Online Appendix

Modeling the Revolving Revolution: The Role of IT Reconsidered

[not intended for publication]

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This Appendix contains an overview of debt collection technologies in the U.S. and its recent evolution. In the first section we summarize how debt is collected in the U.S. Section 2 focuses on collection technology and its recent evolution. The last section describes the data sources used in the analysis.

1 Overview of the Debt Collection Process in the US

We briefly describe the debt collection process in the US. We focus on credit card debt, but similar methods are generally used in the case of other forms of unsecured credit.
Life-cycle of delinquent debt. Delinquent debt is first handled by the original creditors. As far as credit card debt is concerned, the first contact with the borrower is made right 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 original creditor (in case of credit card), meaning that the account 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.\(^1\)

After discharge, unless the consumer has filed for bankruptcy, debt is sent to collection, typically first in-house, and then it is likely to be sold to a third-party debt buyer. Recent evidence on the widespread popularity of ‘informal bankruptcy’ suggests that most delinquent credit card debt is subjected to such treatment (see Dawsey and Ausubel (2004)). The collection effort extends 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 GAO (2009) report to Congress for an overview of the life-cycle of delinquent debt).

In-house collections. In the case of in-house collections, the process is handled either by an in-house collection department or more typically by a third-party credit collection agency that works with the original creditor on a contractual basis. From 1996 onward, in-house collection is \textit{practically} limited to 36 months due to tax regulations.\(^2\) Generally, in-house collection uses

\(^{1}\)See Federal Trade Commission, “Collecting Consumer Debts: The Challenges of Change”, A Workshop Report 2009, FTC, and references therein. Herkenhoff (2012) reports cure rates of delinquent debt. The data pertain to the time period after the 2005 bankruptcy reform. According to this evidence, about 45\% of accounts that are 30 days delinquent become current next quarter. The recovery rate falls by slightly less than half for every 30 days up to 120+ days.

\(^{2}\)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), 1.605P-22). Interestingly, third-party debt collection agencies were excluded from this regulation until about 2003. In 2004-2006, IRS filed a lawsuit to enforce the rule. While the court sided with the IRS, due to the inability of the credit collection industry to
the same technology as third-party collection, although methods may differ because collection takes place earlier.

**Third-party collections.** Uncollected debt by the original creditor, especially after 1996 (see footnote 2), is typically sold to third-party debt buyers.\(^3\) As already mentioned, 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. In fact, tax treatment of uncollected debt might have been a decisive factor in driving the explosive growth of the third-party collection industry in the mid to late 90s.\(^4\)

**Price of discharged debt.** The price of discharged debt crucially depends on the number of previous collection attempts and on the age of bad debt. Average prices of debt portfolios seem to hover around few cents on a dollar, while pre-charge-off debt can be priced around 20 cents on a dollar.\(^5\)

**Collection methods.** To collect debt, credit collection agencies rely on sophisticated statistical models that are based on databases of past collections, the credit history of borrowers, and other supplementary sources. There has been a major improvement in collection methods due to better data and economies of scale employed by the collection agencies. As we detail in the next section, the IT progress within the debt collection industry very much mirrored the

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\(^3\)For example, in Figure 4, Hunt (2007) compares the volume of credit card debt charged-off to the volume of debt sold to third-party debt buyers. The data comes from Nielsen report. Back of the envelope calculations suggest that, in the more recent period, most debt is eventually sold.

\(^4\)See Hunt (2007) and GAO (2009) report to Congress for more information about this industry.

\(^5\)Our estimates are based on the data reported in 10-K forms by one of the major credit card debt collection agency: Portfolio Recovery Associates, Inc. The numbers are consistent with those reported by another large agency, Encore Capital Group, Inc.
IT progress in the lending industry.

In a fraction of cases, collection may involve 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 a lien on debtor’s property. 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 through a formal filing for bankruptcy, they generally do not diminish the attractiveness of the informal default option relative to a formal bankruptcy filing.\(^6\)

According to a study of 1999 credit records by Avery, Calem and Canner (2003) about a third of consumers had one judgment on their record in 1999, and another third had two (judgments stay on record for 7 years). However, very few (15.8\%) of these judgments have been paid, and yet there is no bankruptcy filing that follows thereafter.

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 thereafter. Not surprisingly, cash collected through litigation accounts for only a quarter of the cash collected by major debt buyers, such as Portfolio Recovery Associates, Inc. and Encore Capital Group, Inc. Debt collection agencies explicitly report that they employ information technology extensively to economize on these costs. In addition, about 50\% of such recoveries appear to be absorbed by the legal costs and fees associated with litigation.\(^7\) This aspect of the data underscores the asymmetry of information associated with debt collection and the importance of information technology to properly identify ‘solvent’ debtors prior to litigation.

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\(^6\)According to Hynes (2006), judgments are rather difficult to enforce. See details in the paper.

\(^7\)2006 income statements of Encore Capital Group, Inc.
2 Information Technology and Debt Collection

In this section we provide an overview of the collection technology and its evolution during the last three decades. We first describe the widespread use of information technology in the credit and collection industries’ debt enforcement mechanisms currently in place. We focus on how IT makes possible to sort or, in industry lingo, segment accounts in collection so as to prioritize collection resources. In particular, we argue that, through the use of scoring techniques, that is, the use of signals to inform collection strategies, existing collection technologies are qualitatively captured by our model’s notion of selective monitoring. We then give a detailed account of the evolution of this technology, from its inception in the 70s to its widespread adoption during the 90s and 00s. Our quantitative exercise is meant to resemble such evolution through a switch from indiscriminate to selective monitoring. Finally, we take a look at the existing evidence on the effect of technological improvements on the effectiveness of debt collection.

2.1 An Overview of Modern Collection Methods

There are two main ways in which information technology has transformed the US credit card market during the last three decades: the automation of acquisition and management of credit accounts; and the intensive use of consumer data and statistical models. The former allows lenders, among other things, to engage in mass marketing and approval of new credit card accounts, automated transaction authorizations, and fraud detection. It also allows collection departments within banks to quickly flag late payment and delinquent accounts, as well as limit overdrafts, and also to automate phone calls, letter dunning to delinquent customers and assigning accounts to litigation. Access to consumer and credit bureau databases helps collection departments to quickly locate delinquent borrowers through techniques such as skip tracing. Most importantly, statistical models based on consumer data inform these processes
by providing lenders and collectors with a risk assessment of both credit applicants and existing borrowers. Such assessments are known, respectively, as credit scores (new credit applications) and behavior or performance scores (existing accounts)—see Makuch (2001) and the FED report to congress on credit scoring (2007) for an overview.

Focusing on the enforcement of credit card contracts, behavior scoring is applied to determine the default risk of each delinquent account based on borrower characteristics and their credit and payment history. By doing so, collectors can estimate expected recoveries from potential collection attempts, and engage in what is known in the industry as segmentation of accounts and prioritization of collection resources. That is, collection effort is targeted selectively to the accounts with the highest expected recovery yield and adaptive control systems are used to identify the most successful collection strategies for each account segment (see Hopper and Lewis (1992) for a description of the approach and Rosenberg and Gleit (1994) for a survey of the different methodological approaches, such as decision trees, neural networks and Markov chains). For instance, the system developed by GE Capital to manage the collection of credit card debt, called PAYMENT, was based on modeling their portfolio of delinquent accounts as a Markov matrix that summarizes the transition probability from $X$ to $X + y$ days of delinquency. Such probability was a function of both borrower and account characteristics and the collection action undertaken (Makuch et al., 1992). A computer algorithm then used this matrix to perform cost-benefit analysis and choose the best action for each delinquent account.

Segmentation of accounts typically consists on the application of behavior scoring models to derive a collection score for each delinquent account, e.g. between 400 and 800, with a higher score predicting a higher probability of debt repayment. Such scoring models can be proprietary to the institution or supplied by credit bureaus (Makuch, 2001). Nowadays, the three major credit bureaus in the US provide a variety of collection scoring solutions specifi-
cally targeted to different stages of delinquency: early detection scores predict the likelihood that a current account will become delinquent in the near future; risk scores estimate the probability that a delinquent account will be charged-off, recovery scores rank charged-off accounts according to the probability that collection attempts will yield any recoveries; and, finally, legal collection scores focus on accounts at very late stages of collection (litigation).\textsuperscript{8}

Collection scores provided by credit bureaus are currently computed by combining different sources of information: payment and account histories, credit bureau data, employer-provided information and consumer data.\textsuperscript{9}

In addition, many companies, including the leading ERP solution providers, such as Oracle and SAP, and firms specialized in collection software, offer both off-the-shelf and customized collection management tools that include segmentation and prioritization.\textsuperscript{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.\textsuperscript{11}

On the technology demand side, the three major debt collection agencies, representing 19% of the industry’s market share, use collection scoring,\textsuperscript{12} so as to determine which accounts


\textsuperscript{9}For instance, Experian offers Debt-to-income Insight and Income Insight solutions to assess the debt burden and income level of delinquent borrowers (http://www.experian.com/business-services/collection-of-debt.html), while Equifax Decision 360 includes employer-provided data and other sources to better segment delinquent borrowers by capacity and propensity to pay (http://www.equifax.com/collections/en_us).


\textsuperscript{11}http://www.collectone.com/debt_collection_software.

\textsuperscript{12}According to IBISWorld (2013b), the top three major collection agencies are NCO Group (9.1% market share), Encore Capital Group (4.9%) and Portfolio Recovery Associates (4.7%). For evidence on the use of collection scoring see, for instance, NCO’s overview of their proprietary scoring model (http://www.ncogroup.com/Turnkey/Analytics/Analytics_Scoring.html); Encore Capital’s description of their scientific approach
to pursue and optimize collection resources. Such optimization typically involves pursuing only the segments of accounts most likely to pay.\textsuperscript{13} It is important to emphasize that the credit card receivables market is the largest sector for the debt collection industry, representing approximately a third of its $13-billion expected revenue in 2013 (IBISWorld, 2013\textsuperscript{b}). Similarly, all the major credit card users employ segmentation and prioritization in collection (Cleaver, 2002). Specific examples include Capital One (Chin and Kotak, 2006), City Bank (Fair Isaac Corporation, 2013), GE Capital (Makuch et al., 1992) and Wells Fargo.\textsuperscript{14}

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 revenue for 2013 (IBISWorld, 2013\textsuperscript{a}), 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.

\subsection*{2.2 Recent Evolution of Collection Technologies}

In this section we overview the operations research and industry literature on the development of collection scoring technologies and their application by the US credit card industry. The picture that emerges from this literature is one from mostly conceptual and theoretical advances...

\textsuperscript{13} For example, Encore Capital, in its Annual Report (10-K filed with SEC) 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 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 analysts 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.”

\textsuperscript{14} See FICO’s history at http://www.fico.com/en/about-us/history/.
during the 70s and 80s with scant industry applications, to one of development of the technology and gradual implementation in the 90s, followed by widespread adoption during the late 90s and over the 00s, with further technological improvements fueled by IT advances and a greater availability of consumer data.

Throughout the 1970s, while there was progressive experimentation and adoption of credit scoring for new credit applications, the first theoretical collection models based on statistical segmentation of accounts appeared (Liebman, 1972), as well as the first applications of behavior scoring and adaptive control for optimizing credit card collections, developed by FICO: Montgomery Ward in the late 60s (Lewis, 1992) and Wells Fargo in the mid 70s.\footnote{See FICO’s history at http://www.fico.com/en/about-us/history/ .}

The 1980s witnessed the spread of credit scoring, as well as an increase automation of credit card account management, although the use of segmentation and prioritization in collections was still rare and the technology quite underdeveloped (Rosenberg and Gleit, 1994).\footnote{They mention in their survey paper 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 some collection scoring models were developed (e.g., Chandler and Coffman, 1983) and the idea appeared in industry magazines (Coffman and Darsie, 1986), its implementation remained very limited.

The development of modern collection technologies based on the intensive use of IT and its progressive adoption by the credit card and collection industries started in the early 90s. In 1990, GE Capital, at the time the largest provider of “private label” consumer credit in the US, underwriting cards such as Macy’s and Apple’s and with $12 billion in consumer credit outstanding, implemented its landmark PAYMENT system for credit card collections (Makuch et al., 1992). PAYMENT managed over 50 million accounts. Its core philosophy was to segment portfolios of delinquent accounts and use adaptive control techniques to pick the best strategy for each portfolio so as to maximize “the net delinquent dollar amount collected

16 They mention in their survey paper 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.”
subject to collection resource constraints.” In line with our quantitative exercise of switching to selective monitoring, the introduction of PAYMENT led to a much greater use of ‘no-action’ in collections. While such system was developed in-house, some companies such as FICO provided adaptive control systems to credit card processors such as First Data Resources and TSYS. In this context, Panczyk (1999) describes technological advances during the 90s made by software suppliers developing and installing artificial intelligence (AI) systems for collection management. For instance, in 1990 the software company Quandrax introduced *Intelec* and reported over a hundred installed systems by the late 90s that help prioritize collections, including some agencies part of NCO Group, the leading debt collection agency in the US. Importantly, in the mid 90s credit bureaus started offering collection scores to financial institutions and collection agencies: Experian introduced RecoveryScore for charged-off accounts in 1995 (personal communication), while TransUnion have been offering collection scores since at least 1996 (Pincetich and Rubadue, 1997). On the research front, the development of new models of behavior scoring and collection management was very active during the 90s (Till and Hand, 2003).

By the early 2000s most credit card issuers were turning to segmentation and prioritization through the use of behavior data and other borrower characteristics. For instance, (Cleaver, 2002) reports that many issuers are “baking off from a shotgun approach to collection calls and are focusing resources on accounts with the highest projected returns,” and also quotes US Bankcorp 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

18 Other companies mentioned in Panczyk (1999) include Neuristics and Trajecta. Neuristics’ introduced *Collections Triage* software in the first quarter of 1999, which was designed to segment delinquent accounts in three categories: those which will be charged-off, regardless of collection effort (*straight rollers*); those who will get back into good standing by themselves (*self-cures*); and those which 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).
collection scoring, the focus since the early 00s has turned on making collection solutions more efficient by using better processing and additional data sources. That is, making segmentation, collection scores and predictive metrics in general more precise. As an example, Chin and Kotak (2006) describe the overhaul of Capital One’s collection management 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, as mentioned above, employer-provided and consumer data. Collection Scoring models have also benefited from advances in data mining techniques. See for instance the recent study by Ha and Krishnan (2012).

Before turning to the evidence on increased effectiveness of debt collection, it is worth mentioning that the described timeline on the adoption of selective monitoring is also suggestively validated by the recent evidence regarding the relative volume of default-related litigation (such as court filings to obtain a judgement allowing for wage garnishment). In this regard, Hynes (2006) documents court data on wage garnishments (data for the state of Virginia, but partially validated nationally). He finds that, while the number of personal bankruptcy filings were rapidly growing over the 90s, the growth of garnishment orders was negative (see Figure 1). We find that this downward trend continued over the 2000s: the rate of litigation against delinquent borrowers fell by 16% between 1999 and 2007 (see Figure 4 in the main document).

2.3 Changes in the Effectiveness of Debt Collection

The exiting evidence on efficiency gains at the collection stage mostly comes from case studies and industry reports. The message emanating from this literature is quite unanimous in pointing to the substantial gains brought by the adoption of collection scoring and segmentation techniques, with typical improvements in collection returns of 40% and higher (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.

**Credit Card Companies**

- After introducing behavior scoring in the late 60s, Montgomery Ward reduced the ratio of average good to bad credit card balances from 1/3 to 1 (Blake, 1981).
- Using a randomized control experiment, Makuch et al. (1992) estimate that GE Capital’s PAYMENT system increased both the yield per delinquent account by 7-9% and also reduced the costs by allocating resources strategically. 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 over 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 life 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 option of 'no-action.' Average gross recoveries were about 7% higher for the PAYMENT group compared to the second group and third groups. The authors emphasize that the economic gains were likely much higher given that the new system used significantly less collection resources due to the frequent use of 'no-action.' They also report unspecified gains in customer goodwill due to a better selection of the appropriate action for each consumer. Independently, this study also illustrates that collection is quite costly: GE capital spent $150 million to collect about $400 million (as of 1990).

- Banerjee (2001) studies the introduction of segmentation and prioritization in a large bank in eastern US during 1998, with a particular emphasis in the selective use of costly arbitration/litigation. A sample of delinquent accounts was randomly assigned to two groups: the control group and the treatment group. All accounts in the control group were sent to litigation, whereas 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 arbitration letter dunning (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.

- 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.

- Trustmark National Bank ($8 billion in assets) also 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
Debt Collection Agencies. Regarding evidence of increased efficiency in the debt collection industry, Portfolio Recovery Associates, the third largest agency, documents in its 2005 Annual Report a 120% increase in cash collected per hour paid between 1998 and 2005 (from $60 to $133). They argue that their IT-driven approach – which utilizes two large scale proprietary statistical models – is the main culprit of their successful operations and growth.

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 90s 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 dollars collected, despite only representing 45% of total charge-offs. Although these studies do not control for the possibility of self-cure, they nonetheless point to the usefulness of using collection scoring to optimize debt enforcement resources.

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19 This figures include overall recoveries, including credit cards, mortgages and other products.
3 Data Sources and Notes

1. Data used to estimate delinquency, informal default and bankruptcy filing rates is from Experian’s credit bureau records of a panel of 250,000 individuals. The panel includes observations every two years of each individual, starting in July 2001, the earliest data available, and ending in July 2013. Half of the individuals were randomly selected in 2001 and half were randomly selected in July 2013 and tracked back. Such sampling criterion was used to account for new entrants in Experian’s database and also for attrition due to death. The definitions of the variables used in the analysis are:

(a) 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.

(b) Delinquent: an individual who experienced a major delinquency on a credit card opened in the previous 24 months and was still (major) delinquent in at least one credit card account.

(c) Informal Default: the criterion we use flags as a defaulter an individual considered delinquent who has not filed for bankruptcy in the last 2 years and satisfies the following two conditions in the next 2/4 years: he does not file for bankruptcy; and the total number of credit accounts (not only credit cards) with a major delinquency that are fully paid does not increase.

(d) Formal default: an individual considered delinquent who filed for bankruptcy in the last 24 months or does so in the next 24/48 months.

(e) Collection Inquiry: a collection department or agency made an inquiry to Experian database to gather information about a delinquent individual in the last 24 months.

(f) Bankcard RecoveryScore: 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.
2. Data for net credit card charge-offs, revolving consumer credit (here referred to as credit
card debt), and interest rate on revolving consumer credit are taken from the Federal
Reserve Board Statistical Releases, G.19, historical data.

3. Median household income is taken from the US Census Bureau.

4. Credit card interest rate data on accounts assessing interest are available only from
1994 (Federal Reserve Board, G.19). Previous discontinued series reported interest rates
based on a survey of credit card products, not actual rates. As an input to our regression,
we used data from 1994 and subtracted the cost of funds measured by 5-ytm Treasury
yields, and estimated the trend. The reported value for 1990 is the value implied by the
regression.

5. Unsecured debt discharged to income per bankrupt is taken from Sullivan, Westbrook
and Warren (2001), who conducted an extensive survey of formal bankruptcy filers in
1981, 1991, and 1997 (see Table 4.2, 4.3). We are not aware of any corresponding data
reporting the average amount defaulted on informally, and we used this number as an
imperfect proxy. Given that we lack any other data, we have used these three values to
obtain a trend line and extrapolated the value for 2004 from this trend. While they are
only 3 observations here, the trend line fits perfectly.

6. Data on credit limits and utilization rates of revolvers are from the 1989 and 2004 Survey
of Consumer Finances (SFC). A revolver is a household with positive credit card balances
after subtracting their last payment.

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