ONLINE APPENDIX

Modeling the Revolving Revolution: The Debt Collection Channel

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Contents

1 Sensitivity and robustness analysis

1.1 Credit lines with interest rates

We consider a version of our quantitative model with credit line contracts featuring proportional interest rate charges (henceforth *alternative model*). That is, unlike the *benchmark model* in the paper, finance charges are assessed in proportion to borrowing. Specifically, in the case of repayment, the budget constraint of the consumer is given by

$$C \leq Y(z,t) - B + B' - IB' - dE(z),$$

where $0 \leq I < 1$, as opposed to

$$C \leq Y(z,t) - B + B' - I - dE(z)$$

in the benchmark model.

Parameter values are the same except for β, θ, and λ. The value of these parameters is similarly chosen to target the same moments in the paper. Since the case of $\pi = 0.76$ cannot be calibrated because signal precision is too low to match the targets, we report only the remaining two cases, that is, $\pi = 0.78$ and $\pi = 0.80$. Table 1 lists the parameter values.

Table 2 and Figure 1 present the results. They are almost identical to those of the benchmark model. The figure additionally plots efficiency gains from IT adoption (relative to the $\pi = 0$ economy) for different π.[1]

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[1] As the figure shows, because of costs of strategic default, gains from IT become positive only at high precision levels. IT adoption takes place at a much lower signal precision level. The reason why this is the case is because lenders in our model maximize borrowers' utility and, hence, internalize the fact that only a fraction of losses associated with strategic default are deadweight losses.

Table 1: Jointly Calibrated Parameters of the Alternative Model

		Model	
	Data*	$\pi = .78$	$\pi = .80$
Targeted moments (in %)			
Debt / income	15.1	15.0	15.1
Net charge-off rate	5.2	5.2	5.2
Collection costs / charge-offs	4.0	4.0	4.0
Collection costs / debt	0.21	0.21	0.21
Use of IT in collections	$> 90\%$	59.9	58.4
Calibrated parameter values			
Discount factor β		0.6969	0.6980
Cost of defaulting $1 - \theta$		0.0660	0.0670
Collection cost λ		0.1080	0.1205

*Reported data values for debt-to-income ratio and charge-off rate pertain to trend values for 2004. See the paper for how we measure collection costs.
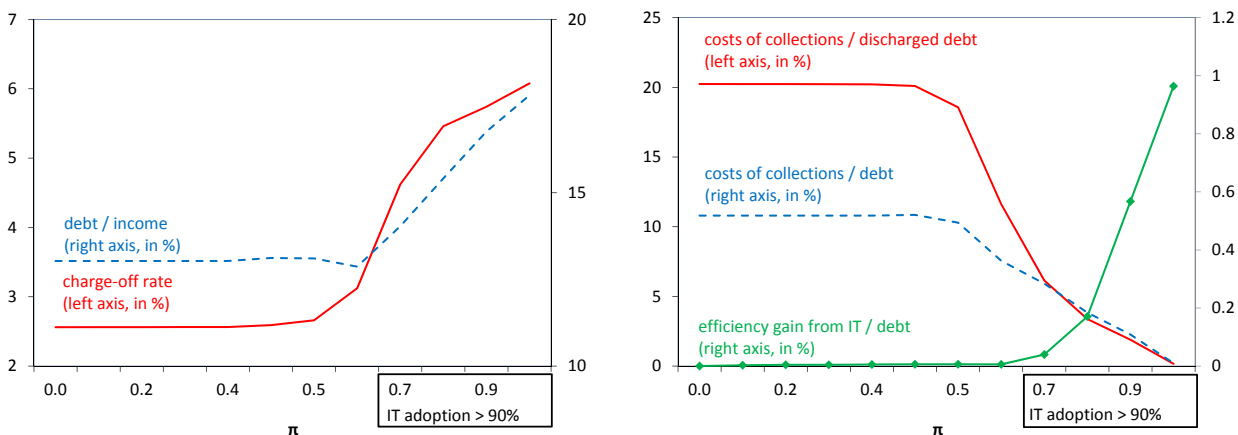

Figure 1: Effect of Improved Signal Precision in the Alternative Model ($\pi = .78$ calibration)

1.2 IT progress as a drop in transaction costs

We next show that a reduction in the transaction cost of issuing credit leads to a counterfactual decline in the charge-off rate. This exercise is analogous to the one considered by Livshits, MacGee and Tertilt (2010). Since simple wedges are often considered to capture the effect of

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Table 2: Effect of Reducing Signal Precision in the Alternative Model

Statistics	Model		Data
Signal precision π	**0.78**	**0.80**	2004
	0	**0**	1989
Use of IT in collection (in %)	100	100	
	0	0	

A. Use of Credit (in % unless otherwise noted)

Debt/income	15.0	15.1	15.1[a]
	13.0	13.3	8.5[a]
Charge-off rate	5.2	5.2	5.2[b]
	2.9	3.0	3.4[b]
Persistent delinquencies per 1000	15.5	15.5	20[c]
	9.3	9.7	
Strategic delinquencies per 1000	2.0	1.8	
	0	0	
Utilization rate	62	62	47[d]
	65	63	46

B. Debt Collection (in % unless otherwise noted)

Efficiency gains from IT/debt	0.08	0.31	0.31[e]
Efficiency gain from using IT/charge-offs	3.0	9.9	9[e]
Efficiency gain from using IT/charge-offs (myopic)	35	37	
Frequency of debt collections	10	9	9.2[f]
	37	49	
Collection costs/debt	0.21	0.21	0.21
	0.52	0.80	1.25[g]
Collection costs/ charge-offs	4	4	4[h]
	20	26	37[g]

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

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IT progress in a reduced-form way, here we establish that such modeling of IT progress has very different implications than our micro founded specification.

Table 3 considers two formulations of the transaction costs. The first one considers a proportional cost to borrowing τ paid by lenders, and the second one considers a fixed cost ψ per credit line. We show that both fail in producing an increase in the charge-off rate.

To assess the effect of these costs on credit markets, we start from the initial value of $\tau = 0.0816$ as in our benchmark model and increase it to $\tau = 0.11$ to match the observed fall in the interest rate premium on credit card lending over the 1990s.[2] We perform a similar exercise with ψ, except that in this case we start from $\psi = 0$ (this parameter is absent from the benchmark model). We assume $\tau = 0.0816$. We report the results for the $\pi = .8$ calibration of the benchmark model as described in the paper.

As Table 3 shows, in both cases an increase in costs raises the charge off rate. The change in the debt-to-income ratio goes in the right direction. Intuitively, the charge-off rate is the ratio of the flow of discharged debt to total debt outstanding. Lower transaction costs, by reducing the cost of credit, generally increase debt far more than they increase discharged debt, and hence the charge off rate goes down.

In addition, the bottom panel of Table 3 shows that the effect of changing wedges and precision of signals is still positive as in our benchmark model. This underscores the strength of the microfounded channel we consider. In particular, the observed change in the charge off rate is still in line with the data while the change in debt-to-income is closer to the observed one.

To complete our analysis, we also considered a perfect information case featuring $\pi = 1$ (λ

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[2]To calculate interest rate premium, we used the average interest rate on credit card debt assessing interest rate reported by the Board of Governors of the Federal Reserve System. As described in the paper, to obtain the premium, we subtract the yield on 5-year to maturity government bonds and the charge-off rate. Since credit card interest rate data starts in 1994, we regress the trend line between 1994 and 2004 and extrapolate the corresponding value for 1989.

Table 3: Effect of IT Progress Modeled as a Change in Simple Wedges ($\pi = .8$ calibration)

Parameter change		Debt / income (in %)	Charge-off rate (in %)	Use of selective monitoring (in %)	Gains from IT / charge-offs (in %)
Effect of higher wedges:					
$\tau = 0.087 \uparrow 0.113$	2000s	15.11	5.22	100.00	
	1990s	11.80	6.49	100.00	
$\psi = 0 \uparrow 0.02$		15.11	5.22	100.00	
		13.12	6.13	99.79	
Combined effect of reduced signal precision and higher wedges:					
$\pi = 0.8 \downarrow 0\%, \tau = 0.087 \uparrow 0.113$		15.11	5.22	100.00	
		10.68	3.86	2.32	9.48
$\pi = 0.8 \downarrow 0\%, \psi = 0 \uparrow 0.02$		15.11	5.22	100.00	
		11.84	3.16	0.00	13.50

is indeterminate). The results were almost identical.

1.3   Alternative calibration of collection costs

This section considers an alternative calibration of the benchmark model. Instead of targeting the aggregate characteristics of the credit card market in 2004, we target the numbers reported by Makuch et al. (1992) from early 1990s. That is, we choose parameters λ, β, θ to target a charge-off rate of 3.3%, costs of collections-to-debt ratio of 1.25%, and costs of collections relative to charged-off debt of 37%. We drop debt-to-income from calibration targets. Since these numbers characterize GE Capital before IT adoption in collections took place, we require that no more than 10% of risky contracts are sustained using signals. Hence, we set $\pi = 0$. The model is able to match all targets. The calibrated value of λ is significantly higher (0.27)
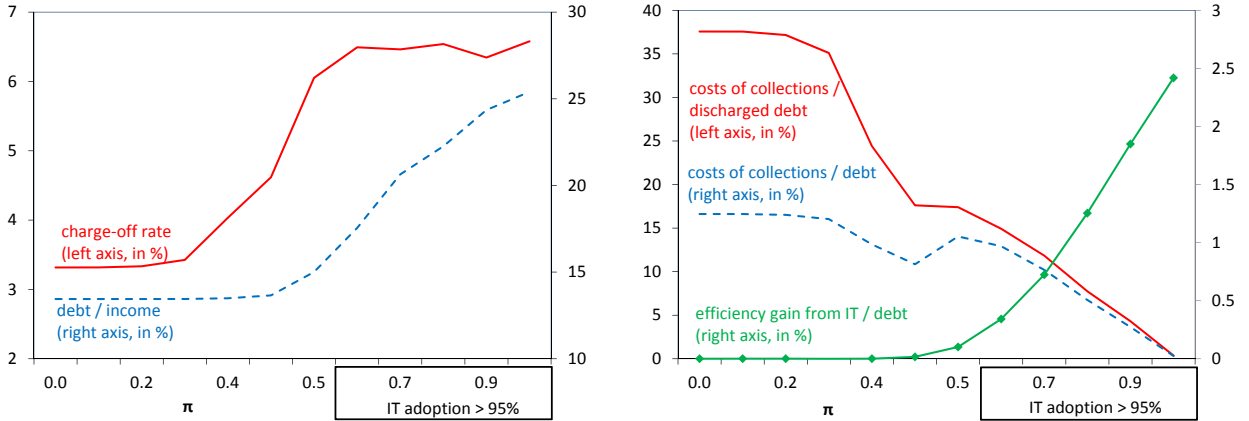
Figure 2: Effect of IT Progress under an Alternative Calibration of Model Parameters

than in the benchmark calibration (0.1).

Figure 2 illustrates the effect of raising signal precision to induce IT adoption in collections. The exercise is analogous to the one considered in the paper. Because the alternative calibration exhibits a higher value of parameter λ, the effect of higher π is far more pronounced than in the benchmark model.

1.4 The effect of removing debt collection technology

In this exercise we remove debt collection technology from the benchmark model to show that this feature of the model is essential to match the debt-to-income ratio and the charge-off rate in 2004.

Specifically, we set λ to an arbitrarily high number and set $\pi = 0$. We then look for a combination of β and θ to match the debt-to-income ratio and the charge-off rate, as targeted in the benchmark calibration. (By setting λ arbitrarily high, we eliminate lender's ability to use debt collection to sustain risky contracts.)

The results are illustrated in Figure 3. Each dot in the figure reports a different combination of β and θ from a feasible set of values between 0 and 1. As is clear from the figure, there

is no parameter combination that matches the assumed set of calibration targets. This result is not surprising. It is well known that standard models of consumer default have a difficulty simultaneously matching high gross levels of indebtedness and high default rates.
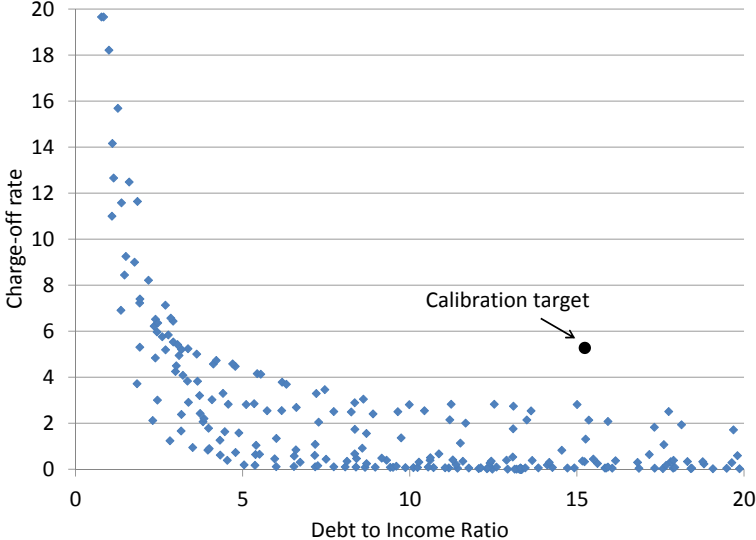

Figure 3: Charge-off Rate and Debt-to-Income ratio in The Model Without Debt Collection

2   Simulation of a sample agent in the benchmark model

As an illustration of the effect IT progress, we show the simulation of a low-income consumer who faces the same sample path of income and signals in the pre- and post-IT adoption economies. The sample path of this hypothetical consumer is illustrated in Figure 4.

The top panel of Figure 4 illustrates the realized income, which is the same in both simulations, and the bottom panels present this consumer's credit market outcomes in each respective economy during her working age. The consumer borrows constantly because her income is low relative to the expected value throughout her entire lifetime. The dotted line denotes credit limit, and the solid line denotes borrowing. The marks below the plot indicate when the consumer receives risky contracts ('-'), and how they are sustained ('o' denotes selective

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—◆—Income

◇ Financial distress

1

0

1   6   11   16   21

Age

$\pi = .78$

—▲—Borrowing   ✗ Default
······ Credit limit   — Risky contract
● Fully monitored contract   ○ Selectively monitored contract

L=.25   L=.28

✗

1   6   11   16   21

Age

$\pi = 0$

—▲—Borrowing   ✗ Default
······ Credit limit   — Risky contract
● Fully monitored contract   ○ Selectively monitored contract

L=.15

borrows exclusively on
risk-free contracts

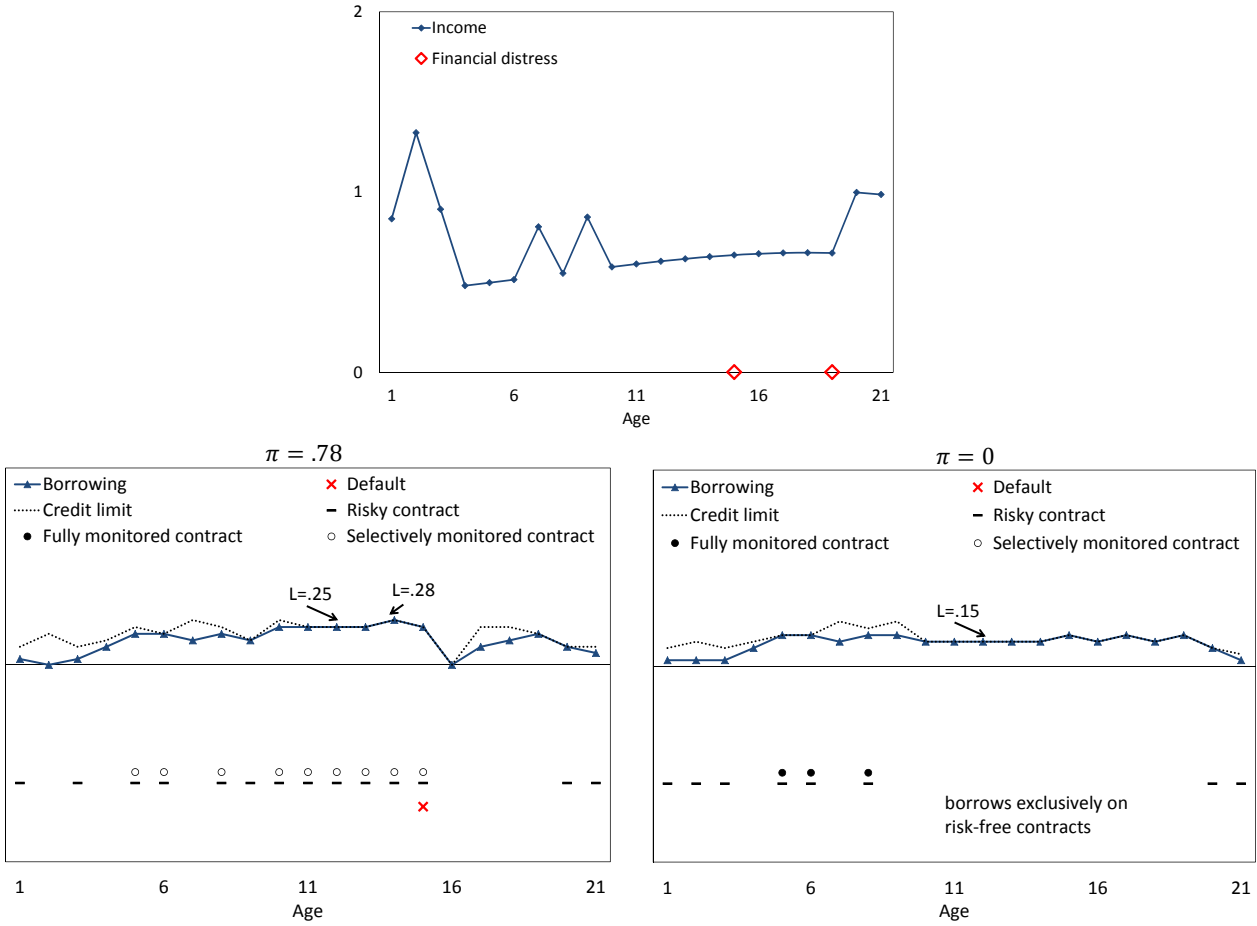1   6   11   16   21

Age

Figure 4: A Sample Simulation of an Identical Consumer under the Post- and Pre- IT Adoption Regime ($\pi = .78$ calibration)

collection).

As is clear from the figure, the key difference between the two simulations is that the consumer receives risky loans far more frequently in the $\pi = .78$ economy than in the $\pi = 0$ economy. As a result, she defaults more often in the former than in the latter.

3   Overview of debt collection methods and technology

In this section we provide a extended discussion of debt collection in the U.S.

Lifecycle of delinquent credit card debt.— Delinquent credit card debt is typically first handled by the original creditors. The first contact with the borrower is made after 30 days of delinquency. The collection effort intensifies every 30 days. Between 120 and 180 days, credit card debt enters a pre-charge-off stage. The debtor might be offered a settlement deal at this point. After 180 days, in the case of credit cards, debt must be charged off by the creditor. Discharged debt is no longer listed as an account receivable on the creditor's books, and its value is charged against the creditor's reserves for losses. Any payment on the charged-off debt obtained later in the collection process is then treated as income.[3] Debt collection can extend until the statute of limitations on debt expires, which varies from 3 to 10 years depending on the state, unless a judgment is obtained beforehand (see Government Accountability Office (GAO) (2009) report to Congress for an overview of the life-cycle of delinquent debt). At this point unpaid debt is likely handed over to a collection agency on a contractual basis. Since the 2000s, a substantial amount of credit card debt is also sold to debt buyers.

Tax treatment of delinquent credit card debt.— Starting in 1996, if creditors discharge debt, after 36 months of bona fide collection efforts, they are required to file a 1099 cancellation of debt form with the IRS. In practice, only ongoing litigation or packaging of debt for resale is a valid exception to this rule (see 6 CFR Ch. I (4112 Edition), 1.6050P-22). However, until 2003, debt handled by debt collection agencies was not subject to the same rule. Between 2004 and 2006, the IRS filed a lawsuit to enforce the rule in the case of debt collection agencies. While the court sided with the IRS, the IRS suspended the enforcement of the 36-month rule in the case of debt collection agencies (see amendment RIN 1545-BH99 of 1.6050P-1 26 CFR 1 in Federal Register Volume 73, Number 218 (Monday, November 10, 2008), Rules and Regulations, pp. 66539-66541). In practice, because to the statute of limitations applying to IRS audits (3 or 6 years depending on the amount), cancellation of debt handled by debt

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[3]See Federal Trade Commission, "Collecting Consumer Debts: The Challenges of Change," A Workshop Report 2009, FTC, and references therein.

collection agencies is not taxed (see, for example, *David Scott Stewart and Carla Annette Stewart v. Commissioner of Internal Revenue Service,* Docket No. 10374-11S, United States Tax Court). By selling discharged debt, the original creditors can avoid premature tax-related closure of the debt collection process while cashing out on the residual value of the outstanding bad debt.

The role of litigation in debt collection.— Debt collection often involves litigation. By entering the legal path, collectors usually seek a judgment in state courts, allowing them to garnish debtors' wages, seize bank accounts, or place liens on debtor properties. Judgments may also be obtained to extend the option of collecting unpaid debt beyond the expiration of the statute of limitations. Since judgments can be eliminated by filing for bankruptcy, they generally do not diminish the attractiveness of informal default.[4] According to a study of 1999 credit records by Avery, Calem and Canner (2003) about one-third of consumers had one judgment on their record in 1999, and another third had two (judgments stay on record for seven years). However, very few (15.8%) of these judgments have been paid, and in most cases there is no bankruptcy filing on record. Evidence suggests that lawsuits carry significant risk for debt collectors. This is because they entail substantial upfront administrative costs, and these costs are sunk in cases in which a delinquent debtor is found insolvent or chooses to file for formal bankruptcy protection. Not surprisingly, cash collected through litigation accounts for only a quarter of the cash collected by major debt collection agencies and debt buyers, such as Portfolio Recovery Associates and Encore Capital Group. Debt collection agencies explicitly report that they employ information technology (IT) to economize on these costs. In addition, about 50% of such recoveries appear to be absorbed by the legal costs and fees

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[4]According to Hynes (2006), judgments are rather difficult to enforce. For example, in many states, the plaintiff simply cannot force a sale of the defendant's home, even if a lien is placed against debtor property. In terms of wage garnishments, federal law prohibits a creditor from taking more than the lesser of 25% of the debtor's take-home pay or the amount by which the debtor's weekly take-home pay exceeds 30 times the minimum wage. Bank deposits are also protected in cases in which the debtor can show that these deposits are derived from exempt wages or exempt income of any kind.

associated with litigation.[5] This aspect of the data underscores the asymmetry of information associated with debt collection and the importance of IT to properly identify the "solvent" debtors prior to litigation.

The role of IT in collections.— IT plays the important role of economizing on the use of collection resources, such as reducing litigation in cases when it is unlikely to yield any results. Large collection agencies rely on sophisticated statistical models that are based on databases of past collections, credit history of borrowers updated in real time, and other supplementary data sources that can be matched with credit records. For example, the major debt collection company, Encore Capital, in its Annual Report to shareholders, describes the company's methods as follows:

"We pursue collection activities on only a fraction of the accounts we purchase, through one or more of our collection channels. The channel identification process is analogous to a decision tree in where we first differentiate those consumers who we believe are unable to pay from those who we believe are able to pay."

In the same report, Encore Capital also states:

"We have assembled a team of statisticians, business analysis and software programmers that has developed proprietary valuations models, software and other business systems that guide our portfolio purchases and collection efforts. (...) Our valuations are derived in large part from information accumulated on approximately 4.8 million accounts acquired since mid-2000."

Portfolio Recovery Associates (PRA) describes its methods in a similar manner, mentioning two econometric models that it uses to price delinquent debt portfolios and to select an appropriate action. PRA reports significant gains in collection effectiveness due to the use of their proprietary IT systems. PRA and Encore Capital are two of the largest debt collection

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[5]2006 income statements of Encore Capital Group, Inc.

agencies, together accounting for about 10% of the market.

Current state of debt collection technology.— Today, IT companies, including leading enterprise resource planning (ERP) solution providers, such as Oracle or SAP and firms specialized in collection software such as Fair Isaak Corporation (FICO), offer both off-the-shelf and customized collection management tools. Regarding ERP firms, Oracle offers collection software integrated into the two ERP suites it commercializes: Receivables and Collections Management for Oracle E-suite (Walker, 2007) and Collections Workbench (Oracle, 2013); SAP offers Collections Management (SAP, 2013), and SAS offers Intelligent Debt Management (SAS, 2009). Other companies offering collection software include credit scoring pioneer FICO[6], Quandrax[7], SunGard[8], CDS software[9] and FirstData.[10] The menu of solutions is quite diverse, even including systems specifically designed for legal collections—for instance, CollectOne from CDS Software incorporates a legal collection suite.[11]

In addition, all three credit bureaus (TransUnion, Experian, Equifax) offer comprehensive collection solutions to the industry since the mid 1990s, including the sales of collection scores and real-time monitoring of delinquent borrowers.[12] Collection scores provided by credit bureaus are currently computed by combining different sources of information, including payment and account histories, credit bureau data, employer-provided information and consumer data. As further evidence of the widespread use of collection scoring and predictive metrics in the management of delinquent accounts, debt collection services represent a sizable part of the credit bureau and rating industry's revenue: about 7.5% of the $10.4 billion in expected rev-

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[6]www.fico.com/en/products/fico-debt-manager-solution

[7]www.quantrax.com

[8]financialsystems.sungard.com/solutions/corporate-liquidity/consumer-collection-scoring

[9]www.collectone.com/debt_collection_software

[10]www.firstdata.com/en_us/products/financial-institutions/security-and-fraud-solutions/collections-and-recovery.html

[11]See www.collectone.com/debt_collection_software.

[12]See, for example, Experian's Collection Advantage (www.experian.com/business-services/collection-of-debt.html); Equifax Decision 360 (www.equifax.com/collections/en_us); and TransUnion's first- and third-party collection solutions (www.transunion.com/corporate/business/collections/collections_landing.page?portal=y&ref=c).

enue for 2013 (IBISWorld, 2013a), with 5.2% coming directly from debt collection agencies. To put these numbers into perspective, 37% of the overall industry revenue comes from banks and financial institutions. This is quite a big number, especially given that such industry not only includes credit bureaus but also rating agencies such as Standard & Poor's.

Finally, it is important to emphasize that the credit card receivables market is the largest sector for the debt collection industry, representing approximately one-third of its $13-billion expected revenue in 2013 (IBISWorld, 2013b). Similarly, all of the major credit card issuers use segmentation of delinquent accounts and prioritization of collection resources (Cleaver, 2002). Specific examples include Capital One (Chin and Kotak, 2006), Citibank (FICO, 2013), GE Capital (Makuch et al., 1992), and Wells Fargo.

The evolution of debt collection technology.— The first collection models appeared in 1970s (Liebman, 1972), as did the first applications of behavior scoring and adaptive control for optimizing credit card collections, developed by FICO: Montgomery Ward in the late 1960s (Lewis, 1992) and Wells Fargo in the mid 1970s.[13] While the use of IT in the credit industry become prevalent by the late 1980s, the use of IT in debt collection was still rare. In their survey, Rosenberg and Gleit (1994) note that:

"By far the most mature branch of quantitative methods is in deciding whether to accept or reject a credit applicant (or in loan review). The use of statistical methods and experiments to determine optimal start treatment levels and collections strategies is less well established, and is much more of an art."

Although collection scoring models were being developed (e.g., Chandler and Coffman, 1983) and the idea was often circulated in industry magazines (Coffman and Darsie, 1986), its practical implementations were scant.

The development of modern collection technologies took off in the early 1990s when GE

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[13]See FICO's history at www.fico.com/en/about-us/history.

Capital—at the time the largest provider of "private-label" consumer credit in the U.S., underwriting credit cards issued by large retailers such as Macy's—implemented its landmark PAYMENT system for credit card collections (Makuch et al., 1992). PAYMENT managed more than 50 million accounts, and a $12 billion portfolio. Its core philosophy was to segment portfolios of delinquent accounts and use adaptive control techniques to pick the best strategy for each portfolio to maximize "the net delinquent dollar amount collected subject to collection resource constraints." The introduction of PAYMENT, according to Makuch et al. (1992), led to a much greater use of "no-action" in collections. The technology gradually diffused throughout the industry. For instance, in the 1990s, the software company Quandrax introduced *Intelec* and reported more than 100 installed systems by the late 1990s that helped prioritize collections (Panczyk, 1999), including some agencies part of NCO Group, the leading debt collection agency in the US (accounting for almost a 10% market share).[14] Importantly, in the mid 1990s, credit bureaus started offering collection scores to financial institutions and collection agencies: Experian introduced RecoveryScore for charged-off accounts in 1995 (personal communication), and TransUnion has offered collection scores since at least 1996 (Pincetich and Rubadue, 1997).

By the early 2000s, most credit card issuers turned to segmentation and prioritization using extensive data sources. For instance, Cleaver (2002) reports that many issuers are "backing off from a shotgun approach to collection calls and are focusing resources on accounts with the highest projected returns," and also quotes U.S. Bancorp vice president as saying that all the major card issuers were using the same techniques to segment their credit card portfolios. Along with the widespread adoption of collection scoring, the focus since the early 2000s

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[14]Other companies include Neuristics and Trajecta. Neuristics introduced Collections Triage software in the first quarter of 1999, that was designed to segment delinquent accounts in three categories: those that will be charged-off, regardless of the collection effort (*straight rollers*); those that will get back into good standing by themselves (*self-cures*); and those that will not self-cure but will respond to collection (*efficient collectibles*). Trajecta introduced collection software Decision Optimizer 1.6 in 1998. Other companies specialized in collection scoring and predictive metrics include PredictiveMetrics, founded in 1995 and now part of SunGard (SunGard, 2011).

has turned toward making collection solutions more efficient by using better processing and additional data sources; that is, by making segmentation, collection scores, and predictive metrics more precise. As an example, Chin and Kotak (2006) describe the overhaul of Capital One's collection system aimed at improving segmentation and strategy testing capabilities. Overall, while collection scoring models were based mostly on credit bureau data and account history (Thomas, Ho and Scherer, 2001), nowadays they rely on more up-to-date, multiple data sources, including employer-provided and consumer data. Collection scoring models have also benefited from advances in data mining techniques. See, for instance, the study by Ha and Krishnan (2012).

Efficiency gains from using IT in collections.— Evidence on efficiency gains from employing modern IT systems comes from case studies and scattered industry reports. The message emanating from these sources is quite unanimous and points to substantial gains brought by the adoption of collection scoring and segmentation techniques, with at least double digit improvements in collection returns (Cleaver, 2002). First, we present a list of specific case studies of technological adoption in chronological order, and then we discuss efficiency increases in the debt collection industry. We finish the section by mentioning studies assessing the ability of credit bureau collection scores to segment portfolios of delinquent accounts.

1. *Credit card companies:*
   (a) After introducing behavior scoring in the late 60s, Montgomery Ward increased the ratio of average good to bad credit card balances from 1/3 to 1 (Blake, 1981).
   (b) Using a randomized control experiment, Makuch et al. (1992) estimate that GE Capital's PAYMENT system increased both the yield per delinquent account by about 9%. Overall, it led to an estimated $37 million annual drop in default losses (equivalent to 10% of write-offs in 1990), while reducing collection expenditures by targeting a smaller fraction of accounts. The study randomly assigned a sample

of more than 100,000 delinquent credit cards to three different groups: 60% of the accounts to PAYMENT, 20% to the collection department as usual, and 20% to a live telephone call with a collection agent. PAYMENT segmented accounts intro different bins according to borrower and account characteristics and then used an algorithm to select the collection action that maximized expected net revenue, including the recommendation of taking no action. Average gross recoveries were about 7% higher for the PAYMENT group compared with the second and third groups. The authors emphasize that the economic gains were likely much higher given that the new system used significantly less collection resources because of the frequent recommendation of taking no action. They also report unspecified gains in customer goodwill because of a better selection of the appropriate action for each consumer. Independently, this study illustrates that collection is also quite costly: GE capital spent $150 million to collect about $400 million (as of 1990).

(c) Banerjee (2001) studies the introduction of segmentation and prioritization in a large bank in the eastern U.S. during 1998, with a particular emphasis in the selective use of costly arbitration or litigation. A sample of delinquent accounts was randomly assigned to two groups: the control group and the treatment group. Whereas all accounts in the control group were sent to litigation, the treatment accounts were subject to the new collection system. The new system used borrower and account information to segment the accounts in three bins, ranked by likelihood to respond to litigation letters. He reports a two-thirds increase in response to an arbitration dunning letter (from 24% to 40%) by focusing on the segment the model predicts to be more responsive. The bank, which held $30 billion in outstanding credit, estimated that the new system led to an average reduction in write-offs of $217 per account and to an overall saving of $40 million. Depending on whether we interpret

outstanding credit as reflecting credit card balances or total credit granted, such savings represent between 11% and 33% of total write-offs.

(d) Chin and Kotak (2006) report Capital One savings to be in the tens of millions of dollars per year from upgrading their debt collection system. The exact amount has not been carefully specified in this study nor explained how it was calculated.

(e) Trustmark National Bank ($8 billion in assets) reported a two-thirds increase in charge-off recoveries (from 37% in 1999 to 58% in 2004), thanks to the use of FICO's Recovery Management System using the same collection staff (FICO, 2006).[15]

2. *Debt collection agencies:* Regarding evidence of increased efficiency in the debt collection industry, PRA, the third largest agency, documents in its 2005 annual report to shareholders a 120% increase in cash collected per hour paid between 1998 and 2005 (from $60 to $133). PRA argues that its IT-driven approach—which utilizes two large scale proprietary statistical models—is responsible for their successful operations and growth.

3. *Credit bureaus:* We finish this overview by mentioning a couple of studies showing the effectiveness of off-the-shelf collection scoring provided by credit bureaus in categorizing delinquent accounts by the likelihood of repayment and expected recoveries. The first one refers to a bank case study in the second half of the 1990s that tested the ability of TransUnion collection scores to "rank order repayment on delinquent accounts" (Fishelson-Holstine, 1998). Of the 5,000 randomly selected accounts, a score could be assigned to 87% of them. Collection scores were successful in segmenting accounts by repayment amount six months later, despite balances being similar across the sample. In a similar fashion, a study by Experian (2004) reports a successful segmentation of charged off accounts using Experian RecoveryScore in terms of dollars recovered and probability of repayment six months after being charged-off. Specifically, it showed that the top 40% quantile of accounts (those with scores between 596 and 800) accounted for 70% of

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[15]These figures include overall recoveries, including credit cards, mortgages and other products.

dollars collected, despite only representing 45% of total charge-offs. It is important to note that these studies do not control for the possibility of self-cure. Nonetheless, they point to the usefulness of using collection scoring to optimize debt enforcement resources. Our credit bureau database includes historic Bankcard RecoveryScores from Experian. Since such collection scores directly speak to the presence of signals of solvency in the data, we show that they are indeed informative. Table 4 presents an estimated logit regression in which the dependent variable is the default status of delinquent borrowers two or four years later (after the score was reported) and the independent variable is Experian Bankcard RecoveryScore. Such 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: 1) all delinquent borrowers and 2) those having an inquiry to the credit bureau made by a collection department or a third-party collection agency.

Table 4: Recovery Scores and Propensity to Default (Logit Regressions)

	Default[a] (2 years) Coefficient[b] (std. error)	Default (4 years) Coefficient (std. error)
All delinquent		
RecoveryScore	-0.0039^*	-0.0036^*
	(0.0003)	(0.0003)
No. obs.	13,477	13,470
With a collection inquiry in 24 months		
RecoveryScore	-0.0036^*	-0.0039^*
	(0.0004)	(0.0004)
No. obs.	7,077	7,073

[a]Delinquent borrowers who 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.

4 Data sources and notes

In Section II (fact 1) of the paper, we use microlevel data purchased from Experian. The data set provides records of a panel of 250,000 individuals observed biannually, starting in July 2001 (earliest year available) and ending in July 2013. Half of the individuals were randomly selected in 2001, and half were randomly selected in July 2013. Such sampling criteria accounts for new entrants and attrition. We used the following definitions in our analysis:

1. *Major delinquency:* A credit account that is at least 90 days past due on payments, is at a collection department/agency, or has been charged off.

2. *Delinquent individual:* An individual who experienced a major delinquency on at least one credit card opened in the previous 24 months and is still delinquent in at least one credit card account.

3. *Persistent delinquency (a.k.a. informal bankruptcy):* An individual considered delinquent who has not filed for bankruptcy in the last 24 months and satisfies the following three criteria in the next 24/48 months: 1) does not file for bankruptcy, 2) the total number of credit accounts (not only credit cards) with a major delinquency that are fully paid does not increase, and 3) the total number of credit accounts with a major delinquency that are unpaid does not decrease. We use the latter two criteria to generate the data reported in the paper.

4. *Bankruptcy filing.* An individual considered delinquent who filed for bankruptcy in the past 24 months or does so in the next 24 (48) months.

5. *Legal collection.* A judgement, suit, or wage assignment filed against a delinquent borrower.

6. *Collection inquiry.* A collection department or agency made an inquiry to Experian's database to gather information about the delinquent individual in the past 24 months.

7. *Bankcard recovery score.* A score designed to assess the likelihood that a delinquent individual will pay back some of the owed credit card debt. It takes on values between 400 and 800.

5   Income process estimation

The income process $Y(z, t)$ during working age $t < 25$ is given by

$$Y(z, t) = A(t)Z(z).$$

The transition matrix for Markov process Z is

$$
P(z|z_{-1}) = \begin{bmatrix}
0.7413 & 0.2846 & 0.06563 & 0.0275 & 0.0045 & 0 \\
0.193878 & 0.38721 & 0.283247 & 0.1425 & 0.053592 & 0.004478 \\
0.053571 & 0.207309 & 0.327288 & 0.27 & 0.156214 & 0.038806 \\
0.009694 & 0.090654 & 0.184801 & 0.27125 & 0.196123 & 0.073134 \\
0.001531 & 0.02811 & 0.120035 & 0.225 & 0.387685 & 0.261194 \\
0 & 0.002108 & 0.018998 & 0.06375 & 0.201824 & 0.622388
\end{bmatrix}, \tag{1}
$$

The $Z(z)$ vector is

$$
Z = \begin{bmatrix} 0.573 & 0.870 & 1.114 & 1.361 & 1.688 & 2.420 \end{bmatrix}, \tag{2}
$$

and the deterministic trend $A(t)$ is $A(1) = 0.76442263$, $A(2) = 0.787326429$, $A(3) = 0.812138$, $A(4) = 0.838816358$, $A(5) = 0.867172078$, $A(6) = 0.89688793$, $A(7) = 0.92753868$, $A(8) = 0.958611851$, $A(9) = 0.989527476$, $A(10) = 1.019658861$, $A(11) = 1.048352332$, $A(12) = 1.074947902$, $A(13) = 1.09879923$, $A(14) = 1.119294098$, $A(15) = 1.135874538$, $A(16) =$

1.14805713, $A(17) = 1.155453$, $A(18) = 1.157789189$, $A(19) = 1.15492678$, $A(20) = 1.146883236$, $A(21) = 1.133851666$, $A(22) = 1.116221194$, $A(23) = 1.094597166$, $A(24) = 1.069821811$, and $A(25) = 1.042993767$. We obtained the age profile of income by fitting a polynomial to the values reported by Livshits, MacGee and Tertilt (2010). The ergodic distribution is

$$P(z_0) = (0.2845, 0.2066, 0.1681, 0.1161, 0.1273, 0.097).$$

During retirement periods there is no income uncertainty and

$$Y(z, t) = 0.7(0.92 + A(25)Z(25))/2.$$

The last term corresponds to the average of the median income in the economy and the agent's realized income in the period preceding her retirement. We multiply this number by 0.7 to obtain a median replacement rate of 0.7 (Munnell and Soto, 2005).

6 Identification of π and λ in the benchmark model

To get a better sense of how the calibration of the benchmark model works, consider the plot in Figure 5. The parameter λ is on the horizontal axis and the costs of collections normalized by the volume of discharged debt is on the vertical axis, while β, θ are set to match the first two moment conditions listed above. The three lines pertain to three different levels of signal precision chosen here for illustrative purposes. As is clear from the figure, it is possible that our moment conditions give rise to two sets of parameters for the intermediate value of π, as claimed in the paper. However, only one of these parameterizations is consistent with our fourth condition (90% percent adoption rate). In addition, note that it is not possible to satisfy all the targets when the signal precision is low. This implies that signal precision must

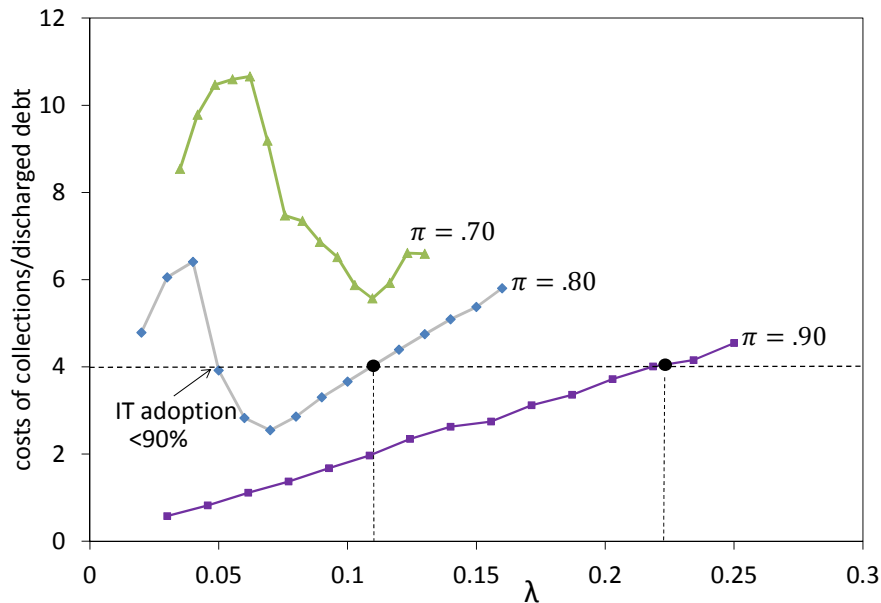be sufficiently high to match the targets, with the threshold being equal to about 0.76.

Figure 5: Joint Calibration of β, θ, and λ

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