Modeling the Credit Card Revolution: 
The Role of Debt Collection and Informal Bankruptcy

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ABSTRACT

The literature views default on unsecured debt as a formal, court-based process, free from asymmetric information and enforcement costs. Motivated by the evidence showing that most defaults are informal, we depart from this view by explicitly considering enforcement costs in the presence of asymmetric information and moral hazard. We use our theory to show how IT may have played a key role in reshaping outcomes in the credit card market by affecting the effectiveness of debt collection. We argue that through this novel channel IT progress can account for all key developments observed in this market in recent years.

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Keywords: credit cards, consumer credit, unsecured credit, revolving credit, informal bankruptcy, debt collection, moral hazard

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1 Introduction

The literature views default on unsecured debt as a formal, court-based process, free from asymmetric information and enforcement costs. The underlying assumption is that consumers always file for personal bankruptcy protection in court, and thus eligibility for debt discharge is determined and enforced by the court system rather than by the lending industry.

The recent evidence, however, puts this assumption into question. This is because at least half of credit card debt defaulted on in the US takes the form of an ‘informal’ bankruptcy, meaning that many consumers default actually without ever formally filing in court.\footnote{Using a panel of 50,831 pre-approved credit card recipients, Dawsey and Ausubel (2004) show that as much as half of discharged credit card debt is not attributable to formal bankruptcy filings thereafter. Our work is very much inspired by their findings. Various recent industry surveys are also consistent with this view. For example, 1999 Annual Bankruptcy Survey by Visa U.S.A. Inc. finds that two-thirds of credit card loans that are charged-off as uncollectible are not attributable to bankruptcy filings.} Furthermore, the lending industry actually devotes significant resources to debt collection, suggesting the presence of substantial enforcement costs.\footnote{According to the BLS, employment in the third-party debt collection industry is about 150,000 people. Price-waterhouseCoopers 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 Price-waterhouseCoopers, prepared for ACA International). According to an ACA-commissioned survey (Ernst &Young “The Impact of Third-Party Debt Collection on the National and State Economies,” ACA International 2012), credit card debt accounts for 20\% of all debt collected by the industry. For comparison, the total size of the US police force stands at about 700,000 officers across all agencies. See the online appendix for an overview of the consumer debt collection process and also Hunt (2007) for an overview of the debt collection industry in the US.}

Motivated by the above evidence, here we depart from the literature and explicitly model the presence of costs assumed by the lending industry to enforce credit contracts. As we show, such costs can have important ramifications on the ex-ante pricing of default risk, which we explore here in the context of the rapidly expanding credit card lending in the late 1980s and over the 1990s. In particular, our paper identifies a novel channel that allows to endogenously link the widespread adoption of information technology by the lending industry to the observed trends in the data. While the literature has generally attributed this expansion to the IT-implied improvements in the quality of information (e.g. information sharing through credit bureaus, automated risk scoring models, etc.), thus far formal models have failed to establish such a link.\footnote{For an overview of the key changes in the US credit card market, see Evans and Schmalensee (2005) and White (2007).} To our best knowledge, our paper is thus the first one to fully attribute the
observed changes in this market to IT progress alone.

To develop this theme, we build on the costly state verification literature (e.g. Townsend (1979)), and propose a theory of unsecured borrowing in which the lending industry must monitor defaulting borrowers in order to extend credit contracts that admit default in equilibrium. Monitoring is necessary in our model because default involves asymmetric information that leads to moral hazard, which are absent from the standard theory under the questionable presumption that formal bankruptcy is the predominant form of default. In contrast, in our model default is (largely) informal and thus does not automatically reveal the true solvency status of defaulting borrowers to lenders. To deal with the resulting moral hazard problem and prevent solvent borrowers from strategically defaulting, lenders use information technology to assess borrowers’ ability to pay back their debt.

The key result of our paper shows that this novel role of information technology crucially influences the equilibrium risk composition of aggregate debt. As a result, our model addresses the Achilles’ heel of this literature: the simultaneous rise of credit card debt and its default exposure, as measured by the fraction of outstanding debt defaulted on by consumers. (Our model also applies to other types of unsecured debt, although our data is limited to the credit card market.)

![Figure 1: The Rise of Revolving Credit in the US](image)

Figure 1 reports our main quantitative findings. As we can see, our model is consistent with three basic observations in the data: \(4 \) 1) expansion of revolving credit in the form of

\(4 \)To estimate the trend line we use the time period 1985-2005. Earlier periods are omitted due to the binding
pre-committed credit lines (credit cards), 2) an increase in the average default exposure of credit card debt, and 3) a decline in interest premia on credit card debt. Using our model, we fully account for all these observations by raising the precision of information that lenders have about their delinquent borrowers by a factor of three, and by assuming a simultaneously declining transaction cost of making credit card funds available to the consumers by about 20%. The change in the transaction cost is independently calibrated using the evidence on the excess productivity growth within the banking industry relative to the other sectors of the economy (Berger, 2003). In addition, as we show in the online appendix, our approach enhances the performance of existing models (e.g. Chatterjee et al. (2007) or Livshits, MacGee and Tertilt, 2006) in their ability to account for the observed high levels of default and indebtedness. This is brought about by the fact that our model naturally breaks the inherent tension between defaultable debt sustainability and the attractiveness of default option for distressed borrowers. This is because full or partial repayment by solvent borrowers is endogenously enforced through monitoring, enhancing sustainability of debt, while the attractiveness of default option among distressed borrowers is maintained because collection is ineffective in their case.

In a nutshell, our model thus paints the following picture of the observed changes in the US unsecured credit market. In the late 80s, the IT technology employed by the industry was underdeveloped, which made it difficult for the lending industry to optimize on the cost of enforcing repayment from the moral hazard-prone debtors. This is because risky contracts could only be sustained during this time period using costly “carpet” monitoring of all defaulting borrowers. As a result, credit limits were tight to prevent costly defaults. However, over the 90s, while learning how to assess credit risk in general, the industry also learned how to economize on unnecessary and wasteful monitoring of truly distressed and insolvent borrowers – whose default is actually constraint efficient from the ex-ante point of view. This effect lead the industry to assume greater default exposure, as the data shows. By studying the impact of information on the ex-post moral hazard problem of enforcing credit contracts, our paper

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. This ruling let credit card issuers apply nationally usury laws from the state in which they were headquartered and some states dropped their usury laws. The increase in credit card lending in the early 80s was likely affected by this decision. Due to a major bankruptcy reform in 2005 we focus on the time period before 2005.
departs from most of the literature, which has solely focused on the link between information precision and adverse selection, i.e., lenders’ ability to assess credit risk ex ante at the contracting stage. As we discuss below, the predictions on default exposure from these models are unclear.

Finally, consistent with the key assumption of our model, the technological improvements in the collection industry largely paralleled those in the credit industry. For instance, TransUnion – the same company that collects credit history data and helps lenders to assess credit risk ex-ante – advertises to debt collectors this way: “TransUnion combines data (...) to provide valuable insight into each account so you can better define consumers’ willingness and ability to repay (...).” More concretely, Portfolio Recovery Associates Inc – one of the major collectors of charged-off credit card debt – reports in its 10-K form filed with the SEC that, from 1998 to 2004, its effectiveness, as measured by cash spent on collection relative to cash collected, increased at least by a factor of two.

Our model is also consistent with other suggestive pieces of evidence. For example, Hynes (2006) studies court data and finds that the growth of garnishment court orders was far slower than the growth of defaults. To the extent that garnishment orders can be interpreted as an imperfect measure of monitoring, this phenomenon is predicted by our theory. Moreover, using recent TransUnion micro-level data, Fedaseyeu (2013) studies the relation between tightness of debt collection laws at the state level and the supply of revolving credit and finds that stricter regulations of debt collection agencies across states are associated with tighter supply of revolving credit, while having no effect on secured borrowing.

**Related Literature** To the best of our knowledge, no other study 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 the literature. These include the adverse selection models of 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 information technology on credit pricing, such as Drozd and Nosal (2007) and Livshits, MacGee and Tertilt (2011).
The first group of papers views events of the 90s as a transition from a pooling to a separating equilibrium. In the latter equilibrium, due to improvements in credit scoring techniques, low-risk types are separated from high-risk types, and consequently borrow more and default more. However, at the same time, high risk types borrow less and default less. Compared to our approach, existing models of adverse selection do not account for the increased default exposure of debt in the data. In addition, adverse selection models also involve an arguably counterfactual reallocation of credit toward the less risky segments of the credit market – to the extent that risk characteristics are correlated with observables such as income, education, wealth, etc. See the discussion in White (2007).

The second group of papers focuses on the choice of formal versus informal bankruptcy, which we do not pursue here. These papers view informal bankruptcy as a renegotiation tool that can add more flexibility to the system. By justifying the attractiveness of the informal default option to borrowers under distress, the findings of this literature generally complement our work by highlighting the importance of informal bankruptcy.

The final set of papers are those that develop models exhibiting fixed costs of extending credit or designing contracts, such as Drozd and Nosal (2007) and Livshits, MacGee and Tertilt (2011). Both papers emphasize the extensive margin of credit card lending. In Drozd and Nosal (2007) the cost can be interpreted as an account acquisition cost, or ex-ante credit risk assessment costs to reveal borrower’s initial state. Their model fails to account for the rising charge-off rate in the data. The fixed cost in Livshits, MacGee and Tertilt (2011) emphasizes contract design costs in the presence of adverse selection. Their cost thus implies increasing returns from lending (on the extensive margin). In contrast to our paper, a higher precision of information in Livshits, MacGee and Tertilt (2011) lowers the default exposure of debt in equilibrium. IT progress manifested through a lower cost of designing risky contracts or a fall

\(^5\)Athreya, Tam and Young (2008) report that the predicted change of discharged debt to income remains unchanged (see Table 3), while it doubles in the data. Given that debt increased faster than income, we infer from that their model fails to generate an increase in average riskiness of debt. A similar exercise is also performed by Sanchez (2012). However, in his comparative statics the riskiness of the income process changes as well, raising the demand for risky credit. The reported experiments suggest that his model fails short of accounting for both the level and the change in the charge-off rate. The predictions of his model are difficult to relate to the charge-off rate in the data. This is because the model is calibrated to net debt rather than gross debt. In the data, the calculation of the charge-off rate in the denominator involves total gross outstanding debt, which is larger than the net position by at least a factor of ten.
in transaction cost can generate effects consistent with the data, although their quantitative implications remain to be explored.\textsuperscript{6}

2 Environment

We begin with a two-period model, which we study analytically. In later sections, we extend this setup to a multi-period life-cycle environment and explore its quantitative implications. The economy is populated by a continuum of consumers and a finite number of credit card lenders. Consumers live for one period composed of two sub-periods. Their objective is to smooth consumption across sub-periods by borrowing from lenders. They enter the period with some pre-existing exogenous stock of unsecured debt $B > 0$, and their income is fixed at $Y > 0$. 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). This shock hits with probability $0 < p < 1/2$ and is the only source of uncertainty in the two-period model (in our full model $Y$ is stochastic and $B$ is endogenous). Lenders have deep pockets and extend credit lines to consumers at the beginning of the period. Their cost of funds is exogenous and normalized to zero. Credit lines are characterized by an interest rate $R < 1$ and credit limit $L \geq 0$, and they are committed to borrowers as of the beginning of the period. Consumers can accept at most one credit line. It is assumed that there are perfect rental markets of consumer durables to justify our focus on unsecured credit.

\textsuperscript{6}Specifically, the setup involves an assumption that designing a risk-free contract is costless. As a result, an exogenous decline in the design cost leads to a change in the relative price of the two contracts, which raises the share of risky contracts in equilibrium. In our model a similar effect arises endogenously as a result of improvements in the precision of information. In addition, Livshits, MacGee and Tertilt (2011) make an interesting point that in the presence of a fixed cost of designing contracts, a decline in the proportional transaction cost or even the risk free interest rate can raise the share of risky contracts. This effect is associated with increasing returns in the lending industry that their setup implies. Specifically, in their model a larger number of revolvers reduces the design cost \textit{per borrower}. Given the assumption that risk-free contracts are costless, this similarly affects the relative price of contracts. Since their model is not quantitative, the empirical relevance of this channel remains to be explored.
2.1 Lenders

Lenders are Bertrand competitors. Hence, they offer a contract that maximizes the ex-ante expected indirect utility of consumers subject to a zero profit condition (in expectation). Since credit lines are accepted and committed to borrowers before the realization of the distress shock \( d \) (and signal), lenders are potentially exposed to the risk of default. In such a case, credit lines offer insurance against the distress shock, which borrowers typically find desirable in our setup.

Information between borrowers and lenders is \textit{asymmetric} upon default, which is brought about by the fact that lenders do \textit{not} directly observe the distress shock \( d \). Instead, they observe a noisy signal \( s \in \{0, 1\} \) with exogenous precision \( 0 \leq \pi \leq 1 \). The parameter is assumed to fully summarize \textit{the state of information technology} available to lenders. In the presence of a formal option of bankruptcy, the crucial assumption here is that distressed agents marginally prefer informal default to formal default (which we do not model for simplicity).

Asymmetric information creates \textit{moral hazard} among the non-distressed borrowers: they may choose to default \textit{strategically} in expectation of informal debt forgiveness by lenders. To deal with moral hazard, lenders are equipped with a \textit{monitoring technology}. Monitoring results in repayment by a non-distressed consumer, and it is ineffective on distressed consumers. This is justified by the fact that distressed borrowers are assumed to be insolvent and thus ‘monitoring proof’; alternatively, they subsequently file for (formal) bankruptcy protection. At the same time, non-distressed borrowers are assumed to possess assets that a bankruptcy court could seize, and their propensity to default \textit{formally} is significantly lower than their propensity to default \textit{informally}. Their eligibility for formal bankruptcy may also be limited, as is the case under the current law.\(^7\)

To keep our model simple, we assume that lenders can ex-ante commit to a monitoring probability distribution: \( 0 \leq P(s) \leq 1 \), which depends on the signal \( s = 0, 1 \). Such an approach parsimoniously implements the efficient contract as far as monitoring is concerned, and conveniently abstracts from any institutional characteristics of the debt collection industry. Formally, in the beginning of the period lenders choose a credit line contract \( K = (R, L) \) and

\(^7\)After 2005 bankruptcy protection involves income means testing. Borrowers who do not qualify must partially repay their debt.
a monitoring strategy \( P(s) \) to maximize the ex-ante expected utility of consumers:

\[
\max_{K,P} V(K,P) \tag{1}
\]

subject to ex-ante zero profit condition

\[ \mathbb{E}\Pi(I, K, P) \geq \lambda \sum_{I=(d,s)} \delta(I, K, P) P(s) Pr(I), \]

In the above problem, \( \mathbb{E}\Pi(I, K, P) \) is ex-ante profit of the lenders from a customer pool with normalized measure one (gross of monitoring cost), \( I = (d, s) \) is the interim state of the consumer, \( \lambda \) is monitoring cost (per measure one of borrowers), and \( \delta(I, K, P) \) describes the consumer’s default decision function (defined formally in the next section), which equals one in case of default and zero otherwise. The interim profit function is given by

\[
\Pi(I, K, P) = \begin{cases} 
2\rho(K, b(I, K, P)) & \text{if } \delta(I, K, P) = 0, \\
-L + L(1 + \bar{R})(1 - d)P(s) & \text{if } \delta(I, K, P) = 1, 
\end{cases} \tag{2}
\]

where \( b(I, K, P) \) is the consumer borrowing and \( \rho(K, b) \equiv R \max\{b, 0\}/2 \) is interest income of the lender (collected in each sub-period when the consumer does not default). The function conveys the basic idea that default is costly for the lender because it allows the consumer to discharge \( L \) (and any thus far assessed interest), while revenue is derived from the interest payments when the consumer chooses not to default. Monitoring reverts any non-distressed defaulting consumer back to repayment by recouping \( L(1 + \bar{R}) \), where \( \bar{R} \) is an exogenous penalty interest paid whenever collection is successful.\(^8\)

### 2.2 Consumers

Consumers choose first sub-period consumption \( c \), second sub-period consumption \( c' \), borrowing within the period \( b \), and default decision \( \delta \in \{0, 1\} \). For simplicity, these choices are made

\(^8\)Although we generally assume \( \bar{R} \) is non-negative, there is nothing that precludes \( \bar{R} \) to be negative (as long as it is not too negative). Hence, our model could incorporate the idea of partial debt forgiveness.
at the interim stage, that is, after the signal $s$ and the distress shocks $d$ are observed. However, the consumer still faces the residual uncertainty associated with being monitored, which is denoted by $m \in \{0, 1\}$. Clearly, this residual uncertainty only matters in the case of default. Formally, given $K$ and $P$, the consumer chooses the default decision $\delta$ to solve

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

where $N(\cdot)$ is the indirect utility function associated with repayment and $D(\cdot)$ is the indirect utility function associated with defaulting.

Under repayment, the consumer chooses $b, c, c'$ to solve

$$N(I, K) \equiv \max_{b \leq L} U(c, c')$$

subject to

$$c = Y - B + b - \rho(K, b)$$

$$c' = Y - b - dE - \rho(K, b),$$

where $U$ is a utility function satisfying the usual assumptions. The budget constraint states that the consumer can borrow $b$ in the first sub-period up to $L$. In such a case, she pays interest $\rho$ in each sub-period and $b$ in the second sub-period.

To define indirect utility under default, we assume that consumers cash out the credit line in the first sub-period. In addition, they also default on a fraction $\phi$ of their distress shock, which is discharged regardless of whether they are monitored. Consistent with our earlier discussion, defaulting *distressed* consumers incur a pecuniary cost of defaulting equal to $\theta Y$. They can always fully discharge their debt. *Non-distressed* defaulting consumers can discharge their debt only if they are not monitored. If they are monitored, they revert back to repayment, pay back the principal $L$, a penalty interest $\bar{R}L$, and incur a smaller pecuniary cost associated with the state of temporary delinquency $\theta' Y < \theta Y$.

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9This assumption is consistent with the data, see Herkenhoff (2012).
Formally, the defaulting consumers choose $b, c, c'$ to solve

$$D(I, K, P) \equiv \max_{b \leq 0} E_I U(c, c')$$

subject to

$$c = Y - B + L + b$$
$$c' = (1 - \theta)Y - (1 - \phi)dE - b - m(1 - d)[((\bar{\theta} - \theta)Y + L(1 + \bar{R}))],$$

where the expectation operator $E_I$ integrates over the unknown realization of the ex-post monitoring decision of lenders $m \in \{0, 1\}$, and the term in the square bracket captures the impact of monitoring on the consumer budget constraint.

Finally, to make our model non-trivial, we maintain two assumptions to ensure that: 1) non-distressed consumers do not always want to default, and 2) in the case of completely uninformative signals, the excess penalty interest rate associated with debt collection over the interest normally paid under repayment is insufficient to cover the monitoring cost needed to identify a non-distressed defaulting borrower. These assumptions are formalized below.

**Assumption 1.** $\theta Y + \bar{R}L$ is sufficiently high to ensure that a non-distressed consumer does not default when monitored with certainty.$^{10}$

**Assumption 2.** $\lambda > (1 - p)(\bar{R}L - \rho(K, b^*))$ for any feasible contract $K = (R, L)$, where $b^*$ is optimal borrowing associated with repayment (given $K$).

**Optimal default decision** We next turn to the characterization of the policy function that governs the default decision in our model. This result is summarized in the proposition below. It implies that there are both risky and risk-free contracts in this environment. Furthermore, sufficiently high credit lines always bundle a potentially welfare enhancing transfer of resources from the state of no distress toward the state of distress.$^{11}$ In the rest of the paper, we refer to

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$^{10}$This can be globally assured by assuming $\theta Y + \bar{R}L > \max_R \bar{R}b^*(R, L)$, where $b^*(R)$ is borrowing associated with repayment given $R, L$.

$^{11}$When intertemporal smoothing needs are particularly high, it is possible that the transfer associated with the equilibrium contract is inefficient (too high) and the presence of a default option lowers welfare. This arises rarely in our parameterized model and overall the presence of default option is welfare enhancing.
default by a distressed consumer as non-strategic, and to default by a non-distressed consumer as strategic. Unless otherwise noted, all proofs are relegated to the Appendix.

**Proposition 1.** For any feasible $K = (R, L)$ and $P(s)$, the default decision of consumers is consistent with the following set of cutoff rules:

1. There exists a cutoff $L_{\text{min}}(d = 1, R) > 0$, continuous and strictly decreasing in $R$, such that a distressed borrower defaults (repays) if $L > (<) L_{\text{min}}(d = 1, R)$, regardless of $P$.
2. There exists a cutoff $L_{\text{min}}(d = 0, R) > 0$, continuous and strictly decreasing in $R$, such that a non-distressed borrower repays if $L < L_{\text{min}}(d = 0)$, regardless of $P$.
3. If $L > L_{\text{min}}(d = 0, R)$, there exists a cutoff $\tilde{P}(R, L) \in (0, 1)$, continuous increasing in $R$ and independent of information precision $\pi$, such that a non-distressed borrower repays (defaults) when $P(s) > (<) \tilde{P}(R, L)$, and she is indifferent between defaulting or not for $P(s) = \tilde{P}(R, L)$.

In the case of zero-profit contracts, we denote $L_{\text{min}}(d) \equiv L_{\text{min}}(d, R)$. If no agent defaults when indifferent between defaulting or not, then $L_{\text{min}}(\cdot)$ is independent of information precision $\pi$, with $L_{\text{min}}(d = 1) = \theta Y - \phi E$.

The above result allows us to distinguish between the following three classes of contracts in our model.

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

i) risk-free contract, if $L < L_{\text{min}}(d = 1)$,

ii) non-monitored insurance contract, if $L \in [L_{\text{min}}(d = 1), L_{\text{min}}(d = 0))$,

iii) monitored insurance contract, if $L > L_{\text{min}}(d = 0, R)$.

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

### 2.3 Characterization of Equilibrium

The goal of this section is to characterize the impact of information precision $\pi$ 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 insurance contracts, and then discuss the pricing implications of our model.

However, before we proceed with the analysis, we introduce a technical assumption that helps us isolate the effect of information precision from an uninteresting effect of ex-ante segmentation of consumers into types unrelated to information. This assumption allows us to eliminate potential exotic equilibria in which lenders might want to use the signal as a segmentation device, without any regard for their informational content. Under reasonable conditions this problem never arises, and it is best to assume it away to keep the paper focused.

**Assumption 3.** When the signal is completely uninformative lenders monitor to prevent strategic default from occurring within both signal types or none of them. Formally, if \( \pi = 0 \) then \( P(s) \geq \bar{P} \) for all \( s \) or \( P(s) < \bar{P} \) for all \( s \).

### 2.3.1 Optimal Monitoring Strategy

In this section, we demonstrate that only two types of monitoring strategies will be used by lenders to sustain monitored insurance contracts under Bertrand competition: 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 in the case of signal of no distress, while defaulting consumers associated with the signal of distress are not monitored enough to prevent them from defaulting strategically. Selective monitoring might also involve some monitoring of the distressed signal types. A *necessary* condition for this to be the case is that the ex-post yield from monitoring is strictly positive. To make clear how our results depend on the precision of information, throughout the paper we write \( P_\pi(\cdot) \) instead of \( P(\cdot) \) to indicate all

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12 For example, consider the following setup: the utility function is Leontief across the sub-periods, but across states the agent is risk neutral (e.g. \( U(c, c') = U(G(c, c')) \), where \( G \) is Leontief and \( U \) is linear). In such a case, the consumer does not care about consumption smoothing across states, and interest rate is non-distortionary across sub-periods. If monitoring cost is sufficiently high, the equilibrium may involve monitoring to prevent default only within a random subset of borrowers identified by some uninformative signal (e.g. first letter of the last name). This is because credit lines are still useful in this case to relax borrowing constraints, and if the cost of strategic default is small enough, it is optimal to economize on monitoring costs by setting \( P(s) \geq \bar{P} \) and \( P(1 - s) < \bar{P} \), with \( s \) being used just as a tool to segment the market independently of its information content. Since these forces are difficult to compare analytically, we directly assume away the possibility of such strange equilibria.
cases in which monitoring strategy actually directly depends on the precision of signal $\pi$.

**Proposition 2.** Monitored insurance contracts consistent with (1) are exclusively supported by one of the following two monitoring strategies:

i) full monitoring: $P(s) = \bar{P}(R, L)$, $s = 0, 1$, or

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

where $\bar{P}(R, L)$ is uniquely defined by $N(d = 0, s = 0, K) = D(d = 0, s = 0, K, \bar{P})$. Furthermore, if $\pi > \pi^* \equiv 1 - \frac{\lambda}{L(1+R)(1-p)}$, then $P_\pi(1) = 0$.

**Corollary 1.** Monitored insurance contracts consistent with (1) involve:

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

ii) strategic default by borrowers with signal $s = 1$ under selective monitoring.

The above corollary additionally establishes that at the monitoring intensity that makes non-distressed borrowers indifferent between defaulting or not, lenders prevent default. That is, lenders can and will raise the monitoring infinitesimally to eliminate strategic default.

### 2.3.2 Pricing of Defaultable Debt

Pricing of defaultable debt is more complex in our model due to the use of credit line contracts. This is because such contracts involve a varying rate of utilization, which depends on the interest rate. Nevertheless, partial characterization is still possible by decomposing the zero profit interest rate into a monitoring premium and a default premium, and separating the endogenous utilization rate in the form of a scaling factor. The next proposition provides a decomposition of the zero profit interest rate for the class of fully monitored insurance contracts. It is derived from the corresponding zero profit condition associated to a credit line of size $L$ given Proposition 2 and Corollary 1. This zero profit condition is given by

$$R \mathbb{E}b(L, R) - pL - p\bar{P}(R, L)\lambda = 0,$$

(6)

where $\mathbb{E}b(L, R)$ is the expected debt level associated with repayment. The remaining terms capture the the expected losses attributable to defaults and the overall cost of monitoring. The proof of the proposition directly follows from the equation above and is therefore omitted.
Proposition 3. Given a monitored insurance contract, the zero profit interest rate under **full monitoring** can be decomposed into a monitoring premium $\mathcal{M}$ and a default premium $\mathcal{D}$ as follows:

$$
R = (\mathcal{D} + \mathcal{M}) \times \frac{L}{\mathbb{E}b(L, R)},
$$

where

$$
\mathcal{D} = p \quad \text{and} \quad \mathcal{M} = p\frac{\lambda}{L} \bar{P}(R, L),
$$

and $\mathbb{E}b(L, R)/L$ is the expected utilization rate associated with repayment. Furthermore, $\mathcal{M} = 0$ and $\mathcal{D} = p$ in the case of non-monitored insurance contracts, and $\mathcal{M} = \mathcal{D} = 0$ in the case of 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 the default risk, which we refer to as *default premium*. Second, lenders must be also compensated for the expected cost of monitoring. This cost is referred to as *monitoring premium*, and it is given by $p\lambda\bar{P}/L$. To obtain the final effect of these premia on the interest rate charged in equilibrium, the formula scales them depending on the expected utilization rate of the credit line. This adjustment is necessary because the borrowers default on the entire credit line, while interest is assessed only when borrowing takes place.

The next proposition derives the pricing of *selectively* monitored contracts.

**Proposition 4.** Given a monitored insurance contract, the zero profit interest rate under **selective monitoring** can be decomposed into a monitoring premium $\mathcal{M}$ and a default premium $\mathcal{D}$ as follows:

$$
R = (\mathcal{D} + \mathcal{M}) \times \frac{L}{\mathbb{E}b(L, R)},
$$

where

$$
\mathcal{D} = p + \frac{p(1-p)(1-\pi)}{P} \quad \text{"strategic" default premium}
$$

$$
\mathcal{M} = p(1-p)(1-\pi) \left( \frac{\bar{P}(R, L) + \frac{P\pi(1)}{(1-p)(1-\pi)}}{\lambda} \right) \frac{\bar{P}(R, L) - (1 + \bar{R}) P\pi(1)}{L}.
$$
Furthermore, as $\pi \to 1$, $D$ and $M$ converge to $p$ and 0, respectively.

As we can see, the default premium involves an additional cost associated with strategic default of non-distressed borrowers under the signal of no distress. Thus, $D$ is in this case strictly higher than under full monitoring, and the difference is a function of the precision of information. At the same time, a smaller mass of agents is monitored, and the monitoring premium is generally lower, although the difference depends on the precision of information. Moreover, $M$ is reduced by the expected recovery rate whenever lenders monitor distressed signal types with some intensity ($P_\pi(1) > 0$). Under Assumption 2, expected recoveries net of monitoring costs do not fully offset the losses implied by strategic default.

![Figure 2: Equilibrium Interest Rate Schedule](image)

Figure 2 illustrates the resulting pricing schedule. By Proposition 1, we know that some contracts do not require monitoring at all, and some of them are risk-free. This makes the pricing schedule discontinuous. The figure shows the case in which selective monitoring is more expensive, but this need not be the case.\(^ {13}\)

\(^{13}\)Furthermore, selective monitoring may prevail in equilibrium even if it leads to a higher interest rate. This is because Bertrand competitors internalize the fact that strategic default also raises utility.
2.3.3 Effects of IT Progress on Prices and Risk Composition of Debt

We next turn to the comparative statics exercise. Before we begin, we introduce an additional assumption to gain analytic tractability: the utility function is quadratic across sub-periods. By introducing this assumption, we effectively restrict attention to intertemporal borrowing policy functions that are linear. It can be interpreted as an approximation of a more general case.\(^\text{14}\)

**Assumption 4.** Let the utility function be of the form \(u(G(c, c'))\), where

\[
G(c, c') = c + c' - \mu(c - c')^2, \quad \mu > 0,
\]

and let \(u\) be any utility function satisfying the usual assumptions (e.g. CRRA).

Our first result completes the characterization of the selective monitoring strategy. Namely, we establish that \(P_\pi(1)\) singled out in Proposition 2 is monotonically decreasing in the precision of information \(\pi\).

**Proposition 5.** Given any zero profit selectively monitored insurance credit line, \(P_\pi(1)\) is monotonically decreasing w.r.t. \(\pi\) and \(\lim_{\pi \uparrow \pi^*} P_\pi(1) = 0\), where \(\pi^*\) is defined in Proposition 2.

The above results allow us to establish that, as the precision of information improves, the optimal monitoring strategy that sustains any fixed credit line eventually switches from *full* to *selective* monitoring. This is because pricing under selective monitoring is a function of the precision of information, while under full monitoring it is not.

**Proposition 6.** For each \(L > L_{\text{min}}(d = 0)\) there exists \(\bar{\pi}(L) < 1\) such that for all \(\pi > \bar{\pi}(L)\) the preferred zero profit contract under selective monitoring yields a strictly higher utility than the preferred zero profit contract under full monitoring.

The proof directly follows from Propositions 3, 4, and 5.

\(^{14}\)Quadratic intertemporal utility guarantees that the following intuitive result holds: a decline in the interest burden \((Rb(R))\) for any fixed \(L\) and \(P\) by some infinitesimal amount due to a drop in \(R\) leads to a higher gain in indirect utility \(N\) the higher the initial value of \(R\) is. Numerical simulations suggest that this applies broadly, but we could not prove it for generic utility (it can be shown for log utility).
As illustrated in Figure 3, the above results imply that selectively monitored insurance contracts become relatively more attractive relative to risk-free or non-monitored insurance contracts (note that, by Proposition 1, the range of \( L \) that can be sustained without monitoring remains unchanged). Moreover, above a certain level of signal precision, selective monitoring surely prevails. Consequently, our results imply that more precise information is consistent with a larger share of risky contracts in the contract pool, as such contracts will appeal to a broader range of borrowers in the space of \( B \) and \( Y \) due to their lower price. The exact quantitative effect of this mechanism will be studied in the next section. Non-monitored insurance contracts can arise as well, but in our full model they are dominated by either risk-free contracts or monitored insurance contracts.

Furthermore, as it is illustrated in Figure 3, Proposition 4 shows that the higher the risk of distress is (\( p \)), the more sensitive prices should be to the precision of information. 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 credit contracts declines relative to the price of the risk-free contracts as the precision of information improves. This result is qualitatively consistent with the idea of “democratization of credit”, as discussed in Johnson (2005) and White (2007). In our quantitative model we follow a parsimonious approach of not incorporating any ex-ante heterogeneity in risk types. To the extent that an additional source of ex-ante heterogeneity

\[ \text{Up to an ambiguous effect of } p \text{ on } P_r(1), \text{ which matters only in the case of } \pi < \pi^*. \]
in risk types is a feature of the US data, our results might only understate the quantitative potential of our model.

3 Quantitative Analysis

In this section, we extend our baseline setup to a quantitative $T$-period life-cycle model ($T = 27$ in our calibration). We use this model to demonstrate that our mechanism can quantitatively account for the US data. At the end of this section we also provide a comparison of our model to the standard theory.

3.1 Extended Life-cycle Model

The dynamic aspects of the model are fairly standard and similar to Livshits, MacGee and Tertilt (2010). The previously presented static model describes the environment within each period, which is also divided into two sub-periods for the sake of consistency with the above setup. However, the consumer now borrower across the periods and $B$ is endogenous. Furthermore, in order to reasonably capture income risk in the data, $Y$ is allowed to be stochastic. Since contracts last only one period, dynamics only affect the consumer problem, which we discuss below.

**Persistent income shocks.** Income in period $t$ is given by $Y_t = e_t z_t$ and is governed by a Markov process characterized by a transition matrix $P_t(z|z_{t-1})$, and an age-dependent deterministic component $e_t$. The transition matrix is identical from period 1 through $T - N$, and then again from period $T - N$ to period $T$. The first set of periods is identified with working-age, while the second correspond to retirement.\(^\text{16}\) During retirement, it is assumed that there is no income uncertainty, and so $P_t(z|z) = 1$, and zero otherwise.

**Endogenous intertemporal borrowing.** The consumer can carry debt across the periods,

\(^\text{16}\)Retirement income is determined to yield a replacement rate of 55%, as assumed by Livshits, MacGee and Tertilt (2010). It is given by a weighted average of realized $T - N$ income of the agent (20%), and the average income in the economy (35%).
implying a modified second sub-period budget constraint given by
\[ c' = Y + B' - b - \rho(K, b), \]
where \( B' \leq L \) is the consumer choice of next period’s debt level.

**Intertemporal preferences.** The utility function is assumed to be CES,\(^{17}\) and it is discounted at rate \( \beta \). We follow the standard approach of adjusting the units of consumption to account for the varying family size over the life-cycle. Specifically, consumption is scaled by a factor \( 1/s_t \) in any given period. This gives rise to a hump-shaped consumption profile over the life-cycle consistent with the data. The adjustment factors are taken from Livshits, MacGee and Tertilt (2010).

**Life-cycle optimization.** Agents in the model live for \( T \)-periods and solve a dynamic life-cycle optimization problem. This optimization problem determines the evolution of debt \( B \) across the periods. For example, the interim value from not defaulting is given by
\[
V_t^{\delta=0}(\cdot) = \max_{b,B'} \{ U(c/s_t, c'/s_t) + \beta V_{t+1}(B', Y') \}. \tag{7}
\]
The remaining value functions are defined analogously.

**Formal bankruptcy.** We explicitly allow both distressed and non-distressed borrowers to file for formal bankruptcy. It is introduced to facilitate calibration. This feature plays a role only in the case of non-distressed consumers, and places an upper bound on the maximum credit limit that is sustainable in equilibrium. Under formal bankruptcy, we assume that debt can always be discharged, although at a higher pecuniary cost denoted by \( \tilde{\theta} > \theta \) (also applies to non-distressed agents). Formal bankruptcy is never used in equilibrium by a non-distressed consumer in our environment, but it can be used by a monitored distressed consumer (after she finds out she is monitored). This, however, arises rarely.\(^{18}\)

\(^{17}\)The utility function is assumed to be of the form \( U(c, c') = u(G(c, c')) \). We assume \( u \) is CES, and assume that within the period \( G \) is a quadratic function given by: \( G(c, c') = c + \beta c' - \mu(c - c')^2 \). We select \( \mu \) to be consistent with CES utility (specifically, we consider a median income consumer, and fit the function around the point \( 1 = c = \beta c' \) for \( R = 0 \).

\(^{18}\)It would be cumbersome but possible to extend our model so that both types of default actually coexist in equilibrium. Since such models already exist, we do not consider such extension here. The simplest extension would entail a random dis-utility associated with monitoring. In such a case, all distressed borrowers who
Temporary exclusion to autarky. We incorporate the standard feature of excluding a borrower to autarky for one period after default of any kind.\textsuperscript{19}

Transaction costs. To facilitate calibration, we introduce a transaction cost of making credit card funds available to consumers. This cost is denoted by $\tau$ and lenders incur it in proportion to consumer borrowing $b$.

3.2 Parameterization

Model parameters are calibrated to account for the trend values of various moments in the US data for 2004. The comparative statics exercise is designed to take the model back to the 1990s. Details on how we obtain trend values are in the online appendix. Period length is 2 years (each sub-period is 1 year long).

Income process. We start from the annual AR(1) process for income taken from Livshits, MacGee and Tertilt (2010) (the original AR(1) specification is of “RIP” type, and features a single income profile). In addition, we place any income drop above 25% is under the distress shock (see below). We convert the residual to obtain a biannual Markov process using the Tauchen method. We start our simulation from the ergodic distribution of the fitted Markov process.

Distress shocks. The distress shock absorbs all income shocks involving a drop of 25% or more within the original AR(1) process used to obtain the income process. We augment this shock by including three major lifetime expense shocks singled out by Livshits, MacGee and Tertilt (2010): medical bills, the cost of an unwanted pregnancy, and the cost of divorce. We use their estimated values, although adjusted to obtain a single biannual distress shock. This procedure gives $E = .4$ (40% of median annual household income), and the shock hits with 10% biannual frequency. We consider medical bills to be the only shock that can be defaulted on, and consequently set $\phi = .24$. We should emphasize that this approach crucially departs

\textsuperscript{19}In autarky the agent can save but cannot borrow. At an arbitrary penalty interest rate of 30%, she can roll-over a fraction $\phi$ of the distress shock. In the data, delinquency status stays on record for 7 years, which is somewhat longer than in our model.
from the usual practice of treating the distress shock as almost fully defaultable. In our model only a small fraction of the shock is actually accounted for by medical bills, which results in a largely non-defaultable distress shock.

**Discount factor.** We set the discount factor to match the level of credit card debt to median household income of 15%, which corresponds to our estimated trend value for 2004. We chose median household income as the base because we consider it a better measure than the mean.\(^\text{20}\)

**Transaction costs.** 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 \(\tau\). We set \(\tau = .12\) (biannual) to match the trend-implied annual interest premium on revolving credit card accounts of 4.0% in 2004 (as reported by FRB). This premium is defined by the difference between the average interest rate on revolving credit card accounts assessing interest, and an approximate measure of the opportunity cost of credit card funds (measured by 5-ytm yield on Treasuries),\(^\text{21}\) and the aggregate net charge-off rate on credit card debt (FRB).\(^\text{22}\)

**Risk aversion.** We assume a standard relative risk aversion of 2.

**Pecuniary costs of defaulting.** We set \(\theta = .32\) to match the trend value of the charge-off rate of 5.1% for 2004. We set \(\overline{\theta}\) to match the average credit card debt defaulted on per statistical bankruptcy filer relative to her income of 93% (as reported by Sullivan, Westbrook and Warren (2001), and extrapolated using a linear regression to obtain the trend value for 2004). Due to data limitations, this calibration target pertains to formal rather than informal bankruptcy filers. Nonetheless, our model is not particularly sensitive to this target and could accommodate a lower number. Finally, we set \(\overline{R}\) to assure \(\overline{RL} = \rho(K, b)\) (where \(b\) is borrowing associated with repayment) and assume \(\overline{\theta}\) is zero so that \(\overline{P} = 1\). This simplification only matters for the interpretation of the calibrated value of the monitoring cost.

**Information technology and monitoring.** We arbitrarily set the precision of signal to \(\pi = .5\), and assume a mean-preserving spread of 50% around this number to capture IT

---

\(^{20}\)The increase in the per capita income over the sample period is almost fully accounted for by the top income groups (top 1%). This makes average income ill-suited to study the unsecured credit market serving the bulk of the population. Calibrating our model to lower debt to income would be easier.

\(^{21}\)The trend is almost identical for bond maturities 1-5 (or 1 year LIBOR), although the levels are obviously higher when shorter maturities are used instead. We chose 5-ytm to match the maturity of credit card accounts in the data, and to avoid the volatility associated with the short-term rates.

\(^{22}\)The net charge-off rate is the fraction of credit card debt discharged by lenders (180 days or less) net of recoveries. It is an aggregate measure of the idiosyncratic default risk premium borne by lenders.
progress. We choose the monitoring cost so that the transition to selective monitoring is centered around the middle of the signal precision interval, obtaining $\lambda = .3$. This value implies that monitoring cost is about 30% of annual median household income (per monitored borrower). This is fairly high, although not unreasonably high. It can be lowered to about 20% by assuming noisier information. If lowered further, our results gradually weaken.

**Comparative statics.** They involve two technology parameters: the precision of information $\pi$ and the transaction cost $\tau$. We vary these parameters to account for the trends in the data.

To discipline the change in $\tau$, we note that the average productivity growth within the banking industry outpaced the rest of the economy by about 22% from 1990 to 2004, as reported by Berger (2003). Consistent with this data, we lower the value of $\tau$ by 20% from the base value of .15 to .12. Regarding the precision of information $\pi$, as already pointed out, we choose a mean-preserving spread around 50% precision to ensure a transition from full to selective monitoring over the 1990s, resulting in $\pi_{90s} = .25$ and $\pi_{00s} = .75$.

### 3.3 Quantitative Findings

Table 1 reports our key findings. Figure 1 illustrates the implied trends, and compares them to the data. In what follows next, we discuss the implications of our model for trends. In the online appendix we also compare our model to the standard model, emulated using our framework to facilitate a consistent comparison, and show that our mechanism also allows to improve the performance of existing models in terms of levels. The key reason behind such improvement is that monitoring induces different default penalties for distressed and non-distressed consumers, which breaks the inherent tension between debt sustainability and the attractiveness of default consumers. The tension is brought about by the fact that a high default penalty is necessary to sustain the high levels of indebtedness seen in the data, but at the same time this feature lowers default rates.

As is clear from Figure 1 and rows 1, 2 and 5 of Table 1, our model fully accounts for the key trends seen in the US data. Importantly, all of these effects can be traced back to technological progress within the credit card industry (in the case of $\tau$, in excess of the technological progress in the rest of the economy).
# Table 1: Quantitative Results from the Benchmark Model

<table>
<thead>
<tr>
<th>Data(^a)</th>
<th>Model</th>
<th>Data</th>
<th>Model</th>
<th>Decomposition</th>
</tr>
</thead>
<tbody>
<tr>
<td>00s</td>
<td>00s</td>
<td>90s</td>
<td>90s</td>
<td>(\tau = \tau_{90s})</td>
</tr>
<tr>
<td>(\pi_00s)</td>
<td>(\tau_{00s})</td>
<td>(\pi_{00s})</td>
<td>(\tau_{00s})</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>(in % unless otherwise noted)</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
<th>(7)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1) CC Debt to Median HH Income</td>
<td>15.1</td>
<td>15.1</td>
<td>9.0</td>
<td>9.0</td>
<td>11.2</td>
<td>13.9</td>
<td>15.1</td>
</tr>
<tr>
<td>2) Net CC Charge-off Rate</td>
<td>5.3</td>
<td>5.4</td>
<td>3.5</td>
<td>3.5</td>
<td>5.5</td>
<td>4.1</td>
<td>4.1</td>
</tr>
<tr>
<td>3) Defaults (households per 1000)</td>
<td>-</td>
<td>10.8</td>
<td>-</td>
<td>4.5</td>
<td>9.0</td>
<td>7.5</td>
<td>7.9</td>
</tr>
<tr>
<td>- fraction monitored ((m = 1))</td>
<td>-</td>
<td>18</td>
<td>-</td>
<td>30</td>
<td>17</td>
<td>31</td>
<td>32</td>
</tr>
<tr>
<td>- fraction strategic ((m = 0, d = 0, s = 1))</td>
<td>-</td>
<td>19</td>
<td>-</td>
<td>0.0</td>
<td>19</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>4) Frequency of insurance contracts(^b)</td>
<td>-</td>
<td>36.6</td>
<td>-</td>
<td>21.4</td>
<td>35.7</td>
<td>31.3</td>
<td>31.1</td>
</tr>
<tr>
<td>- fraction fully monitored</td>
<td>-</td>
<td>1</td>
<td>-</td>
<td>100</td>
<td>0</td>
<td>100</td>
<td>100</td>
</tr>
<tr>
<td>- fraction selectively monitored</td>
<td>-</td>
<td>99</td>
<td>-</td>
<td>0</td>
<td>100</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>5) CC Discharge to Income of Defaulters(^c)</td>
<td>93</td>
<td>89</td>
<td>48</td>
<td>74</td>
<td>82</td>
<td>80</td>
<td>82</td>
</tr>
<tr>
<td>6) Mean CC Interest Premium(^d)</td>
<td>4.0</td>
<td>4.4</td>
<td>6.6</td>
<td>6.5</td>
<td>6.1</td>
<td>5.3</td>
<td>4.6</td>
</tr>
<tr>
<td>7) Fraction of Revolvers in Population</td>
<td>40</td>
<td>53</td>
<td>27</td>
<td>49</td>
<td>50</td>
<td>57</td>
<td>57</td>
</tr>
</tbody>
</table>

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All values in % unless otherwise noted.

\(^a\)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.

\(^b\)As a fraction of the total number of revolving contracts \((b > 0)\).

\(^c\)Reported data value 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 preferred measure of the opportunity cost of cc-funds is the yield on 5-ytm US Treasuries).
Columns 5-7 of Table 1 decompose the contribution of $\pi$ and $\tau$. Specifically, column 5 reports the contribution of an increase in $\pi$, by fixing $\tau$ at the level from the 90s, while the next column considers an analogous exercise with $\tau$. Finally, column 7 aims at fitting the change of indebtedness over this time period by changing $\tau$ alone ($\tau_{fit} = .11$). Together, these exercises demonstrate that, while $\tau$ is important to account for the growing indebtedness of the household sector, its contribution to the rise in the default exposure of credit card debt is modest and falls short of the data. As already discussed, this result is intuitive: the most powerful channel that raises default exposure is the one that affects the relative price of risky contracts to risk-free contracts. Furthermore, the comparison of the last two columns reveals that the effect of $\tau$ is non-linear. This is because it relies on the effect of “bunching” at the discontinuity point of the pricing schedule.

Simulated time-series from the model confirm the intuition behind the results discussed earlier in the paper. For example, consider the simulation illustrated in Figure 4. The figure presents a life-cycle profile of a highly distressed consumer. As illustrated in the top panel, this
consumer has low income over her entire life, and suffers from several distress shocks. Bottom panels compare the simulation of this consumer assuming the equilibrium from the 00s and the 90s, respectively. Bars below each plot indicate when a given contract involves insurance. The circle indicates whether a given contract is sustained using full or selective monitoring strategy. As we can see, while the consumer defaults three times in the 00s, she only defaults once in the 90s. The other defaults are simply eliminated through tighter credit limits. Furthermore, the only default that occurs in the 90s is associated with a lower discharge. This is because contracts prior to the event also feature tighter credit limits, making it more difficult for the borrower to accumulate debt prior to defaulting.

The 3rd row in Table 1 shows that our model implies an annual default rate of about 11 per 1000 households. This is about twice as high as the observed formal bankruptcy filling rate in the data, which is not surprising. Given that we have calibrated our model to match the charge-off rate from the data, and also required that the model matches the average discharge per bankruptcy filer in the data, the default rate generated by our model should be about twice as high as the formal default rate in the data. Had we calibrated our model to a lower target, default rate would be correspondingly higher.

Row 4 of the table shows that the share of insurance contracts increases along the transition, and monitoring intensity per insurance contract declines. These effects confirm the intuition that follows from the static model. The prediction is also qualitatively consistent with the data, as discussed earlier in the paper.

Row 5 of the table shows that our model falls short of accounting for the changes on the extensive margin. However, by incorporating some degree of ex-ante heterogeneity in $p$, our model could account for these changes as well. As noted earlier, such extension would only reinforce our results.

4 Conclusion

Existing theories of consumer bankruptcy rule out the option of informal default by assumption, and abstract from costs of debt collection. Here we argue that this assumption is not only at odds with the data, but it can drastically change the predictions regarding the impact of IT
progress on the ex-ante pricing of unsecured credit. In particular, we show that an endogenous 
link to IT progress operating through this margin is potent enough to account for all the facts 
underlying the IT-driven expansion of credit card borrowing in the 1980s and over the 1990s. 
Indepdently, our approach can help account for the high default rates and credit card debt 
recently observed in the data.

Appendix

A1. Omitted Proofs

Proof of Proposition 1. We begin by noting several properties of our model: i) indirect utility 
function \( D \) (defined in (5)) is decreasing in \( P \) (strictly for \( d = 0 \)), and indirect utility function \( N \) 
(defined in (4)) is independent from \( P \); ii) \( N \) is (strictly) decreasing in \( R \), and \( D \) is independent 
from \( R \), implying that the incentives to default monotonically increase with \( R \) for any \( L > 0 \); 
iii) default eventually takes place for sufficiently high \( L \), given any fixed \( P < 1 \); iv) for \( L \) 
sufficiently close to 0, any \( R < 1 \) and also any \( P \), the consumer strictly prefers not to default; 
v) \( D \) and \( N \) are continuous in \( R \) and \( P \). These properties follow from the effect of \( P \) and \( R \) on 
the size of the consumer budget set. The proof is trivial and is omitted.

Part 1): Fix \( R = 0 \). Compare problems (4) and (5) assuming \( d = 1 \): they share the same 
objective function, and the first sub-period budget constraint is identical (notice the difference 
in the constraint on \( b \) across (4) and (5)). As a result, the decision to default boils down to 
the comparison of the second sub-period ‘net’ resources between repayment and default. The 
former are given by \( Y - E \), while the latter are given by \( (1 - \theta)Y - (1 - \phi)E + L \). Thus, the 
consumer always defaults when \( L > \phi E - \theta Y \), regardless of \( R \) by ii) (This fact will be used 
the establish the last part of the proposition). Given iv), there exists a strictly positive cut-off 
value of \( L \) at which the consumer switches her decision (given fixed \( R \) and \( P \). We refer to this 
value as \( L_{min}(d = 1, R) \), and note that the cutoff must be decreasing and continuous w.r.t. \( R \) 
by ii) and v).

Part 2): Assume the worst case scenario of \( P = 0 \) and fix \( R = 0 \). Using the same reasoning 
as in part 1), if net resources under repayment, \( Y \), are higher than under non-monitored default,
(1 − θ)Y + L, a non-distressed consumer will certainly choose not to default. By ii) and iv) this establishes the existence of a (positive) cutoff. We refer to it as \( L_{\text{min}}(d = 0, R) \). By i), ii) and v) it is continuous and decreasing in R.

To prove part 3), we note from i) that the default decision of a non-distressed consumer must be weakly decreasing in the underlying monitoring probability; that is, if a non-distressed consumer decides not to default for \( P(s) = \hat{P} \), she will not default for any \( P(s) > \hat{P} \). Furthermore, we note that for \( P(s) = 1 \) the consumer will choose not to default (by Assumption 1), and for \( P(s) = 0 \) she will prefer default given the definition of \( L_{\text{min}}(d = 0, R) \). Accordingly, there must exist some \( \bar{P} < 1 \) – which generally depends on contract terms \((R, L)\) – such that a non-distressed agent defaults if \( P(K, s) < \bar{P} \), and does not default when \( P(K, s) > \bar{P} \). Continuity of the indifference point w.r.t. \( R \) follows from v). It is decreasing w.r.t. \( R \) by i) and ii). \( \hat{P}(R, L) \) being independent of \( \pi \) is trivial since precision does not enter the consumer problem at all.

To prove that \( L_{\text{min}}(d = 1) = \phi E − \theta Y \) note that, when charged \( R = 0 \), distressed consumers are indifferent between defaulting or not at \( L = L_{\text{min}}(d = 1) \) while non-distressed consumer strictly prefer not to default. Hence, if indifferent consumers do not default, lenders face no default losses and can feasibly offer \( R = 0 \). Finally, \( L_{\text{min}}(d = 0) \) being independent of \( \pi \) trivially follows from the fact that at \( L_{\text{min}}(d = 0) \), monitoring does not affect consumer indirect utility for any realization of \( d \) since non-distressed agents are indifferent between defaulting or not. Thus, if they do not default as assumed, lenders will not monitor, regardless of precision, and their zero profit condition does not depend on \( \pi \).

**Proof of Proposition 2 and Corollary 1.** Fix \( L > L_{\text{min}}(d = 0) \), implying that non-distressed consumers will want to default as long as they expect to be monitored with sufficiently low probability (see Proposition 1). By Assumption 2, in order for lenders to break even, it must be the case that \( P(s) \geq \hat{P}(R, L) \) for at least one signal realization, where \( \hat{P}(R, L) \) stands for the cutoff identified in part 3) of Proposition 1. Hence, there are three possible scenarios that can arise in equilibrium: (i) \( P(s) \geq \hat{P}(R, L) \) for \( s = 0, 1 \), (ii) \( P(0) \geq \hat{P}(R, L) \) and \( P(1) < \hat{P}(R, L) \); and (iii) \( P(0) < \hat{P}(R, L) \) and \( P(1) \geq \hat{P}(R, L) \). We next show that (i) and (ii) must satisfy the conditions of the proposition, and we rule out (iii) under the stated assumption.
Case (i): Since monitoring is costly, lenders should commit to the lowest monitoring probability to sustain any targeted level of default. Thus, if equilibrium is of type (i), it must be that $P(s) = \bar{P}(R, L)$ for all $s \in \{0, 1\}$. This is because in the case of $P(s) > \bar{P}(R, L)$, a lender has a profitable deviation. In particular, he can offer a contract with the same credit limit $L$ and a slightly lower $P(s)$ without changing agents’ default choices. By doing so, the lender incurs in lower monitoring costs and thus can charge a lower $R$, raising agents’ utility while earning strictly positive profits. Note that $\bar{P}(R, L)$ declines as $R$ is lowered by Proposition 1, which only reinforces the argument. Furthermore, none of the non-distressed agents default under (i). To see why, note that if the mass of non-distressed defaulters is positive under some signal realization, a lender could increase the associated monitoring probability infinitesimally, driving such fraction to zero and unambiguously increasing profits. At the same time, we know that defaulting non-distressed consumers under $s$ are indifferent between defaulting and not defaulting, and so their utility does not go down with the increase in $P(s)$. Utility of distressed agents or non-distressed agents who do not default remains the same as well. Since this deviation implies left-over resources for lenders, $R$ can be lowered, raising ex-ante utility – recall that $\bar{P}(R, L)$ is increasing in $R$.

Case (ii): $P(0) = \bar{P}(R, L)$ by a similar argument as in case i) so non-distressed agents under $s = 0$ do not default in equilibrium. To show that $P(1) = 0$ if $\pi \geq \pi^*$, note that, since all agents default under $s = 1$ if $P(1) < \bar{P}(R, L)$ and borrowing under repayment is independent of $P$, for fixed contract terms, the marginal increase in profits due to a infinitesimal increase in $P(1)$ satisfies

$$
\frac{\partial \mathbb{E} \Pi(I, K, P)}{\partial P(1)} = Pr(s = 1) (Pr(d = 0|s = 1)L(1 + \tilde{R}) - \lambda) \\
\leq p \left( (1 - p)(1 - \pi)L(1 + \tilde{R}) - \lambda \right)
$$

for all $P(1) < \bar{P}(R, L)$. It is easy to check that $\frac{\partial \mathbb{E} \Pi(I, K, P)}{\partial P(1)} \leq 0$ when $\pi \geq \pi^*$. As a result, lowering monitoring probabilities all the way down to $P(1) = 0$ with $R, L$ unchanged is profit feasible and increases consumer welfare, since consumers prefer lower monitoring probabilities. Furthermore, due to the lower cost of monitoring under $s = 1$, lenders can offer a (weakly)
lower interest rate $R$, which also lowers monitoring costs under $s = 0$, since $\bar{P}$ is decreasing in $R$.

*Case (iii):* Next, we rule out type iii) equilibria. By way of contradiction, assume $P(0) < \bar{P}(R, L)$ and $P(1) = \bar{P}(R, L)$, with $K = (R, L)$ such that (1) is satisfied. This implies that, in equilibrium, all non-distressed agents default whenever the signal (correctly) indicates no distress. At the same time, none of them defaults when $s = 1$ by the same argument used in (i). To see the contradiction, note that that whenever $P(1) = \bar{P}(R, L)$, we must also have $P(0) = \bar{P}(R, L)$. This is certainly the case when $\pi = 0$ by Assumption 3. Furthermore, monitoring costs associated with $P(0) = \bar{P}(R, L)$ are strictly decreasing in $\pi$, as they are given by

$$Pr(s = 0)Pr(1|0)\bar{P}(R, L)\lambda = p(1-p)(1-\pi)\bar{P}(R, L)\lambda.$$  

At the same time, monitoring costs are independent of $\pi$ for any fixed $P(0) < \bar{P}(R, L)$, as all agents default under $s = 0$. Accordingly, if setting $P(0) = \bar{P}(R, L)$ at $\pi = 0$ for a zero profit contract $(R, L)$ is preferred to having another zero profit contract associated with a lower monitoring probability $P(0)$, the same must be true for any $\pi > 0$. This is because monitoring costs are lower and ex-ante utility can be increased by lowering the interest rate (again, recall that $\bar{P}(R, L)$ is decreasing w.r.t. $R$).

The last part of the proposition is trivial: by Proposition 1, if $L < L_{min}(d = 1)$ either only distressed consumers default or nobody defaults. In such cases, lenders optimally set monitoring probabilities to zero. Obviously, if nobody defaults monitoring costs are zero regardless of monitoring probabilities so lenders are indifferent between any $P$. Corollary 1 directly follows form the above. \hfill $\blacksquare$

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

\[ 0 = R \mathbb{E} b(L, R) - \left[ p + p Pr(0|1) \right] L - \left[ (1 - p) Pr(1|0) \bar{P}(R, L) + p P(1) \right] \lambda \\
+ p Pr(0|1) L (1 + \bar{R}) P_\pi(1). \]

To derive the expression stated in the proposition, we substitute \( Pr(0|1) = (1 - p)(1 - \pi) \), \( Pr(1|0) = p(1 - \pi) \), solve for \( R \) and rearrange terms. The last part follows from the fact that, as \( \pi \) increases, \( Pr(1|0) \) and \( Pr(0|1) \) monotonically decrease to zero, and \( P(1) = 0 \) for all \( \pi > \pi^*(< 1) \) by Proposition 2.

\[ \square \]

**Proof of Proposition 5.** Fix credit limit \( L \) and signal precision \( \pi_L \), and let \( P^*(0) = \bar{P} \) and \( 0 \leq P^*(1) < \bar{P} \) be the monitoring probabilities under the best selectively monitored contract with credit limit \( L \). Also, let \( R(\pi_L, P^*) \) denote the associated zero profit interest rate. Suppose the precision of information improves to some level \( \pi_H = \pi_L + \varepsilon \), for some infinitesimal \( \varepsilon \) and that \( P^{**} \) denotes the monitoring probabilities of the best selectively monitored contract with \( L \) under \( \pi_H \). We need to prove that \( P^{**}(0) = \bar{P} \) and \( P^{**}(1) \leq P^*(1) \), with strict inequality if \( P^*(1) > 0 \). We focus on showing \( P^{**}(1) \leq P^*(1) \), and comment at the end why a strict inequality applies.

By contradiction, suppose that \( P^{**}(1) > P^*(1) \). Let \( V_\pi \) denote consumers’ ex ante utility under the precision of information \( \pi \). Our goal is to show that

\[ V_{\pi_H}(L, R(\pi_H, P^{**}), P^{**}) \geq V_{\pi_H}(L, R(\pi_H, P^*), P^*) \]

implies

\[ V_{\pi_L}(L, R(\pi_L, P^{**}), P^{**}) > V_{\pi_L}(L, R(\pi_L, P^*), P^*). \]

We first focus on the case that \( L \) is never binding and deal with the case of binding \( L \) at the end of the proof. Recall that, by Corollary 1, non-distressed consumers repay under \( s = 0 \) and default under \( s = 1 \). Let \( x \) denote the additional revenue collected by lenders under \( \pi_H \)

\[ \infty \]

In the above expression, the second term in the RHS reflects gross default losses, given by the mass of distressed agents \( p \), and the mass of non-distressed agents with \( s = 1 \), which is given by \( p Pr(0|1) \). The third term reflects the costs associated with monitoring. Finally, the last term captures expected recovered debt from defaulting non-distressed borrowers.
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 under $s=1$ implied by the deviation are independent of $\pi$ (the mass of monitored agents is equal to $p$), the increase in revenue by deviating from $P^*$ to $P^{**}$ is strictly higher under $\pi_L$ than under $\pi_H$. This is because the mass of non-distressed agents under $s=1$ is higher when $\pi$ is lower, while the revenue collected from each monitored agent, given by $L(1+\bar{R})$, is independent of $\pi$ and $R$. Specifically, the extra revenue collected by deviating from $P^*$ to $P^{**}$ under $\pi_L$ is $f_x$, 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 $s = y$ when precision is $\pi$.\(^{24}\)

Next, suppose the collected resources under $\pi_L$ are redistributed equally to all repaying consumers by appropriately lowering the interest rate $R$ (to ensure that the zero profit condition holds). Our goal is to show that, if such redistribution justifies the increase in monitoring probability under $\pi_H$ relative to $P^*$, it must justify a similar increase under $\pi_L$. For now, we consider $\bar{P}(L, R)$ unchanged, and comment at the end why its change works to our favor. To this end, we first note that the indirect utility of distressed agents is independent of $P$ and $R$, and so the change in ex-ante utility due to the increase in monitoring probabilities and the corresponding reduction in interest rates under $\pi$ is determined by:

$$
\Delta V_\pi = V_\pi(L, R(\pi, P^{**}), P^{**}) - V_\pi(L, R(\pi, P^*), P^*)
= pPr(0|1;\pi)\Delta D_\pi(0|1) + (1 - p)Pr(0|0;\pi)\Delta N_\pi(0|0),
$$

where $\Delta D_\pi(0|1)$ and $\Delta N_\pi(0|0)$ respectively denote the change in the indirect utility of a non-distressed defaulting consumer under signal $s = 1$ and a repaying consumer under signal $s = 0$. Importantly, the drop in utility of a non-distressed defaulting consumer, $\Delta D_\pi(0|1)$, is the same under $\pi_L$ and $\pi_H$. This follows from the fact that for a non-distressed defaulting consumer the only relevant variable is the monitoring probability $P$, and these probabilities are identical after the deviation in both cases (equal to $P^{**}$). Hence, we can re-write the change in the

\(^{24}\)Note that the extra (gross) revenue collected due to an increase in monitoring probability $\Delta P(1)$ is given by $Pr(s = 1)Pr(0|1)\bar{P}(L(1+\bar{R}))\Delta P(1)$.
ex-ante utility in the case of $\pi_L$ as follows

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

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

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

$$
\frac{g}{f}\Delta N_{\pi_L}(0|0) > \Delta N_{\pi_H}(0|0), \quad (A1)
$$

we show $\Delta V_{\pi_L} > f\Delta V_{\pi_H}$. This is enough to establish the contradiction because we would have proven that $\Delta V_{\pi_H} \geq 0$ implies $\Delta V_{\pi_L} > 0$. To see why the inequality in (A1) must hold, note the following. Under $\pi_L$, all non-distressed consumers under $s = 0$ receive a transfer of resources equal to $fx$. However, comparing to the case of high precision $\pi_H$, their mass is lower by a factor $g < 1$ (by definition of $g$). Hence, comparing to the transfer of resources under the high precision of information $\pi_H$, which in per capita terms (per non-distressed repaying borrower) is $x$, the per capita transfer of resources is actually higher in this case and equal to $\frac{g}{f}x$ (recall $f > 1$). Furthermore, since the default rate is higher under $\pi_L$, the zero profit condition implies that $R(\pi_L, P^{**}) > R(\pi_H, P^{**})$ and, from Lemma 1 below, we know that the marginal utility from an identical transfer is generally higher under $\pi_L$ than it is under $\pi_H$. This finishes the proof that (A1) holds, as the increase in utility more than compensates the differences in masses from the ex-ante point of view. Finally, for the same reason, we note that the change in $P(L, R)$ is higher under $\pi_L$ due a larger impact on $N_{\pi_L}(0|0)$ (and no impact on $D_{\pi}(1|0)$). Moreover, the drop in the overall monitoring cost due to a change $P(L, R)$ is also higher when signal is more noisy (as there are more defaulting consumers to monitor). This implies that our initial assumption of fixing $P(L, R)$ is wlog, as relaxing it would only work to our favor.

When credit limits are binding it is straightforward to show that under Assumption 4 the increase in utility due to an increase in resources of $x$ is the same under both $\pi_L$ and $\pi_H$ so the above reasoning still holds. Here note that when credit limit binds for $R$ it binds for lower $R$ as well. Strictly inequality can be established analogously. One simply needs to show that, since
an infinitesimal deviation to a higher monitoring probability under $\pi_H$ makes the consumer strictly worse off, an infinitesimal deviation to a lower monitoring probability must raise the ex-ante utility under $\pi_L$. Finally, the fact that $P_\pi(1)$ is discontinuous at $\bar{P}$ directly follows from an argument similar to the one we used in part i) of Proposition 2.

Lemma 1. Suppose Assumption 4 holds. Assume $R < R_{\text{max}}$, where $R_{\text{max}} \equiv \arg\max_R \{Rb(R)\}$. Consider an infinitesimal reduction of the interest rate $R$ such that $\Delta(Rb(R)) = -x$. Then, the total gain in utility $N$ under repayment of a non-distressed borrower is greater the higher the initial level of $R$ is.

Proof. First, assume $L$ does not bind. By Assumption 4, $U(c,c')$ is given by $u(c + c' - \mu(c - c')^2)$, where $\mu > 0$ is a consumption smoothing parameter and $u$ is any concave utility function (e.g. CRRA). In such a case, the policy function for borrowing is linear, and given by $b(R) = \left(B - \frac{R^2}{4\mu}\right)/2$. Interest rate has a distortionary effect on the intertemporal margin in this environment, causing a deadweight loss that can be explicitly calculated $\mu(c - c')^2 = \frac{R^2}{16\mu}$.

This deadweight loss is higher the higher the interest rate $R$ is. Furthermore, the total interest revenue collected from the agents is given by a quadratic function, $Rb(R) = \left(BR - \frac{R^2}{4\mu}\right)/2$. and it is concave and single peaked w.r.t. $R$ at $R_{\text{max}} = 2\mu B$.

Using the above properties, assuming borrowing constraints do not bind and the consumer is, in fact, a borrower, we can define

$$\Delta N = u(2Y - B - Rb(R) - x - \frac{R'^2}{16\mu}) - u(2Y - B - Rb(R) - \frac{R^2}{16\mu}),$$

where $R'$ denotes the new interest rate (after the transfer $x$). This expression immediately follows from the assumed redistribution scheme in the lemma. Our goal is to show that $\Delta N(R)$ is increasing w.r.t. $R$. To see why this must be the case, note that, since $\frac{d(Rb(R))}{dR} = (B - \frac{R}{2\mu})/2$, that the sensitivity of $Rb(R)$ is the lowest the closer the initial $R$ is to its peak, $R_{\text{max}}$. By the Fundamental Theorem of Calculus, we observe

$$\Delta(Rb(R)) = -\int_{R'}^{R} \left(B - \frac{R}{2\mu}\right)/2dR,$$

and thus a higher $R$ is generally associated with a larger drop of $R$ as measured by $(R - R')$.
to accomplish the assumed reduction in interest burden by $x$. Now, since the term $\frac{R^2}{16\mu}$ is quadratic in the above expression of $\Delta N$, the drop in $R$ is highest when $R$ is higher, and $2Y - B - Rb(R) - \frac{R^2}{16\mu}$ is lower to begin with when $R$ is higher, it must be the case that $\Delta N$ is higher whenever $R^{**} > R^*$. 

Finally, note that establishing this property in the case of binding credit limit is trivial (in a weak sense). If $L$ binds for $R$ it binds for $R' < R$. When $L$ binds the interest rate distortion is absent, and the change in consumption in each sub-period is identical as the interest rate is reduced (see the budget constraint).

Proof of Proposition 6. The result follows directly from Propositions 3-5. To see why, fix an $L$ associated with the monitored insurance region. By Proposition 3 the full monitoring interest rate associated to $L$ is constant with respect to precision; while it is easy to check that the selective monitoring rate given by Proposition 4 is monotonically decreasing in $\pi$ since $P_\pi(1)$ is decreasing in $\pi$ by Proposition 5. Furthermore, the default premia of both rates are equal at $\pi = 1$ while the monitoring premium is lower under selective monitoring than under full monitoring for fixed $R$. Thus, since $\bar{P}$ is increasing in $R$, there exists a cutoff $\bar{\pi} < 1$ such that $R$ is lower under selective monitoring for precisions higher than $\bar{\pi}$. To complete the proof, note that if a selectively monitored contract exhibits lower interest rates than a fully monitored contract with the same credit limit then consumers strictly prefer the former to the latter. This is because utility under repayment is higher at lower $R$ and, in addition, selective monitoring involves lower monitoring probabilities than full monitoring for fixed $R$, implying higher utility of defaulting non-distressed agents. Finally, notice that, if there is a selectively monitored contract providing higher utility than the preferred full monitoring contract at precision $\pi$, by the above argument this must also be the case at higher precision.

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