

We conclude our discussion of the model by pointing out that the relative drop in the

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[19]Apart from a more cost-effective use of collection resources, Makuch et al. (1992) cites consumer goodwill and avoiding unnecessary hassle as additional reasons for the adoption of a more selective approach to collections by GE Capital. For some anecdotal evidence of reduction in consumer costs, see for example "Technology Brings a Kinder, Gentler Process to Collections", by Louis Barney, in Card and Payments, October 2005.

price of risky contracts can also be generated by a drop in monitoring costs (λ), instead of an increase in signal precision. We chose the latter for two reasons. First, while other costs might have gone down, legal fees and costs have actually gone up. Second, a fall in monitoring costs produces a counterfactual rise in monitored defaults: a drop in λ that matches the change in charge-offs would lead to a switch from risk-free to (fully) monitored contracts, implying a higher fraction of distressed agents being monitored. Such an increase would be at odds with the downward trend in legal collections shown in Figure 3 below and reported in Hynes (2006).

4 Quantitative Analysis

Our next goal is to demonstrate that our mechanism can quantitatively account for the rise in the charge-off rate observed in the US data over the time period 1990-2005. To this end, we extend our setup so that it is amenable to quantitative analysis. In terms of the model, the main differences are that we allow for multiple periods and use a more general specification of the enforcement technology. In what follows next, we first describe our quantitative model, discuss how we calibrate it, and present our quantitative results.

4.1 Quantitative Extension of the Baseline Model

The economy is populated by lenders dealing with a large number of borrowers (households). Each household lives for $T = 40$ periods (in our calibration a model period is two years long). Income $y_t(z_t)$ of a borrower is given by an exogenous stochastic process governed by a Markov chain $z \in \{z_1, ..., z_n\}$. The borrower is additionally subjected to an i.i.d. distress shock $\kappa(z_t, d_t) > 0$, where $d \in \{0, 1\}$ indexes the realization of the shock and $\kappa(.)$ returns the value of the shock for a given state (z, d).

As in our static economy, access to credit is in the form of unsecured credit lines, given by (I, L, P), which are extended for the length of one period. During each period, a household

can borrow or save, and may default.[20] These decisions determine the level of the pre-existing debt in the following period, which evolves endogenously.

Consumption and borrowing are restricted by budget constraints, which are different depending on whether whether the borrower decides to pay back her debt or default. Specifically, in the case of repayment, the budget constraint takes the form:

$$BC^N(B, I, L) \equiv \{(c_t^N, B_{t+1}) : c_t^N \leq y_t - B_t - \kappa(z_t, d_t) + B_{t+1} - I, \; B_{t+1} \leq L\},$$

where c_t^N is consumption, B_t is current debt and B_{t+1} is new borrowing that determines future debt. In contrast, if the borrower decides to default, the borrowing constraint is given by

$$BC^N(B,I,L;m) \equiv$$

$$\{(c_t^D, B_{t+1}) : c_t^D \leq \theta y_t - B_t - \kappa(z_t, d_t)\phi(z_t) + L + B_{t+1} - mX(z_t, d_t; I, L), \; B_{t+1} \leq 0\},$$

where it is assumed that, unless monitoring takes place $(m = 1)$, defaulters fully discharge L and a fraction $1 - \phi(z_t)$ of the distress shock. If $m = 1$ lenders collect X from the borrower, which is a function of state and the contract on hand. Similarly to our theoretical setup, a defaulting agent incurs a pecuniary cost of defaulting $(1 - \theta)y_t$. We next describe how we specify X, which summarizes how enforcement works in our model.

Instead of adopting our previous approach, which simply assumes that no collection takes place when the agent is distressed, here we impose a more general enforcement constraint that better captures the legal environment in the US and also the idea that lenders cannot collect from truly insolvent borrowers. Specifically, we assume that a defaulting agent is entitled to an

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[20]While our model is limited to only one asset, such assumption is standard and should be interpreted as a frictionless environment in which any durables are always financed using secured loans. Thus consumption in the model corresponds to the flow of services from such goods. We do not model here the liquidity considerations of households, which lead them to assume asset positions and credit card debt. We admit the shortcoming of these models in this respect.

exogenous minimum consumption $c_{\min}$, placing a limit on debt collection. As a result, as long as $c_t^D \geq c_{\min}$, $X_t(.) = L + I$ but, if this condition is not satisfied, $X(.)$ is appropriately reduced to assure $c_t^D = c_{\min}$. In contrast to our static model, this specification implies that debt can in principle be collected from distressed agents. However, since those agents must absorb the non-defaultable portion of the shock $\kappa(z_t, d_t)\phi(z_t)$, collection is still less effective in their case.

Consumers decide whether to default or not to maximize their expected utility. That is, default decision δ solves

$$V_t(B_t, z_t) = E \max_{\delta_t \in \{0,1\}} \{(1 - \delta)V_t^N(B_t, z_t; d_t, \hat{d}_t) + \delta V_t^D(B_t, z_t; d_t, \hat{d}_t)\},$$

where $V_t^N(B, z; d, \hat{d})$ and $V_t^D(B_t, z_t; d_t, \hat{d}_t)$ represent household value functions associated to repayment and default, respectively. These value functions are defined as follows:

$$V_t^N(B_t, z_t; d_t, \hat{d}_t) = \max_{c_t^N, B_{t+1}} \left\{ u_t(c_t^N) + \beta V_{t+1}(B_{t+1}, z_{t+1}) \right\}$$

subject to $(c_t^N, B_{t+1}) \in BC^N(B_t, I, L)$, and

$$V_t^D(B_t, z_t; d_t, \hat{d}_t) = E_{(d,\hat{d})} \left(\max_{c_t^D, B_{t+1}} \left\{ u_t(c_t^D) + \beta V_{t+1}^A(B_{t+1}, z_{t+1}) \right\} \right),$$

subject to $(c_t^D, B_{t+1}) \in BC^D(B_t, I, L, m)$. The period utility function is CRRA and it is adjusted by age dependent family size, as is standard in this class of models. Specifically, $u_t(c) = \frac{(c/s_t)^{1-\sigma}}{1-\sigma}$, where σ is the risk-aversion parameter and s_t is an exogenous family size adjustment factor. Note that the continuation value under default V_{t+1}^A is different from the one associated with repayment. This is implied by the fact that the agent with a default flag on record is assumed to spend the next period in autarky. In autarky, the agent is assigned a null contract $L = 0$, and continues to incur a pecuniary cost of defaulting equal to $(1 - \theta)y$.[21]

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[21]The default penalty is not necessary in our model to sustain debt. It is needed to quantitatively match the

The selection of contracts in equilibrium is largely analogous to our static environment and therefore omitted. This is because contracts are assigned for the duration of one period and so the lender problem is almost identical.

4.2 Parameterization

The key parameters of the model governing the results are monitoring cost λ, default penalty $1 - \theta$, and both the level and change in the precision of information, π and $\Delta\pi$, respectively. We discuss the choice of these parameters first. The remaining parameters and features of the model are fairly standard and we discuss them last. Table 2 summarizes our parameter choices and data targets. To avoid issues with data implied by the crisis and law changes, we choose year 2004 as our calibration target for the 2000s. In many cases, we use trend values obtained by regressing data from 1985-2004. These include charge-off rates and revolving debt to income, as well as median household income growth in the economy (see the online Appendix for all the relevant data sources).

Costs of monitoring/enforcement. Our results are very much a function of λ. If these costs are very small, our mechanism is not operational. It thus important to choose a reasonable level of collection costs. To this end, we use industry evidence to estimate collection costs devoted to credit card debt. To stay on the conservative side, we focus on variable costs and calibrate our model to the lowest bound on these costs. Specifically, we use the reported total wage bill of the debt collection industry (IBISWorld, 2013b), and multiply it by the fraction of industry revenue derived from unsecured consumer credit (which is mostly credit card debt). This fraction is 1/3 of revenue, which despite our narrow focus on wage costs,

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high default rates that we see in the data. In the absence of any punishment, the default rate would be hardwired to the probability of the distress shock, and thus we would have no flexibility to match observed default rates. At the same time, it sustains a range of risk free contracts. The pecuniary nature of penalties is not important and similar results can be achieved if agents suffer disutility from being monitored.

gives an estimated cost of about 3.5 billion dollars, or about 0.2% of total revolving debt in 2004. This is the moment we target to obtain the value of λ. These costs represent about 1/25 of total default losses in our model. Nonetheless, such costs can have significant implications for the market when IT improves. As an additional check that these costs are reasonable, note that debt collection costs in late 1980s incurred by GE Capital, our leading case study discussed in Section 2, was about 1.25%. This is well above what our model implies for the 1990s, which reassures as that we stay within a reasonable range of values.

λ is equivalent to about \$8500 (2004 dollars), a value we find sensible for several reasons. First, in our model we do not have 'soft' collection methods, and thus enforcement costs involve full state verification and, arguably, legal lawsuits. More importantly, however, in the data consumers typically default on multiple accounts, implying that the same costs might be incurred by multiple lenders. In contrast, in our model the cost is paid only once. In addition, given our setup, the costs of collection pertain to a defaulting household, which in the data may involve a more complex problem of collecting from more than one person at a time. Finally, note that when we factor in the monitoring rate of defaulters in our model (see Table 4 below), expected monitoring costs per defaulting household are much lower, about \$800 in 2004.

Technological progress in monitoring/enforcement. While it is indisputable that significant progress has taken place in the debt collection industry due to the widespread adoption of IT based solutions – which we discuss earlier in the paper and in the online appendix – quantification of the rate of progress in relation to our model remains difficult. To address this issue and relate our assumptions to evidence, we proceed as follows. First, the evidence suggests that the adoption of IT-based solutions on a wide scale began in the early 90s. This motivates us to set signal precision π in the late 80s at a point where the use of signals is barely profitable, that is, at such π lenders would be close to indifferent between adopting the new technology or not. This gives us the initial level of π, which in the baseline calibration is about

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0.5. From this initial level we proceed by increasing π, knowing that a gradual switch from full to selective monitoring will occur, i.e., the adoption of modern collection technologies based on segmentation and prioritization will take place.

We choose $\Delta\pi$ to assure that: 1) we fully match the data as far as charge-offs are concerned, and 2) the rate of progress in collection technologies is within the range of values implied by the direct evidence from industry case studies discussed above. In particular, we use data from the randomized control study of GE Capital (Makuch et al., 1992).

Table 2: Paramater Choices

Parameter	Value	Calibration Target	Data (%)	Model (%)
λ	0.1	Agg. monitoring costs/total debt	0.2[a]	
π_{04}	0.785	Charge-off rate in 04 (trend)	5.2	5.2
π_{89}	0.538	ΔCharge-off rate 89-04	3.4	3.4
		Enforcement savings/total debt	0.3[b]	0.2-0.6
β	0.74	Debt to median income	15.1	15.1
θ	0.921	Charge-off rate in 89 (trend)	3.4	3.4
τ	0.07	Interest rate Premium	6.4	6.4
$c_{\min}$	0.4	30-40$\times$min.wage$\times$52wks/disp.income	25-33	27[c]
σ	2	Arbitrary		
$(\kappa, \phi, p)(z_t)$	$\begin{cases}(0.24, 0.9, 0.15) & z_t = 1 \\ (0.33, 0.5, 0.05) & z_t > 1\end{cases}$	See text.		

[a]Aggregate wage bill of the debt collection industry/aggregate revolving debt.
[b]Data from GE capital study (Makuch et al., 1992).
[c]We assume that mean disposable income is approximately 0.85 of mean income.

The GE Capital study reports that the company had \$12 billion of outstanding credit card debt at the time of adoption, and about \$400 million in write-offs. Incidentally, the latter are consistent with the aggregate charge-off rate in 1989, which is about 3.3%. The switch from labor intensive collections based on human heuristics to an IT-based system based on signal generation and a much more selective use of collection effort reported GE Capital estimated savings of at least \$37 million, equivalent to 0.3% of total debt or 9.3% of write-offs. These

savings were computed by performing the following experiment: out of a random sample of 100,000 delinquent accounts, 60,000 were subjected to the new collection system, 20,000 to the traditional collection method, and 20,000 were sent to collection agents for telephone interviews. Total reported collection costs in the preceding period, which the company aimed at reducing, were reported at 1.25% of debt – a number lower that what our model will assume.

To relate our model to GE capital case study, we emulate a similar procedure. Specifically, we assume that lenders acquire a new technology that increases signal precision to deal with the pool of contracts that have already been extended. After that, lenders use the new monitoring strategy to re-optimize collection so that average profitability of the same contracts is enhanced. Since in our model borrowers may react to a change in monitoring strategies, we assume two scenarios regarding borrower expectations: i) borrowers are myopic and do not anticipate the change,[22] and ii) borrowers have rational expectations and detect any change in monitoring regime, modifying their default decisions appropriately. Both scenarios are reasonable and can be used as targets for our model. Table 2 reports the range of efficiency gains. As we can see, the choice of $\Delta\pi$ that matches the change in the charge-off rate is close to the efficiency gains under rational expectations, while overshooting the myopic scenario by a factor of two. Since GE Capital was one of the early adopters back in 1990, and the 90s and 00s have experienced large improvements in IT, we find the value in our model reasonable.

Income Process and the Distress Shock. The income process of the households is assumed to be given $y_t = e_t z_t$, where z_t is governed by a Markov process characterized by a transition matrix $P_t(z|z_{-1})$ and e_t is an age-dependent deterministic trend. The transition matrix is identical from period 1 through $T - N$, and then again from period $T - N$ to period T. The last N periods are associated with retirement.[23] During retirement, it is assumed that

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[22]There are three possible cases, depending on whether the new signal is observable. This distinction does not matter for this case, so we use the new signal in the reported results.

[23]Retirement income assumes a replacement rate of 65% relative to recent earnings, which matches the evidence cited by Munnell and Soto (2005). Income level during retirement is given by a weighted average of the realized

there is no income uncertainty, and so $P_t(z|z_{-1}) = 1$, and zero otherwise. The initial distribution of income is given by the ergodic distribution of the driving process. Finally, our model is biannual and so all processes are appropriately adjusted. The biannual nature of the model will also matter later for the distinction between stock and flow variables. Namely, all flow variables will be divided by a factor of two to make the comparison to annual flows observed in the data (charge-off rate, default rate, etc...).

To calibrate the income process z and the distress shock parameters (κ, ϕ, p), we use the available estimates of lifetime income processes in the literature and combine it with the evidence collected by Livshits, MacGee and Tertilt (2010) regarding the size of the major life-cycle distress (expense) shocks, such as unwanted pregnancy, divorce and medical bills. In our analysis, we assume that medical bills are the only (directly) defaultable shock and set ϕ accordingly; unwanted pregnancy and divorce expenses are non-defaultable, unless the borrower can use a credit line to borrow and default. This specification, given we have only a single shock, implies that a good portion of the distress shock is actually non-defaultable.

The starting life-cycle income process that we use in our income/shock estimation is identical to the one used by Livshits, MacGee and Tertilt (2010). This process is discretized to yield a 6x6 biannual Markov chain. The distress shock is obtained by aggregating all 3 major life-cycle shocks occurring at an appropriately rescaled frequency to match the biannual specification of our model.[24] This process is additionally augmented by any income shocks that are larger than 20% relative to the average income realization of the underlying process. We remove such deep negative shocks from our estimation of the Markov chain z and relocate them to the distress shock.[25] For brevity we only report the shock parameters in Table 4,

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$T - N$ persistent component of income (30%) and the average income in the economy (35%).

[24]The original specification assumes a triennial period length. We multiply the original frequency reported by Livshits, MacGee and Tertilt (2010) by 2/3.

[25]Income shocks larger than 20% are assigned to the distress shock and are assumed to only affect the lowest income bracket z_1. This income group faces a higher probability of distress, and generally a lower size of the shock. The size of the distress shock is 33% of the average income (per model period) for all z_i, $i > 1$ and 24% in the case of $i = 1$. The frequency of the shock per model period is 5% (2.5% on annual basis) for higher

which are key to our results.[26]

Other Parameters. As far as the utility function is concerned, we set the discount factor to match the level of credit card debt to aggregate median household income. The target in the data is 15.1%, which corresponds to our estimated trend value for 2004. We chose median household income because, due to utility weights that adjust for family size, the appropriate accounting unit in our model is a single household. We assume a standard relative risk aversion of 2. As stated above, consumption of each unit in the model is equal to c_t/s_t where s_t is an exogenous family size adjustment factor taken from Livshits, MacGee and Tertilt (2010). This feature is standard and helps match the hump shaped consumption pattern over the life-cycle.

The cost of bank funds and the saving rate are both normalized to zero. However, the use of credit lines involves an exogenous transaction cost τ. We set $\tau = .07$ (biannual) so that our model, after adding costs of funds equal to the interest rate on savings, matches the trend-implied annual interest premium on credit card accounts in 2004. This premium is defined by the difference between the average interest rate on revolving credit card accounts assessing interest and the aggregate net charge-off rate on credit card debt.

We set the cost of defaulting $1 - \theta$ to match the charge-off 1989, equal to 3.4%.

Finally, in inconsistency with legal limits on debt collection, we set c_{min} to be about 27% of average disposable income in our model.[27]

Table 3: Quantitative Results

| | 1989 | | 2004 | |
	Data[a] (1)	Model (2)	Model (3)	Data (4)
(in % unless otherwise noted)				
Default				
Net CC Charge-off Rate	3.4	3.4	5.2	5.2
Default Rate[b]	-	1.4	1.9	2.2
Average Discharge Per Defaulter[c] ($)	11,400	15,835	20,360	23,000
Debt				
Aggregate Revolving Debt (millions)	347,850	555,567	746,390	745,428
Credit				
Mean CC Interest Premium[d]	6.4	6.4	5.8	4
Mean Credit Limit of Risky Contracts[e] ($)	10,665	10,416	18,147	21,000
Std. Dev. of Credit limits of Risky Contracts ($)	14,185	6,592	27,833	28,986
Mean Utilization Rate (for revolvers)	46.5	60.0	53.7	47.1

All values in % unless otherwise noted. Amounts are in 2004 dollars.

[a]Data corresponds to trend values for 1990 and 2004 (due to major bankruptcy reform we do not consider here years after 2004). This procedure allows us to abstract from business cycle fluctuations in the underlying variables. Linear trends are estimated using time series from 1985 to 2004, whenever possible. Mean unsecured debt defaulted on per statistical (formal) bankruptcy filer, as default data is only available for formal filings. Linear trends fit all time series reasonably well. See the online appendix for more details and a list of sources.

[b]Average default rate in years 2001-2005 in the Experian dataset.

[c]Reported data values pertain to total unsecured discharged debt to income of formal bankruptcy filers.

[d]See previous footnote; interest rate on revolving consumer credit card accounts assessing interest, less the charge-off rate and the opportunity cost of funds (our measure of the opportunity cost of cc-funds is the yield on 5-ytm US Treasuries).

[e]Data pertains to mean credit limits of revolvers. Credit limits of risk-free contracts are not directly comparable to data since borrowers in our model are always assigned the highest limit that does not trigger default.

4.3 Quantitative Findings

As is clear from Table 3, our model can fully account for the rise in the charge-off rate in the data. As already mentioned, this aspect of the expansion has been the Achilles' heel of existing IT-based models, both in terms of changes as well as level. At the same time, our model is consistent with numerous other static characteristics of the US credit card market in 2004.

Another remarkable feature of our model is its ability to deliver high frequency of defaults in the presence of high levels of gross debt held by households. This aspect is generally difficult to account for using standard models due to an inherent tension between the sustainability of high gross levels of debt – which requires that default must be costly to borrowers – and the appeal of default, which requires it not to be too costly. Our model reconciles this tension in a natural way: in the presence of an endogenous enforcement technology, default is more costly for borrowers who 'should' repay, and not so otherwise.

Finally, our model matches remarkably well the data regarding credit limits. Credit limits describe access to credit in the data, and they are distinct from the use of credit. Our model can speak to this distinction. As is clear from Table 3, we match both the mean credit limit in the data and qualitatively the upward trend in dispersion.

In terms of the change in interest rate premia and indebtedness, our mechanism alone can only partially match the data. In this sense, other aspects of IT are necessary to fully account for the expansion of the credit card market. Accordingly, our paper provides a complementary mechanism which can alter the risk composition of debt to match the data. While we do not

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income brackets, and 15% (7.5% on annual basis) in the case of the lowest income bracket. Moreover, the shock is largely non-defaultable in the case of the lowest income bracket, implying $\phi(z_1) = .9$. This is because in this group medical bills constitute a smaller fraction of the shock, which additionally include income drops beyond the 20% mark. In the case of other income groups, $i > 1$, $\phi(z_i) = .5$.

[26]The transition matrix can be found in the online supplementary files.

[27]Title 3 of the Consumer Credit Protection Act limits debt-related wage garnishments to 25% of disposable earnings, as long as weekly earnings are above 40 times the federal hourly minimum wage. In the latter case collection is further restricted and completely eliminated when earnings are below 30 times the minimum wage. Accordingly, we choose c_{min} to be between the annualized earnings associated to these two limits.

report it here, we have experimented with lowering transaction costs and verified that one can match the full extent of these changes. The required drop in transaction costs would be consistent with evidence from the credit card industry (Berger, 2003).

Table 4 confirms the basic intuition that the increase in the charge-off rate comes from transition to a regime in which 1) more risky contracts are extended (as opposed to risk free), and 2) selective monitoring is more prevalent, which additionally involves strategic default.

Table 4: Technological Progress in Enforcement

(in %)	1989	2004	Data (2004)
Costs			
Enforcement Costs per Dollar of Debt	0.71	0.21	0.2
Efficiency Gain Relative to Write-offs	-	5.7-18.0[a]	9.3[b]
Monitoring Strategies			
Fraction of Defaults Monitored	29.4	9.5	9.2[c]
Share of Risk-free Contracts	60	55	-
Share of Full Monitoring Contracts	34	23	-
Share of Selective Monitoring Contracts	6	22	-

[a]The lower number was obtained assuming fully rational agents, while the higher number refers to the case of myopic agents.
[b]Data from GE capital study (Makuch et al., 1992).
[c]Average number of suits, judgments and wage garnishments filed per delinquent borrower. Computed using the Experian data set for the period between 07/2003 and 07/2005.

Finally, while one should not necessarily associate monitoring with litigation, we report litigation rates as a rough measure of the monitoring rate of delinquent borrowers. Our model matches this number in 2004. We do not know what this number was in the late 80s, but as the next section highlights, the evidence suggests that data trends in this respect are, at least qualitatively, in line with the predictions of our model.

4.4   Other Testable Implications of the Model

The switch to selective monitoring of risky contracts generates two testable predictions, which are shown in Table 4: the monitoring rate of delinquent borrowers falls from 30% to 10%, and

there is a sharp increase in the use of signals as the share of selective monitoring contracts goes from 6% to 22%. Using our credit bureau data we are able to confirm both predictions. The first one is validated by the trend in default-related litigation. As Figure 3 shows, the average number of suits, judgments and wage garnishments filled in court *per delinquent borrower* decreased by about 16.3% during the period 1999-2007. Our findings are consistent with Hynes (2006). Using court data on wage garnishments (data for the state of Virginia, but partially validated nationally) he reports that, while the number of personal bankruptcy filings were rapidly growing over the 90s, the growth of garnishment orders was negative. Regarding the second prediction, Figure 3 illustrates that the number of collection inquiries per delinquent borrower went up by 30%. While these statistics are not readily comparable to enforcement rates in our model, they nonetheless suggest that our mechanism is qualitatively consistent with these developments.
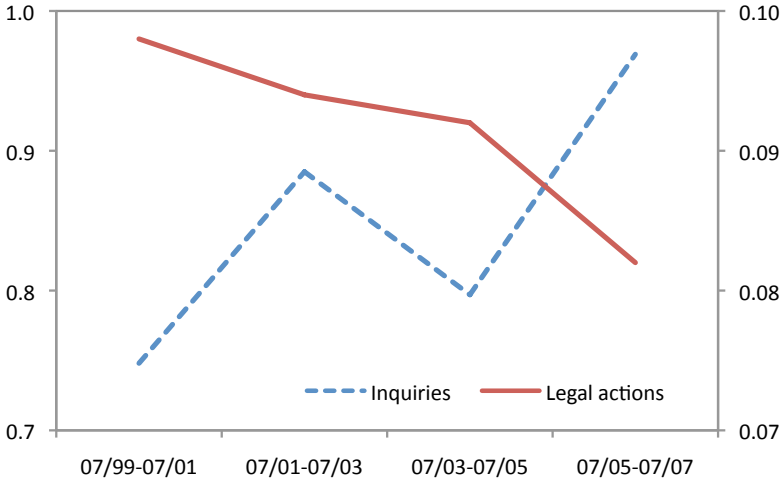

Figure 3: Collection Inquiries (left axis) vs. Legal Collections (right axis).

5 Conclusion

Existing theories of consumer bankruptcy rule out the option of informal default by assumption, and abstract from enforcement costs. Here we argue that this assumption is not only at odds with the data, but neglects an important channel through which IT progress affects the pricing and provision of credit. In particular, we show that this channel is potent enough to account for key facts underlying the IT-driven expansion of credit card borrowing in the 1980s and over the 1990s. Our mechanism is complementary to existing explanations that use IT to account for the rise credit card borrowing. Independently, our approach can help account for the observed high default rates and credit card debt by providing a theoretical foundation for the use contingent default penalties.

The mechanism we study has broad implications, well beyond unsecured credit markets. In particular, it applies to any environment exhibiting asymmetric information and substantial enforcement costs, such as secured credit, insurance markets and taxes. We leave the development of such applications to future research.

Appendix

A1. Collection Scores and Default

The next table presents the estimates of logit regressions, where the dependent variable is the default status of delinquent borrowers 2 or 4 years later, and the independent variable is Experian Bankcard RecoveryScore. Recovery scores take on values between 400 and 800. We run the analysis for two different samples using pre-crisis data from years 2001, 2003 and 2005: all delinquent borrowers, and those having an inquiry to the credit bureau made by a collection department or a third-party collection agency.

Table 5: Recovery Scores and Propensity to Default (Logit Regressions)

	Default[a] (2 years) Coefficient[b] (std. error)	Default (4 years) Coefficient (std. error)
All Delinquent		
Recovery Score	-0.0039^*	-0.0036^*
	(0.0003)	(0.0003)
No. Observations	13,477	13,470
With a Collection Inquiry in 24 months		
Recovery Score	-0.0036^*	-0.0039^*
	(0.0004)	(0.0004)
No. Observations	7,077	7,073

[a]Delinquent borrowers that did not file for bankruptcy, and did not showed an increase in the number of fully paid accounts that were at least 90 days past due.
[b](*) denotes 1% significance level.

A2. Omitted Proofs

Proof of Proposition 1. We begin by noting several properties of indirect utility functions N and D, defined in (4) and (5): i) N is constant in P and D is decreasing in P; ii) N is strictly decreasing in I and D is constant in I; and iii) they are continuous in I and P.

Part 1): Comparing (4) and (5) when $d = 1$, it is clear that $D > N$ iff $(1-\theta)Y + L > Y - b - I$ for all $\hat{d} = 0, 1$. The same is true for $d = 0$ when $P(\hat{d}) = 0$. Thus, since D is decreasing in P, consumers never default when $L \leq L_{min}(I) \equiv \theta Y - I$ for all S and all P, where the weak inequality comes from Assumption 1.

Part 2): D being independent of P when $d = 1$ implies that distressed consumers always default when $L > L_{min}(I)$. For $d = 0$, we note from i) that the default decision of a non-distressed consumer must be decreasing in the underlying monitoring probability; that is, if a non-distressed consumer decides not to default for $P(\hat{d}) = \hat{P}$, she will not default for any $P(\hat{d}) > \hat{P}$. Accordingly, there must exist some $\bar{P} \leq 1$, contingent on contract terms (I, L), such that a non-distressed agent defaults if $P(\hat{d}) < \bar{P}$ and does not default when $P(\hat{d}) \geq \bar{P}$.

Continuity w.r.t. I follows from iii). It is decreasing in I by i) and ii). $\bar{P}(I, L)$ is independent of π since expressions (4) and (5) do not depend on precision.

To prove the last part note that, when $I = 0$ and $L = L_{\min}(0) = \theta Y$, both default losses and monitoring costs are zero since no consumer defaults. Hence, lenders can feasibly offer $I = 0$, given that costs of funds are zero. $\qquad\square$

Proof of Proposition 2 and Corollary 1. The outline of the proof is as follows. Fix $L > L_{\min}$, implying that distressed agents always default and non-distressed consumers will want to default as long as they expect to be monitored with sufficiently low probability (Proposition 1). First, we show that, by Assumption 2, it must be the case that $P(0) \geq \bar{P}(I, L)$. Second, we argue that $P(\hat{d}) > \bar{P}(I, L)$ cannot happen in equilibrium. Finally, we pin down the sufficient condition on π that guarantees $P_\pi(1) = 0$ in selective monitoring.

To show that $P(0) \geq \bar{P}(I, L)$, we first prove that, given a zero profit contract (I, L, P) with $P(\hat{d}) \geq \bar{P}(I, L)$ for $\hat{d} = 0, 1$, any zero profit alternative contract (I', L, P') with $P'(0) < \bar{P}(I', L)$ involves the same utility under distress but, under no distress, (i) fewer resources for consumption due to excessive deadweight losses (burned resources) and (ii) higher consumption risk.

To prove (i), it suffices to show that the total deadweight loss under (I, L, P) is smaller than the deadweight loss associated only to signal realization $\hat{d} = 0$ under (I', L, P'). Deadweight losses are given by the sum of default penalties and monitoring costs (defaulted debt is consumed in some states of the world so it does not count as burned resources). Notice that the deadweight loss associated to default by distressed consumers is the same under (I, L, P) and (I', L, P'). Thus, we just need to compare monitoring costs and non-distressed default penalties across both contracts. The total deadweight loss under (I, L, P) is $p\lambda P(0)$, given that non-distressed agents do not default. Under (I', L, P'), for signal realization $\hat{d} = 0$, monitoring costs are $Pr(\hat{d} = 0)\lambda P'(0)$ while non-distressed default penalties amount to $Pr(0, 0)(1 - P'(0))\theta Y$.

Accordingly, the difference in deadweight loss between contracts (I, L, P) and (I, L, P') is at most

$$p\lambda P(0) - Pr(\hat{d} = 0)\lambda P'(0) - Pr(0,0)(1 - P'(0))\theta Y$$

$$\leq p\lambda P(0) - (1-p)\lambda P'(0) - (1-p)^2(1 - P'(0))\theta Y$$

$$\leq p\lambda - (1-p)\lambda P'(0) - (1-p)^2(1 - P'(0))\theta Y,$$

where the first inequality follows from $Pr(0,0) = (1-p)(\pi + (1-\pi)(1-p)) \geq (1-p)^2$. We now show that the RHS of the last inequality is less than zero by Assumption 2. Rearranging terms, the RHS is less than or equal to zero if

$$p\lambda \leq (1-p)\left(\lambda P'(0) + (1-p)(1 - P'(0))\theta Y\right) = (1-p)\left((1-p)\theta Y + [\lambda - (1-p)\theta Y]P'(0)\right).$$

Since the last term is minimized at either $P'(0) = 0$ or at $P'(0) = 1$, a sufficient condition for this expression to hold is $p\lambda \leq (1-p)\min\{(1-p)\theta Y, \lambda\}$, which is clearly satisfied for $p < 1/2$ whenever $p\lambda < (1-p)^2\theta Y$, i.e., when Assumption 2 holds.

Part (ii) simply follows from the fact, from an ex ante perspective, consumption when $d = 0$ is stochastic under (I', L, P'). This is due to the fact that some non-distressed agents repay in order for lenders to break even and some default since $P'(0) < \bar{P}(I', L)$. In contrast, it is deterministic under (I, L, P), given that all non-distressed agents repay their debts.

Together, (i)-(ii) imply that the distribution of resources for consumption under (I', L, P') can be expressed as the distribution under (I, L, P) plus a risky gamble with negative expected value due to the extra resources burned under (I', L, P'). Accordingly, by the concavity of u and the fact that borrowing constraints and are the same across contracts, the certainty equivalent of expected utility under no-distress is higher under (I, L, P). But then, since both contracts provide the same utility to consumers under distress (it only depends on L), consumers' ex

ante utility under (I, L, P) is higher than under (I', L, P').

To establish that $P(\hat{d}) > \bar{P}(I, L)$ cannot happen in equilibrium, notice that non-distressed borrowers do not default under $\hat{d}$ when $P(\hat{d}) = \bar{P}(I, L)$ by Proposition 1. Hence, setting $P(\hat{d})$ above $\bar{P}(I, L)$ only leads to higher monitoring costs without increasing revenue and thus to higher finance charges – which may additionally increase monitoring costs for $\hat{d} = 1$ under full monitoring, given that $\bar{P}$ is increasing in I.

We finish the proof by showing that if $P(1) < \bar{P}(I, L)$ and $\pi \geq \pi^*$ then $P(1) = 0$. Note that, since all agents default under $\hat{d} = 1$ if $P(1) < \bar{P}(I, L)$, for fixed contract terms, the marginal increase in profits due to a infinitesimal increase in $P(1)$ satisfies

$$\frac{\partial \mathbb{E}\Pi(S, I, L, P)}{\partial P(1)} = Pr(0, 1)(L + \bar{I}) - Pr(\hat{d} = 1)\lambda = p\left((1 - p)(1 - \pi)(L + \bar{I}) - \lambda\right)$$

for all $P(1) < \bar{P}(I, L)$. It is easy to check that $\frac{\partial \mathbb{E}_{I,L,P}\Pi(S,I,L,P)}{\partial P(1)} \leq 0$ when $\pi \geq \pi^*$. As a result, lowering monitoring probabilities all the way down to $P(1) = 0$ with (I, L) unchanged is profit feasible and increases utility, since consumers prefer lower monitoring probabilities. Furthermore, lenders can (weakly) lower I, which also increases utility. $\quad\square$

Proof of Proposition 4. Since all agents with $\hat{d} = 1$ default, and a fraction $P_\pi(1)$ of non-distressed agents are reverted back to repayment under $\hat{d} = 1$, the zero profit condition under selective monitoring is given by

$$Pr(0, 0)I = [p + Pr(1, 0)]L + \left[Pr(0, 1)\bar{P}(I, L) + Pr(\hat{d} = 1)P_\pi(1)\right]\lambda - Pr(1, 0)(L + \bar{I})P_\pi(1).$$

To derive the expressions for $\mathcal{D}$ and $\mathcal{M}$ we just solve for I and rearrange terms. The last part follows form the fact that, as π increases, $Pr(1, 0)$ and $Pr(0, 1)$ monotonically decrease to zero, and $P_\pi(1) = 0$ for all $\pi > \pi^*$ by Proposition 2. $\quad\square$

Proof of Proposition 5. We show that $P_\pi(1)$ is strictly decreasing in π whenever it is positive.

The second part directly follows from $P_\pi(1)$ being decreasing and Proposition 2. Fix credit limit L and signal precision π_L, and let $P^*(0) = \bar{P}(I, L)$ and $0 \le P^*(1) < \bar{P}(I, L)$ be the monitoring probabilities under the preferred selective monitoring contract with credit limit L. Also, let $I(\pi_L, L, P^*)$ denote the associated zero profit interest rate. Suppose the precision of information improves to $\pi_H = \pi_L + \varepsilon$, for some infinitesimal ε and let P^{**} denote the monitoring probabilities of the best selective monitoring contract with L under π_H. We need to prove that $P^{**}(1) \le P^*(1)$, with strict inequality if $P^*(1) > 0$.

By contradiction, suppose that $P^{**}(1) > P^*(1)$ and assume $\bar{P}$ remains constant. Let V_π denote consumers' ex ante utility under π. Our goal is to show that

$$V_{\pi_H}(L, I(\pi_H, P^{**}), P^{**}) \ge V_{\pi_H}(L, I(\pi_H, L, P^*), P^*)$$

implies

$$V_{\pi_L}(L, I(\pi_L, L, P^{**}), P^{**}) > V_{\pi_L}(L, I(\pi_L, L, P^*), P^*).$$

Recall that, by Corollary 1, non-distressed consumers repay under $\hat{d} = 0$ and default under $\hat{d} = 1$. Let x denote the additional revenue collected by lenders under π_H by going from P^* to P^{**}. By assumption, the collected revenue must be strictly higher than the additional monitoring costs, otherwise consumers' ex-ante utility would be lower under P^{**} than under P^*. Note that, while the additional monitoring costs of going from P^* to P^{**} are independent of π (the mass of defaulting agents with $\hat{d} = 1$ is equal to $Pr(\hat{d} = 1) = p$), the increase in revenue is strictly higher under π_L than under π_H. This is because the mass of non-distressed agents with $\hat{d} = 1$ is higher when π is lower. Specifically, the extra revenue collected under π_L is fx, where $f = \frac{Pr(0|1;\pi_L)}{Pr(0|1;\pi_H)} > 1$ and $Pr(y|z; \pi)$ is the probability that $d = y$ conditional on signal $\hat{d} = z$ when precision is π.[28]

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[28]The extra (gross) revenue collected due to an increase $\Delta P(1)$ is given by $Pr(\hat{d} = 1)Pr(0|1, \pi)(L + \bar{I})\Delta P(1)$.

Next, suppose the collected resources under π_H are used to lower I so that the zero profit condition holds. Our goal is to show that, if such drop in I justifies the increase in monitoring probability under π_H relative to P^*, it must justify a similar increase under π_L. To this end, note that the utility of distressed agents is independent of P and I, and so the change in ex-ante utility under π is determined by:

$$\Delta V_\pi = V_\pi(L, I(\pi, L, P^{**}), P^{**}) - V_\pi(L, I(\pi, L, P^*), P^*)$$

$$= pPr(0|1; \pi)\Delta D_\pi + (1 - p)Pr(0|0; \pi)\Delta N_\pi,$$

where ΔD_π and ΔN_π denote the change in the indirect utility of non-distressed consumers under signals $\hat{d} = 1$ and $\hat{d} = 0$, respectively. Importantly, ΔD_π is the same under π_L and π_H. This follows from the fact that for a non-distressed defaulting consumer the only relevant variables are L and P, and these probabilities are identical in both cases. Hence, we can express the change in the ex-ante utility under π_L as follows

$$\Delta V_{\pi_L} = pPr(0|1; \pi_L)\Delta D_{\pi_L} + (1 - p)Pr(0|0; \pi_L)\Delta N_{\pi_L}$$

$$= f\left(pPr(0|1; \pi_H)\Delta D_{\pi_H} + (1 - p)Pr(0|0; \pi_H)\frac{g}{f}\Delta N_{\pi_L}\right),$$

where $g = \frac{Pr(0|0; \pi_L)}{Pr(0|0; \pi_H)} < 1$ since $\pi_H > \pi_L$. This implies that, if we establish

$$\frac{g}{f}\Delta N_{\pi_L} > \Delta N_{\pi_H}, \tag{A1}$$

we would have shown that $\Delta V_{\pi_L} > f\Delta V_{\pi_H}$. This is enough to establish the contradiction since $\Delta V_{\pi_H} \geq 0$ would imply $\Delta V_{\pi_L} > 0$. To see why (A1) holds, note the following. Under π_L, all non-distressed consumers with $\hat{d} = 0$ receive a transfer of resources equal to fx. However, compared to π_H, their mass is lower by a factor $g < 1$. Hence, the transfer of resources from

$\hat{d} = 1$ to $\hat{d} = 1$ under π_H caused by the increase in monitoring probability, which in *per capita* terms is x, is lower than $\frac{f}{g}x$, which is the per capita transfer under π_L. Furthermore, as we show in Lemma 1 below, the zero profit condition implies that $I(\pi_L, L, P^{**}) > I(\pi_H, L, P^{**})$ when $\bar{I} < \lambda$. But then the marginal utility from an *identical* transfer is higher under π_L than under π_H. Specifically, by the symmetry of u,

$$N(S, I, L, P) = \begin{cases} u(y - B + L, y - L - I) & L < \frac{B+I}{2} \\ u(y - \frac{B+I}{2}, y - \frac{B+I}{2}) & L \geq \frac{B+I}{2}. \end{cases}$$

Accordingly, if u_i denotes the marginal utility of consumption in sub-period $i = 1, 2$, we have that

$$\frac{\partial N(S, I, L, P)}{\partial I} = \begin{cases} -u_2(y - B + L, y - L - I) & L < \frac{B+I}{2} \\ -u_2(y - \frac{B+I}{2}, y - \frac{B+I}{2}) & L \geq \frac{B+I}{2}, \end{cases}$$

where the last term comes from the FOC for borrowing $(u_1(c, c') = u_2(c, c'))$. Hence, by the concavity of u, the higher I the higher the increase in N following a decrease in I.

This finishes the proof that (A1) holds, as the increase in utility more than compensates the differences in masses. In addition, the drop in $\bar{P}(I, L)$ is (weakly) higher under π_L due a larger impact on N (and no impact on D). This implies a (weakly) larger reduction in monitoring costs due to a change $\bar{P}(I, L)$, as there are more defaulting consumers with $\hat{d} = 1$ at lower precision. Hence, our initial assumption of fixing $\bar{P}(I, L)$ in the above argument was without loss. Finally, the continuity of V_π w.r.t. P yields the strict inequality $P^{**}(1) < P^*(1)$. $\qquad\square$

Lemma 1. *Fix $L > L_{\min}$ and $P(\cdot)$ with $P(1) < \bar{P}(I, L) \leq P(0)$. If $\bar{I} < \lambda$ then the zero profit I is strictly decreasing in π.*

Proof. We need to show that $\mathcal{D} + \mathcal{M}$ from Proposition 4 goes down with π when we replace

$\bar{P}(I, L)$ and $P_\pi(1)$ with $P(0)$ and $P(1)$, respectively. That is, we need to show that

$$\frac{p}{Pr(0,0)} + \frac{Pr(1,0)}{Pr(0,0)} + \frac{Pr(0,1)P(0) + pP(1)}{Pr(0,0)}\frac{\lambda}{L} - \frac{Pr(1,0)}{Pr(0,0)}P(1)\left(1 + \frac{\bar{I}}{L}\right)$$

is decreasing in π if $L > \bar{I} - 2\lambda$. Since $Pr(1,0) = Pr(0,1)$, the above expression yields

$$\frac{Pr(1,0)}{Pr(0,0)}\left(1 + P(0)\frac{\lambda}{L} - P(1)\left(1 + \frac{\bar{I}}{L}\right)\right) + \frac{p}{Pr(0,0)}\left(1 + P(1)\frac{\lambda}{L}\right).$$

The last term is clearly decreasing in π. The first term is decreasing in π if the expression in brackets is positive. But this is the case whenever $\bar{I} < \lambda$, given that $P(0) > P(1)$. □

Proof of Proposition 6. The result follows directly from the arguments laid out in the proofs of Propositions 2-5. To see why, fix $L > L_{\min}$. By Proposition 3, I^{FM} and thus consumers' ex ante expected utility, are constant with respect to π. In contrast, ex ante utility under selective monitoring must eventually be increasing in π since, by Proposition 4, I^{SM} must be decreasing in π and $P_\pi(1) = 0$ at high enough π. Furthermore, ex ante utility is higher under selective monitoring when $\pi = 1$, given that the $\mathcal{D}$ is equal in both regimes while $\mathcal{M}$ is lower under selective monitoring. Thus, there exists $\bar{\pi} < 1$ such that I is lower under selective monitoring at any precision higher than $\bar{\pi}$. The fact that $\underline{\pi} > 0$ follows from the same argument used to show that $P(0) \geq \bar{P}(I, L)$ in the proof of Proposition 2: when signals are uninformative ($\pi = 0$) the costs associated with monitoring with intensity $\bar{P}(I, L)$ under $\hat{d} = 1$ are lower than the default penalties of strategic default. Hence, utility is higher under $P(1) = \bar{P}(I, L)$ than under $P(1) < \bar{P}(I, L)$ when $\pi = 0$, since there are more aggregate resources for consumption and better risk sharing across different paths. □

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