Unsecured Credit Supply over the Credit Cycle: Evidence from Credit Card Mailings

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Using a unique dataset of credit card mailings, we show that during the recent credit boom, consumers with mediocre credit scores received more credit card solicitations than those with high credit scores. However, this relationship reversed after the nancial crisis. We also nd that consumers with a bankruptcy history, a conspicuous signal of higher default risk, were not excluded from the credit market, but received fewer and less-favorable o ers, especially as they approach being eligible for re- ling. These disparities deepened in the wake of the credit bust and widened further after the implementation of the CARD Act.

JEL Classi cations: D14, D82, G01, G21, K35
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1 Introduction

Household debt of every type expanded substantially during the credit boom of the 2000s. This growth was driven in large part by expanded access to risky borrowers, including those previously excluded from the market. The \subprime" expansion in secured credit markets, such as auto loans and home loans, has been well documented (Adams, Einav and Levin (2009), Mian and Su (2009), and Keys, Mukherjee, Seru and Vig (2010), respectively). However, largely due to data limitations, there has been little analysis of the growth of unsecured consumer credit, which was as dramatic as the increase in secured consumer debt. In particular, credit card debt outstanding doubled between 1997 and 2008, a period when median household income was stagnant.[1] Taking a longer perspective, the growth of credit card debt has been even more spectacular: While secured consumer debt grew ve-fold between 1980 and 2010, credit card debt grew seventeen-fold over this same period. Furthermore, much of the growth in credit card debt was along the extensive margin, as the share of households with a credit card account more than doubled over this period.[2]

The expansion of credit card debt is striking because unsecured creditors have the greatest exposure to borrowers' credit risk, as unsecured claims are generally wiped out in the event of consumer bankruptcy. Further, such bankruptcy risk has heightened substantially over the past three decades | personal bankruptcy lings increased vefold, from fewer than 300,000 lings in 1980 to over 1.5 million lings in 2010.[3] Recent research suggests that improvements in information technology and nancial engineering have made it possible for lenders to target speci c consumer groups, to narrowly tailor credit o ers, and, in particular, to price-discriminate against default risk (Livshits, MacGee and Tertilt, 2007*b*; White, 2007; Dick and Lehnert, 2010). However, there is little empirical evidence on how the supply of unsecured consumer credit is related to default risk, especially among high-risk consumers.

[1] Source: Federal Reserve: http://www.federalreserve.gov/releases/g19/Current/.

[2] In contrast, the homeownership rate increased less than one percentage point (64.4% to 65.1%) over the same 30 year span. See Federal Reserve Board (2006) and Bricker, Kennickell, Moore and Sabelhaus (2012).

[3] Source: The Administrative O ce of the U.S. Courts. Personal bankruptcy lings peaked at roughly 2 million in 2005, the year of the most recent bankruptcy law reform.

In this paper, we attempt to fill this void by providing direct micro-level evidence on the supply of unsecured consumer credit over the boom and bust of the credit cycle. In particular, we focus on the dynamics of credit supply to individuals who previously filed for personal bankruptcy | a group of consumers exhibiting some of the clearest and most conspicuous default risk. Using a unique proprietary survey data set of credit card mail offers that is administratively linked to survey participants' credit records, we study how the likelihood of receiving a credit card offer varies with their credit scores and contrast this relationship estimated during the credit boom with the one estimated during the bust. Furthermore, we examine how likely consumers with a bankruptcy history are to receive such offers and characterize the terms therein, controlling for survey participants' credit scores as well as demographic and balance sheet characteristics. Throughout the paper, we refer to a consumer whose credit record has a bankruptcy flag as a "filer" and a consumer whose credit record does not have a bankruptcy flag as a "nonfiler." We analyze both the general terms of the offered credit card contracts, such as credit limits and regular interest rates, as well as often-neglected elements | terms that are referred to as "hidden" costs in the literature | such as fees and charges that are only disclosed in the fine print.

The central innovation of this paper is that we are able to observe directly a proxy for the supply of unsecured credit | credit card mail offers.[4] This unique opportunity allows us to identify supply responses over the credit cycle without relying on variation in equilibrium quantities and prices to infer changes in supply and demand separately.[5] In this regard, recent studies have examined post-bankruptcy use of credit using households surveys (Han and Li, 2011) or credit bureau data (Musto, 2004; Cohen-Cole, Duygan-Bump and Montoriol-Garriga, 2009). However, they have done so by examining the amount of debt borrowed (equilibrium quantity) and the interest rates at which loans were taken (equilibrium price). Consequently, these studies have not identified how credit supply *per se* is associated with

[4] We provide a detailed discussion of the accuracy of using mail offers as a measure of credit supply later in the paper.

[5] Gross and Souleles (2002*a*) analyze a panel of individual credit card accounts and are thus able to infer the intensive (but not extensive) margin of credit supply.

an impaired credit history and heightened credit risk.

In addition, studying credit supply to consumers with a personal bankruptcy history sheds essential light on consumers' bankruptcy decisions. In theory, the welfare of a rational debtor depends critically on his post-bankruptcy access to credit markets, a prospect which the debtor should take into account when deciding whether to file for personal bankruptcy. Conceivably, a bankruptcy record that permanently traps filers in financial autarky would inflict much greater economic costs than if lenders are immediately forgiving or if filing is anonymous. A growing literature examines households' bankruptcy decisions.[6] However, to the best of our knowledge, little has been done to empirically characterize the supply of unsecured credit to bankruptcy filers. Moreover, our analysis complements a rapidly growing literature that uses dynamic equilibrium models to study unsecured credit markets, particularly by providing a set of statistics against which these models should be calibrated and stylized facts that should be matched (see, for example, Li and Sarte (2006), Chatterjee, Corbae, Nakajima and Rios-Rull (2007), and Livshits, MacGee and Tertilt (2007*a*)).

Our data cover three distinct time periods of the latest credit cycle: First, the boom period of 2007, when lenders mailed roughly 600 million credit card offers per month; second, the bust of 2009-2010, prior to the implementation of the Credit Card Accountability, Responsibility, and Disclosure Act of 2009 (henceforth the CARD Act), when aggregate offers plummeted to a low of 100 million offers per month; and third, the recovery of 2010-2011, after the CARD Act was in effect, when aggregate credit supply began to rebound. The solid line in Figure 1 shows the time-series of total credit card offers in the U.S. from 2001 through 2011.[7] As of late 2011, lenders were mailing over 300 million offers per month, a substantial recovery but at levels considerably below that of the 2007 peak. Exploring credit card offers and terms over these distinct periods provides some of the first detailed evidence of fundamental changes in credit supply over the credit cycle and the effects of the CARD

[6] See, e.g., Fay, Hurst and White (2002), Gross and Souleles (2002o cc356(of(2007)-278(p)-471(Hus88s s88s s88t43c)27(

Act on the supply of unsecured consumer credit.

Our main results from this analysis are summarized as follows: First, during the credit boom, consumers with mediocre credit scores were *more* likely to receive an o er than super-prime consumers. The composition of credit supply has shifted dramatically in the wake of the bust, with the most creditworthy consumers now much more likely to receive an o er. In addition, we present suggestive evidence that the subsequent implementation of the CARD Act has further limited the supply of unsecured credit to riskier households.

Second, consumers are not excluded outright from the unsecured credit market after ling for bankruptcy, even in the aftermath of the most severe nancial crisis in recent history. On average, nearly 40 percent of consumers with a history of personal bankruptcy receive at least one credit card o er in a given month. Indeed, we nd both anecdotal and statistical evidence that o ers to consumers with a bankruptcy history are not the result of a non-discriminatory \blanket campaign." Rather, some lenders design their o ers speci cally to such consumers. The likelihood of a ler receiving an o er is only moderately lower than a non ler with comparable observable characteristics, including credit scores. Further, those who led fewer than two years earlier are about as likely to receive an o er as comparable non lers. By contrast, those who led for bankruptcy more than ve years earlier receive signi cantly fewer o ers, suggesting that lenders are wary of re- ling risk and accordingly extend less credit to such lers.

Third, we nd that, despite relatively small di erences in the probability of receiving a credit card o er, o ers to lers are more restrictive, more expensive, and provide fewer take-up incentives than o ers to their non ler counterparts. Furthermore, lers bene t far less from improving their credit scores than non lers. For instance, while the o ered credit limit triples for non lers who improve their credit scores from the lowest quartile to the maximum of the lers' score range, lers' credit limits do not improve whatsoever over the same range of credit scores. This pattern further supports the hypothesis that lenders narrowly tailor

For example, the header of one mail o er from a top credit card lender states *You deserve some credit for getting through bankruptcy."*

o ers to subgroups of consumers.

Fourth, we present (to the best of our knowledge) the rst set of evidence on potential \shrouding" in credit card o ers. In particular, we examine the e ect of bankruptcy status on a set of contract terms that often appear only in the ne print, such as fees related to less frequently used transactions (for example, transactions involving foreign exchange). We nd that credit card o ers received by lers tend to contain higher \hidden" costs than o ers to comparable non lers. These results are consistent with the predictions of Gabaix and Laibson (2006), in that even in a fairly competitive market, lenders may choose to shroud terms in credit o ers to consumers who may be either myopic or imperfectly informed (see, for example, Angeletos, Laibson, Repetto, Tobacman and Weinberg (2001) and Agarwal, Driscoll, Gabaix and Laibson (2011)).

Finally, exploring the geographic heterogeneity of unsecured credit supply, we nd that consumers are more likely to receive credit card o ers in areas with stronger local macroeconomic indicators. In particular, consumers in states with greater house price appreciation, who likely received increased access to secured credit in the form of home equity loans during the boom, were also more likely to receive credit card o ers. Thus, our analysis suggests that the leverage cycle was geographically correlated across secured and unsecured credit markets. Disproportionate house price appreciation in subprime areas, as documented in Mian and Su (2011), thus can help to explain why subprime consumers received more unsecured o ers than any other population during the boom period.

The rest of the paper is organized as follows. Section 2 reviews the relevant legal and theoretical background; Section 3 describes the data and provides an overview of the changes of unsecured credit supply over the recent credit cycle; Sections 4 and 5 present descriptive statistics and regression results, respectively, contrasting the likelihood of receiving an o er and credit card contract terms by bankruptcy ling status and how these di erences evolved over the credit cycle; and Section 6 concludes.

2 Legal Background and Conceptual Framework

2.1 Legal Background

One of the most important features of bankruptcy law is the provision of debt discharge. A debtor can file under Chapter 7 of the U.S. bankruptcy code to obtain a discharge of unsecured debts.[9] Alternatively, the debtor can file under Chapter 13 of the code, whereby he or she obtains a debt discharge after paying off a portion of the debt through a three-to-five-year debt repayment plan.

The bankruptcy code also affects the post-bankruptcy supply of credit through its restriction on repeated discharges. Since the Bankruptcy Abuse Prevention and Consumer Protection Act became effective in 2005, the law now prohibits a debtor from obtaining another bankruptcy discharge (Chapter 7) until eight years after a previous debt discharge.[10] The implications of such refiling restrictions on credit supply are discussed in detail later in the paper.

In addition, credit supply to bankruptcy filers is affected by the Fair Credit Reporting Act (FCRA). The FCRA regulates how a bankruptcy filing is reported by the credit bureaus. In particular, the FCRA permits a bankruptcy record to stay on credit reports furnished by the credit bureaus for up to 10 years after the date of relief or the date of adjudication (FCRA 605 (a)(1)). In addition, all other nonbankruptcy defaults can stay on a credit report for up to seven years (FCRA 605 (a)(5)). Because we use credit bureau data to identify filers, we can only identify those consumers who filed fewer than ten years earlier. Likewise, if credit bureau data are lenders' only source for bankruptcy information, then lenders cannot distinguish the consumers who filed more than ten years before from those who never filed for bankruptcy. Indeed, Musto (2004) finds that filers' credit scores increase appreciably after their bankruptcy flags are removed, inducing greater access to and subsequent use of

[9] Some debts, such as student loans and unpaid tax liabilities, are deemed not dischargeable. See, for example, Administrative Office of the United States Courts (2006).

[10] The restriction on repeated Chapter 7 filing was six years prior to the 2005 reform.

credit.

The CARD Act was enacted in May 2009 and took effect in February 2010. The legislation strengthens consumer protection for credit card contracts and imposes various new restrictions on credit card lending. For example, the CARD Act limits the fees that can be charged on some cards, most notably types of over-limit fees and "subprime" fees. In particular, the Act limits non-penalty fees to 25 percent of the total amount of the card's credit line. In addition, the law bans most rate increases on existing balances (such as in the event of a late payment) and requires introductory or promotional interest rates to last at least six months, thereby largely limiting lenders' ability to quickly re-price contracts based on risk. On balance, the CARD Act makes credit card lending to risky consumers more restrictive, which in turn may lead lenders to reduce the supply of unsecured credit to such consumers.

2.2 Conceptual Framework

The market for unsecured credit is a classic setting with information asymmetries. As Stiglitz and Weiss (1981) show, the contract terms posted by lenders will directly affect the riskiness of borrowers who take up loans, leading to a credit rationing (pooled) equilibrium. Even when provided with information about the income and credit histories of consumers, some lenders nonetheless have difficulty in identifying "bad" versus "good" borrowers *ex ante* (adverse selection). Further exemplifying the information asymmetry, borrowers who accept contracts with higher interest rates may subsequently undertake riskier financial behavior that heighten their *ex post* credit risk (moral hazard). In this environment, the bankruptcy filing contains a number of different and possibly competing signals about a consumer's credit risk. As a conceptual framework guiding our empirical analysis, we use a stylized setup introduced by Einav, Jenkins and Levin (2012) to illustrate how bankruptcy filing status may affect various aspects of lenders' credit card offering decisions.

2.2.1 Setup

Consider a two-period model. At $t = 0$, the borrower earns y_0 and, conditional on having received a credit card o er, decides whether or not to respond and apply for the card. For simplicity, assume that all applications responding to outstanding credit card o ers will be approved. The borrower then carries a debt of level L on the card to the next period. At $t = 1$, the borrower realizes his income y_1 and then, if he has a loan, he decides whether to pay it o or default. We assume that y_1 is su ciently larger than y_0 so that the borrower has no incentive to save in $t = 0$. The borrower is characterized by his previous bankruptcy ling status b | with $b = 1$ for lers and 0 otherwise | and a vector of other nancial and non nancial characteristics $[x; \ ]$, drawn from a joint distribution of $[B; X; Y_1; \ ]$. The lender observes b and x but not , though she knows the conditional distributions of and Y_1 given $X = x$ and $B = b$. Thus, the lender faces two underlying sources of default risk: income risk | the uncertain borrower income y_1, and information risk | the unobservable borrower type .

The x variables include credit score and other observable nancial information | such as household liabilities and delinquency status | that the lender may legally use in the underwriting process. Though correlated with x, the bankruptcy status indicator b may contain additional information beyond x because the joint distribution of $(Y_1; \ )$ conditional on x depends on b. To the extent that we control for consumers' credit scores and a rich set of liability variables, the e ects that we will identify in the empirical analysis are those of bankruptcy ling on credit supply above and beyond its direct impact on credit scores and other x variables.

One important characteristic of credit card contracts is that they are notoriously complex (Agarwal et al., 2011; Agarwal, Chomsisengphet, Liu and Souleles, 2006). O ers specify not only quantity and price, but also many other features, which a lender can tailor to in uence potential borrowers' take-up and credit usage decisions. We focus on the following most frequently used terms in typical o ers | $= [f; L^u; R; w]$, where f, L^u, R, and w denote

annual fees, credit limits, interest rate, and rate of rewards, respectively.[11] The borrower's take-up decision can be solved backward as follows. At $t = 1$, with the realization of y_1 and credit card debt L, the borrower decides to default if

$$u(y_1 \quad L(1 + R \quad w)) \quad v(y_1; b); \tag{1}$$

where $u(\ )$ is the borrower's utility function over disposable income net of loan repayment. The utility derived if choosing to default, v, depends on the borrower's bankruptcy status. As described earlier, the law prevents lers from repeatedly ling within a certain period. Therefore, while non lers (b=0) have the option of ling for bankruptcy should they choose to default, lers can only enter a scenario known as \informal bankruptcy" should they choose to default. In such a scenario, creditors can pursue repayment aggressively through various debt collection methods, such as wage garnishment (Ausubel and Dawsey, 2004). Thus, other factors held constant, lers have a lower v (or higher default penalty) than their non ler counterparts and, as a result, are less likely to default.

Given the above debt payment rule and the o er vector , a borrower with $(b; x;\ )$ chooses his optimal debt L^* according to:

$$W(L^*;\ ; b; x;\ ) = \max_{0<L\leq L^u}[u(y_0 + L \quad f) + \quad \mathsf{E}_{y_1} \max(u(y_1 \quad L(1 + R \quad w)); v(y_1; b))]; \tag{2}$$

where $W(\ )$ is the value function, and E_{y_1} denotes that the expectation is taken with respect to stochastic y_1. If a borrower decides not to respond to the credit card o er ($L^* = 0$), the value function of the nancial autarky state can be written as $\overline{W} = u(y_0) + \quad \mathsf{E}_{y_1} u(y_1)$.[12] A borrower applies for the card if $W(L^*;\ ; b; x;\ ) \quad \overline{W}$.

Because the lender does not observe , a credit card o er depends on only $(b; x)$ and the distribution of conditional on observed bankruptcy status b. Given $(b; x)$, the set of

[11] For notational simplicity, we assume the fee, f, occurs only in $t = 0$.
[12] Recall that we assume y_1 is su ciently larger than y_0.

borrowers who take up the o er thus can be represented as :

$$\widehat{\ } = f \ : W(L^*; \ ; b; x; \ ) \quad \overline{W}g: \tag{3}$$

In this context, adverse selection occurs if changes in , such as an increase in interest rates, lead to the departure of less risky borrowers and thus a gradually riskier pool of applicants.

Following Einav et al. (2012), we assume that the lender acts monopolistically: given $(b; x)$, she chooses to maximize her expected pro ts, , by taking into account the e ect of on the applicant pool ^ and loan demand function L^*:

$$(b; x) = \max_{\phi} P(\ ; b; x) \ \ \mathsf{E}_{\theta}(\ (L^*; \ ; b; x; \ )jW(L^*; \ ; x; \ ) \quad \overline{W}) \quad C; \tag{4}$$

where $P(\ ; b; x)$ is the probability of borrowers with $(b; x)$ taking up the credit o er , C is the unit cost of producing and mailing the o ers, and $(L^*; \ ; b; x; \ )$ is the lender's realized pro t from the loan to a borrower with $(b; x; \ )$. Speci cally,

$$(L^*; \ ; b; x; \ ) = f + M L^*; \tag{5}$$

with M being the net rate of return on the loan excluding the fee revenue f. That is,

$$M = (1 \quad \mathbb{I}^D)(1 + R \quad w) + \mathbb{I}^D(1 \quad c) \quad (1 + r); \tag{6}$$

where $\mathbb{I}^D(L; R; w; v)$ is an indicator for whether or not the borrower defaults ($\mathbb{I}^D = 1$ if default occurs and 0 otherwise), c the charge-o rate on a defaulted account, and r the rate of funding costs. The lender mails an o er if $(b; x) \quad 0$.

The rst order condition (FOC) for the lender's pro t maximization problem, in compact

notation, is:

$$
\begin{aligned}
0 = \frac{@P(\ ;b;x)}{@} \ \ & \mathsf{E}_{[\ ,Y_1]|b,x}(\ (L^*;\ \ ;b;x;\ )jW(L^*;\ \ ;b;x;\ ) = \overline{W}) \\
& + P(\ ;b;x) \ \ \mathsf{E}_{[\ ,Y_1]|b,x}\left(\frac{@\ (L^*;\ \ ;b;x;\ )}{@}jW(L^*;\ \ ;b;x;\ ) \quad \overline{W}\right):
\end{aligned}
\tag{7}
$$

The FOC above has two key components that address the extensive and intensive pro t margins, respectively. The rst term of the FOC deals with the adverse selection issue by designing o ers to maintain an optimal extensive margin on the pool of borrowers who will take up the o er, $P(\ ;b;x)$. The classic result from Stiglitz and Weiss demonstrates that raising the interest rate may attract a pool of borrowers of even higher default probability.[13] Such a result also applies to other elements of , such as credit limits, rewards, and fees. Note that P is a function of bankruptcy ling status, b, and that the expectation is taken over the distribution of conditional on the observed b. A monopolistic lender will tailor di erent contracts catering to lers and non lers to optimize their participation, respectively.

The second term of the FOC speci es the optimal intensive margin on pro tability for a given set of consumers who take up the o ers. Speci cally, by the de nition of the pro t function, eq. (4), we have

$$
\frac{@\ (L^*;\ \ ;b;x;\ )}{@} = \frac{@f}{@} + M\frac{@L^*}{@} + \frac{@M}{@}L^*: \tag{8}
$$

In addition to the dollar-for-dollar term $\frac{\partial f}{\partial \phi}$, the contract terms o ered a ect pro tability through two channels, both of which vary with bankruptcy ling status, b. First, the optimal debt level L^* depends on , and, as discussed above, other factors (including) held constant, bankruptcy lers borrow less than non lers. Second, the net rate of return, M, depends on and its sensitivity is di erent between lers and non lers because they have di erent default probabilities and charge-o rates, c. Thus, the solution to the lender's optimization problem requires trading o the extensive adverse selection with the intensive per-contract

[13] For empirical evidence in the credit card market, see Agarwal, Chomsisengphet and Liu (2010).

pro tability.

2.2.2 Extensions and Implications

A bankruptcy history can a ect credit supply in a number of ways that are not modeled explicitly in the setup introduced earlier. For example, like other consumers, bankruptcy lers need credit for smoothing consumption and facilitating transactions. But, because essentially all of their existing lines of unsecured credit become void after bankruptcy, lers could have a more inelastic demand for credit.[14] Moreover, lers need to obtain and use fresh credit to rebuild their credit history, which is substantially damaged by their bankruptcy ling. Both considerations would make lers more willing to apply for a new credit card account, to which lenders may react by reducing the attractiveness of the o ers extended.[15]

In addition, the credit supply e ect of a bankruptcy history may also depend on the time elapsed since the last ling because more recent lers have to wait longer until the restriction on repeated ling expires. Thus, other factors held constant, more recent lers may pose a lower default risk and a potentially higher recovery rate, which may in turn attract more generous o ers from lenders.

To summarize, our stylized model illustrates that a bankruptcy history could a ect lenders' o ering decisions in two opposite directions. On the one hand, the distributions of y_1 and conditional on $b = 1$ imply greater credit risk than those conditional on $b = 0$, inducing lenders to extend less favorable o ers, if at all. Speci cally, we expect the o ers extended to lers to have lower credit limits and charge higher interest rates and annual fees. Moreover, such o ers are less likely to have take-up incentives such as promotional interest rates or rewards programs. On the other hand, restrictions on repeated ling make lers, and in particular recent lers, relatively \safer" risks from the lender's perspective. The net credit supply e ect of a bankruptcy history is ambiguous, and therefore an open empirical

[14] In certain scenarios, such as some Chapter 13 lings, consumers may retain their existing credit card accounts conditional on agreeing to repay all or some of the existing debt on these accounts.

[15] In the context of the model, these factors reduce lers' value function in autarky, $\overline{W}$.

question.

It is important to note that this study focuses on how credit supply varies with bankruptcy filing status and other borrower characteristics during various stages of the credit cycle. We are, however, agnostic about the determinants of the credit cycle itself, which may include changes in capital constraints, the strength of lenders' balance sheets, access to the securitization market, and changes in technology, regulation, or competition. In the context of our simple model above, we treat the cost of funds r as exogenous and assume that loanable funds are perfectly elastic (see also Stiglitz and Weiss (1981) for a similar consideration).

3 Data and Summary Statistics

3.1 Data Description

Our main data source is Mintel Comperemedia's (henceforth \Mintel") proprietary surveys on credit offers to U.S. consumers.[16] Each month, Mintel invites about 8,000 consumers to participate in the surveys by forwarding all incoming mail containing credit solicitations, such as offers of credit cards and home equity loans. Mintel requests that participating consumers forward solicitations sent to any members of the household and, in addition, that they complete an extensive demographic questionnaire.

The sample is stratified to represent the U.S. population in terms of household size and composition, age and education of the household head, geographic region, market size, and total household income. On average, about 3,000 consumers choose to participate in the survey each month. To keep the sample nationally representative, Mintel subsequently assigns a weight to each respondent to account for differential propensities of participation across demographic groups. After processing the forwarded mail offers, Mintel sends the database to TransUnion, one of the three major credit reporting agencies, where participating

[16] Mintel is a consumer and marketing research company headquartered in the U.K. The data we use are compiled by the company's American subsidiary, Comperemedia.

consumers' credit history information is merged in before the final data set is delivered to data subscribers.

Our focus in this paper is credit card offers, which represent the majority of all credit offers received by consumers.[17] Mintel records essentially all information on the forwarded mail offers, allowing us to study not only whether a consumer receives any credit card offers in a given month, but also the full set of terms of the contracts offered. For interest rates, we focus on the so-called "go-to" rate | the regular non-promotional interest rate for purchases.[18] For credit limits, the data reveal a recent change in industry practice. Historically, credit card offers have usually specified a *maximum* credit limit. However, since 2006, an increasing share of credit card offers have specified a *minimum* credit limit, and by early 2009, the vast majority of credit card offers only specified a minimum credit limit. Our analysis will thus focus on the minimum credit limit. Upon examining offers sent in 2007 that specified both the minimum and maximum credit limits, we find the two limits are strongly positively correlated.

In addition to interest rates and credit limits, the Mintel data contain information on whether the card charges an annual fee, whether the offer provides a promotional interest rate, and whether the offer includes enrollment in a reward program. Furthermore, the dataset includes other contract terms that are usually disclosed in the fine print. This additional information helps us better characterize subprime credit offers along a broader set of contract attributes.

3.2 Mail Offers as a Proxy for Credit Supply

To be clear, credit card offers are not equivalent to credit supply in various aspects. Lenders have the option of not approving an application responding to an outstanding offer, even

[17] Credit cards are by far the credit product that relies most heavily on direct mailing. Mortgage and credit card balance transfers are the second and the third most common types of solicitation, respectively.

[18] Mintel also records other interest rates specified in the offers such as the interest rates on balance transfers and cash advances. Broadly speaking, these offered interest rates exhibit similar contrasts between filers and non filers and dynamics over the credit cycle. For more on interest rate pricing, see Ausubel (1991), Stango (2000), and Knittel and Stango (2003).

if these are so-called \pre-approved" o ers. Even for an approved o er, the credit limit ultimately extended is not necessarily identical to the amount speci ed in the o er. In addition, discussions with various major credit card lenders suggest that the volume of mail o ers is frequently a ected by lenders' marketing budget limitations, which may not always re ect changes in willingness-to-lend. That said, instead of merely serving as an advertisement or a marketing tool, we argue that data from credit card mail o ers contain valuable information that speak to credit supply for the following reasons.

First, because sending an o er is costly for lenders, lenders will not send out o ers if they do not have a legitimate intention to approve a large share of all responding applications. Second, selecting o er recipients typically involves a complicated, multi-stage screening process that is similar to the underwriting process. Third, we nd that, despite the low response rate, total credit card mail volume is highly correlated with the aggregate number of credit card accounts opened (estimated using data from the Equifax consumer credit panel). As shown in Figure 1, the two time series track each other very closely over the last ten years with a correlation coe cient of 0.9, suggesting that the aggregate volume of credit card mail o ers provides a close proxy for the supply of unsecured consumer credit.

3.3 Sample Construction and Demographics

Our sample consists of monthly Mintel surveys from three distinct time periods: the credit boom (from January 2007 to December 2007); the bust period prior to the CARD Act (from August 2009 to February 2010); and the bust-and-recovery period after the CARD Act was in e ect (from March 2010 through December 2011). Each observation in our data represents a credit card o er, with detailed information about the o er and its recipient. Demographic and credit history information is also provided for those consumers who did not receive any o ers in the participating month.

For our analysis, we apply the following sample selection rules. First, we keep only offers sent to participants and their spouses, as we do not have credit history information for

other family members residing in the same location. Second, we keep only those consumers with valid credit histories and credit scores. This restriction may bias our sample towards homeowners who have a stable address, because the likelihood of successfully merging between Mintel and TransUnion databases is greater for these consumers.[19] Third, because the credit history data reveal the number of months since the last derogatory public record, with bankruptcy being one possible type of derogatory public record, we keep only those filers whose number of bankruptcy filings is equal to the number of derogatory public records in order to precisely identify the time since filing for bankruptcy. After applying these filters, our final sample contains more than 153,000 consumers (about 6% of whom are filers) who received 197,903 credit card offers.[20]

For our sample, we have essentially the same credit history information that a lender would have if the lender had no pre-existing lending relationship with a potential customer. One piece of information that lenders may have (but our merged data do not) is the chapter of the Bankruptcy Code, Chapter 7 or 13, under which a bankruptcy is filed. This limitation may hinder the identification of some consequences of bankruptcy filing, but we believe that the effect on our conclusions may be quantitatively small. According to the Administrative Office of U.S. Courts, in 2009, Chapter 13 filings accounted for about 30 percent of total initial personal bankruptcy filings. Furthermore, historically, many Chapter 13 filings are converted to Chapter 7 when borrowers fail to complete their repayment plans.

Table 1 presents descriptive statistics on key demographic and socioeconomic characteristics of our sample by bankruptcy filing status and the time elapsed since filing. All statistics, except the number of consumers in each column, are computed using the weights provided by Mintel. For comparison, we also include corresponding statistics on filers based on the

[19] TransUnion merges credit history data using the names and addresses of participants. As a result, the fraction of consumers who are homeowners in our final Mintel sample is higher than in the Survey of Consumer Finances.

[20] It is worth noting that, because the Mintel data are cross-sectional, our identification of how bankruptcy affects the supply of credit comes from comparing consumers with and without a bankruptcy record. The implicit assumption is that unobservable consumer characteristics do not influence credit supply in a way that is systematically different between filers and non filers. Although we view this assumption as rather innocuous, better identification would be possible should longitudinal data become available.

2007 Survey of Consumer Finances (SCF). More than five percent of the consumers in the sample have at least one bankruptcy record on their credit history in the Mintel data. This fraction is only half of what is observed in the SCF. As discussed earlier, this discrepancy is due in part to the mandatory removal of the bankruptcy record from credit reports at the tenth anniversary of the last discharge of debt.[21]

The last two columns of Table 1 compare the Mintel sample with the SCF. The demographic attributes of the two samples are remarkably similar apart from racial and homeownership compositions. In general, filers are younger, less educated, less likely to be married, and less likely to be homeowners. The Mintel sample has fewer black consumers but more homeowners than the SCF. As noted above, this discrepancy likely reflects both the bias in the stratification of the Mintel sample and our sample selection restriction of requiring a valid matched credit history.

3.4 Credit History Data and the VantageScore

The credit history information allows us not only to identify bankruptcy filing and its timing but also to observe past and current credit activities, such as the number of new accounts opened, delinquency status, the number of credit history inquiries, and the amount of various types of household debt.

Additionally, the credit history data contain a credit score measure, the VantageScore. Over the last 30 years, credit scores have become the single most important factor in consumer lending (see, for example, Federal Reserve Board (2007)). The VantageScore is a product developed by the three major consumer credit reporting agencies and ranges from 500 to 990. As shown in Figure 2, the distribution of VantageScores differs significantly by bankruptcy status. First, the distribution of filers' VantageScores overlaps with scores of non filers, but the filers' distribution is substantially lower than the non filers'. The median of the filers' distribution is about 675, compared with 850 for the non filers' distribution.

[21] Consistent with this reasoning, in the 2007 SCF, about 40 percent of filers reported that they filed for bankruptcy more than nine years earlier.

Second, the range of filers' VantageScores overlaps with only the lower end of the non filers' VantageScore distribution. Specifically, the entire distribution of bankruptcy filers' VantageScores falls below 800, covering only a segment of the left tail of non filers' distribution.

VantageScores appear to improve only slowly and moderately after filing for bankruptcy. As shown in Figure 3, the average VantageScore is just above 620 for the most recent filers, increases to about 660 for filers whose last filing was two years earlier, and then slowly rises to an average near 700 for those who filed 8-10 years earlier. Should the cross-sectional relationship between VantageScores and the number of years since filing be consistent with the time series relationship for individual consumers, which we do not observe in the Mintel data, the persistently low VantageScores observed among filers suggest that either bankruptcy depresses the VantageScore as long as the flag stays on the credit history or that some risk characteristics or shocks that led the debtors to bankruptcy are persistent.

3.5 Liabilities

Table 2 presents summary statistics of liabilities by bankruptcy status and the time since last filing. Broadly speaking, the statistics on liabilities and delinquencies in the Mintel data are consistent with the results documented by Han and Li (2011) using the (consumer-reported) SCF data. These patterns suggest that filers may have gained access to various types of credit, including revolving credit, shortly after filing for bankruptcy, and that filers use these credit sources rather intensively, which may eventually lead to renewed debt payment difficulties. The results are also consistent with the findings of Musto (2004), who shows that bankruptcy filers' number of accounts and total credit limits rise with the time since filing.

One concern about interpreting the significant levels of debt borrowed by bankruptcy filers is that such debt may reflect undischarged liabilities from Chapter 13 filings. Because we do not have information on the chapter under which a consumer filed for bankruptcy, we cannot identify directly how much debt was accumulated after filing. To address this

concern, we examine the number of new accounts opened by lers and non lers. As shown in Table 3, similar fractions of lers and non lers have recently opened new accounts and, conditional on having opened at least one account, the number of accounts opened are also comparable. From a lender's perspective, all else being equal, Chapter 13 lers are riskier than Chapter 7 lers because of the former's undischarged debt and greater risk of repeated ling. Therefore, the credit supplied to lers observed in our data likely represents a lower bound of the credit granted to Chapter 7 lers.

Finally, in the lower part of Table 3 we present statistics on credit inquiries by bankruptcy status. Credit inquiries serve as a proxy for demand for credit, as lenders evaluate a potential borrower's credit quality by performing a \credit inquiry" when a loan application is submitted. We nd that lers' credit reports are more likely to have had a recent credit inquiry and, conditional on having at least one inquiry, the number of inquiries is also slightly higher for lers, suggesting that lers are more actively seeking credit than non lers.

4 Unsecured Credit Supply to Risky Borrowers over the Cycle

4.1 An Overview of the Unsecured Credit Cycle

We now explore changes in the supply of unsecured credit over the boom and bust of the credit cycle. Access to new unsecured credit uctuated dramatically over our study period. Figure 4 provides a succinct summary of the trends in credit card o ers across the VantageScore distribution. The gure shows that the VantageScore gradient in the likelihood of receiving an o er in the boom period of 2007 was surprisingly at (the solid blue line). Forty percent of consumers with the worst credit scores (VantageScore below 550) received a credit o er in a given month, compared to sixty percent of consumers with the best credit scores (VantageScore above 950). If anything, consumers in the \subprime" range of the

VantageScore distribution, between 600 and 750, were *more* likely to receive an o er than any other part of the credit distribution. This pattern highlights the dramatic expansion of unsecured credit to less creditworthy consumers during the credit boom.

In the wake of the crisis, access to unsecured credit dropped precipitously, as lenders cut existing lines and signi cantly curtailed the practice of credit card mailings. The overall likelihood of a consumer receiving an o er in a given month fell from 60 percent to 35 percent, but this decrease was not felt evenly over the credit score distribution. As the dashed red line (August 2009{February 2010) in Figure 4 shows, the VantageScore gradient steepened sharply during this time period, with consumers at the top of the VantageScore distribution becoming about ve times more likely to receive an o er as those at the bottom.

The volume of credit card mail o ers has steadily recovered since early 2010. However, as indicated by the dotted green line (March 2010{December 2011), following the implementation of the CARD Act, although the likelihood of receiving an o er is uniformly higher across the credit score spectrum, the improvement is much more subdued for consumers with the lowest credit scores. For the range of VantageScores below 800, the green line represents a steeper credit score gradient than the red line, implying an even wider gap in the likelihood of receiving an o er between the most and the least creditworthy consumers. The trends shown in this gure are central to understanding the heterogeneous patterns of access to new unsecured credit during the boom and bust. The next section explores access to credit over time among the riskiest of consumers | those with a bankruptcy history | as well as the features of the contracts o ered to those consumers.

4.2 Characteristics of O ers to Bankruptcy Filers

Table 4 presents the summary statistics of credit card o ers by bankruptcy ling status for the full sample. Relative to non lers, lers as a whole are less likely to receive credit card o ers | 39 percent of lers received at least one credit card o er, signi cantly fewer than non lers, 51 percent. Even so, these statistics suggest that lers continue to enjoy a

signi cant likelihood of receiving a credit card o er in a given month and do not face outright exclusion from the unsecured credit market.[22] Conditional on having an o er, o ers to lers have signi cantly lower minimum credit limits and higher interest rates. Moreover, o ers to lers are more likely to charge an annual fee but are less likely to have either a reward program or a promotional interest rate.

Among o ers to lers, contract terms also vary relative to the time elapsed since ling. Consumers who led more than six years earlier appear less likely to receive an o er than those who led more recently, especially compared to those who led within the last 24 months. Thirty-six percent of lers who led six to ten years earlier received at least one o er, relative to 43 percent for those who led fewer than two years earlier. However, conditional on having an o er, terms o ered generally improve with the time since ling.[23]

Note that charging an annual fee and o ering rewards programs can be correlated. The credit card industry sometimes refers to cards that do not charge a fee and do not o er rewards programs as \plain vanilla" cards. Cards charging a fee but not o ering rewards programs are referred to as \credit building" cards, cards not charging a fee but o ering rewards programs as \general market" cards, and cards charging a fee and o ering rewards programs as \premium rewards" cards. As shown in the bottom rows of Table 4, we nd that lers are overwhelmingly more likely to receive \credit building" cards, much less likely to receive \general market" cards, and essentially receive no \premium rewards" cards.[24]

4.3 Bankruptcy Filers' Credit Access over the Boom and Bust

As shown in Figure 2, bankruptcy lers, on average, have much lower VantageScores than non lers. If consumers with lower credit scores generally tend to receive fewer and less

[22] Putting the monthly likelihood in perspective, if the probability of receiving an o er was independent across months, more than 99 percent of lers would receive at least one o er in a given year.

[23] The only exception is that the o ers sent to the most seasoned lers have a lower likelihood of having promotional interest rates (52 percent) than more recent lers (57 percent).

[24] Bankruptcy lers, and, for that matter, other high risk consumers, are reportedly more likely to receive o ers of secured cards|cards for which the consumer is required to put down some amount of security deposit. However, we nd only a very small number of secured card o ers in our sample.

consumers.

Studying the dynamics of credit o ers over the credit boom and bust, we nd that subprime o ers were prevalent during the peak years of credit expansion, but that this segment of the market contracted most sharply during the downturn. Indeed, unsecured credit supply to subprime consumers has remained very tight in recent years despite the broad recovery of credit supply to other consumers, likely re ecting, in part, the e ects of the CARD Act. Thus the balance-sheet recession and need for deleveraging has not been felt evenly across the credit score distribution. Our results also suggest that those households who have been hit hardest by the collapse of the housing bubble also likely face signi cant challenges in obtaining unsecured credit, even years after the nancial crisis.

Furthermore, our ndings shed light on the more empirically plausible calibrations of dynamic equilibrium models of consumer credit and default behavior. Research using such models has grown rapidly in the past decade (for example, Chatterjee et al. 2007, Chatterjee et al. 2011, Livshits, MacGee, and Tertilt 2007, Athreya et al. 2009). Our results suggest that, in contrast to the stylized assumption typically made in such models that lers can reenter credit markets with a constant likelihood in each period, bankruptcy lers receive credit o ers soon after ling for bankruptcy, but the credit they receive is limited and costly, and, if anything, diminishes over time. These ndings reveal the crucial complexity of post-bankruptcy access to credit, thereby providing useful empirical guidance for enriching and calibrating such models.

Quantifying the broader welfare implications of changes in credit access for bankruptcy lers represents a potential strand of future research. On balance, lers may continue to nd it di cult to smooth consumption over time or to insure against idiosyncratic income risk using their credit cards because of their low credit limits and expensive interest rates. Finally, we note that this study focuses solely on how unsecured credit supply varied with borrower characteristics over the last credit cycle. We remain agnostic about the determinants of the cycle itself: Many factors, such as capital regulations, willingness of lenders to increase

leverage, and access to securitization markets a ected the supply of unsecured credit to risky borrowers. Understanding the impact of these drivers of cyclical dynamics is also a promising area of future research.

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Figure 1: Credit Card Offer Mail Volume and Number of New Accounts Opened
This figure shows the time series of total credit card mail solicitation volumes in the U.S. from 2001 through 2011 and the number of new credit card accounts opened estimated using the Equifax consumer credit panel. Note that the household-level data used in the microeconometric analysis are available for the periods January 2007 to December 2007 and August 2009 to December 2011. Source: Authors' calculations using Mintel/Comperemedia and Equifax data.

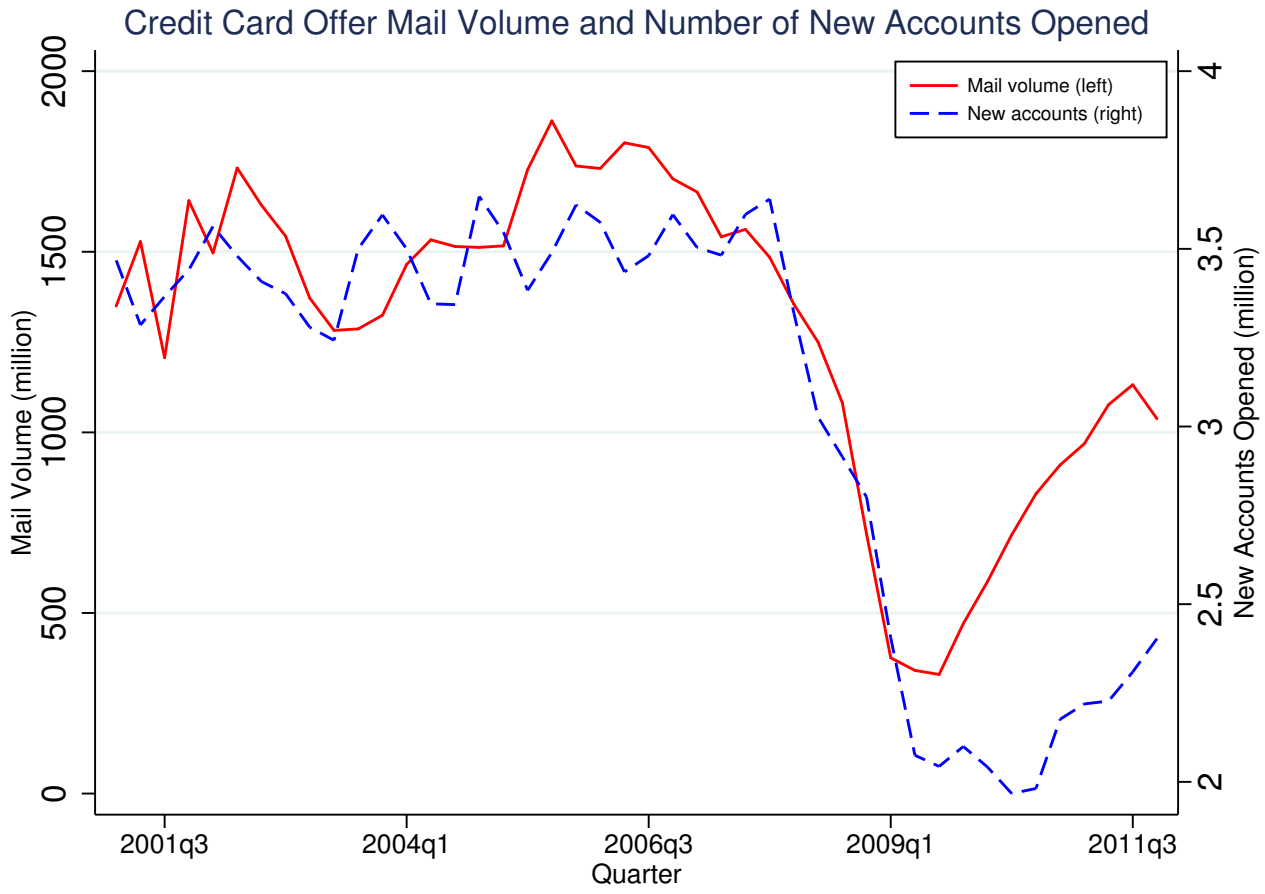


Figure 2: Vantage Score Distribution by Filing Status

This gure shows the frequency distributions of Vantage Scores by bankruptcy ling status. Note that the entire distribution of the lers' Vantage Scores, blue plot, falls below 800, while the non ler distribution covers the whole range up to 1000. The median Vantage Scores for the lers' and non lers' distributions are 675 and 850, respectively.

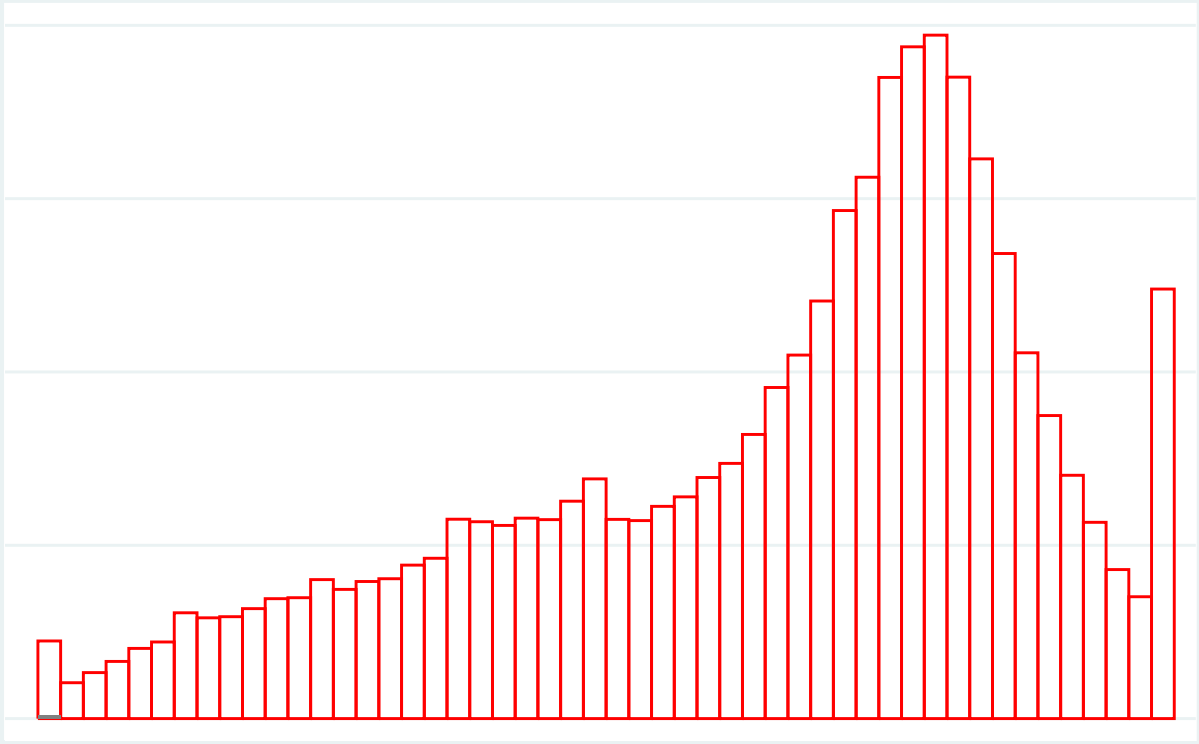


Figure 3: Average Vantage Scores by Year since Filing

This figure shows how Vantage Scores vary with the number of years since last bankruptcy filing in the cross section. This cross-sectional relationship would be consistent with an individual's time-series relationship between Vantage Scores and the time since filing if the heterogeneity among individual filers is constant over time.

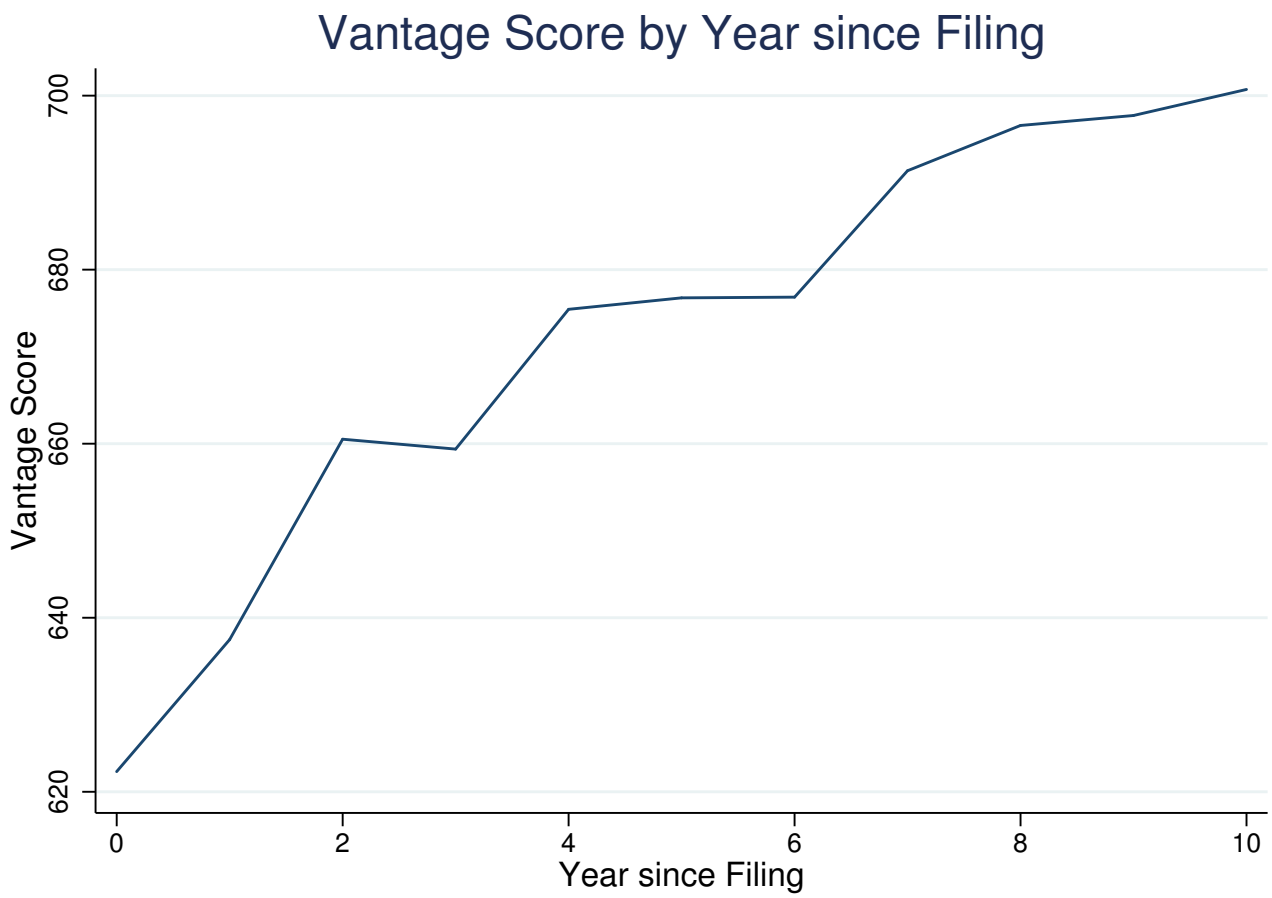


Figure 4: Likelihood of Receiving A Credit Card O er by Vantage Scores over the Credit Cycle

This gure plots how the likelihood of receiving a credit card o er changes with Vantage Scores at the di erent stages of the recent credit cycle: the pre-crisis period (represented by the year of 2007, the solid blue line), the post-crisis and pre-CARD Act period (from August 2009 to February 2010, the dashed red line), and the post-CARD Act period (from March 2010 to December 2011, the dotted green line). The gure shows that non-prime consumers with scores between 600 and 700 were actually more likely to receive credit card o ers than those consumers with near-perfect credit (900-999) prior to the crisis. However, after the crisis, the relationship between Vantage Score and the likelihood of receiving an o er dramatically steepened, with low-creditworthy households' access to unsecured credit o ers falling sharply.

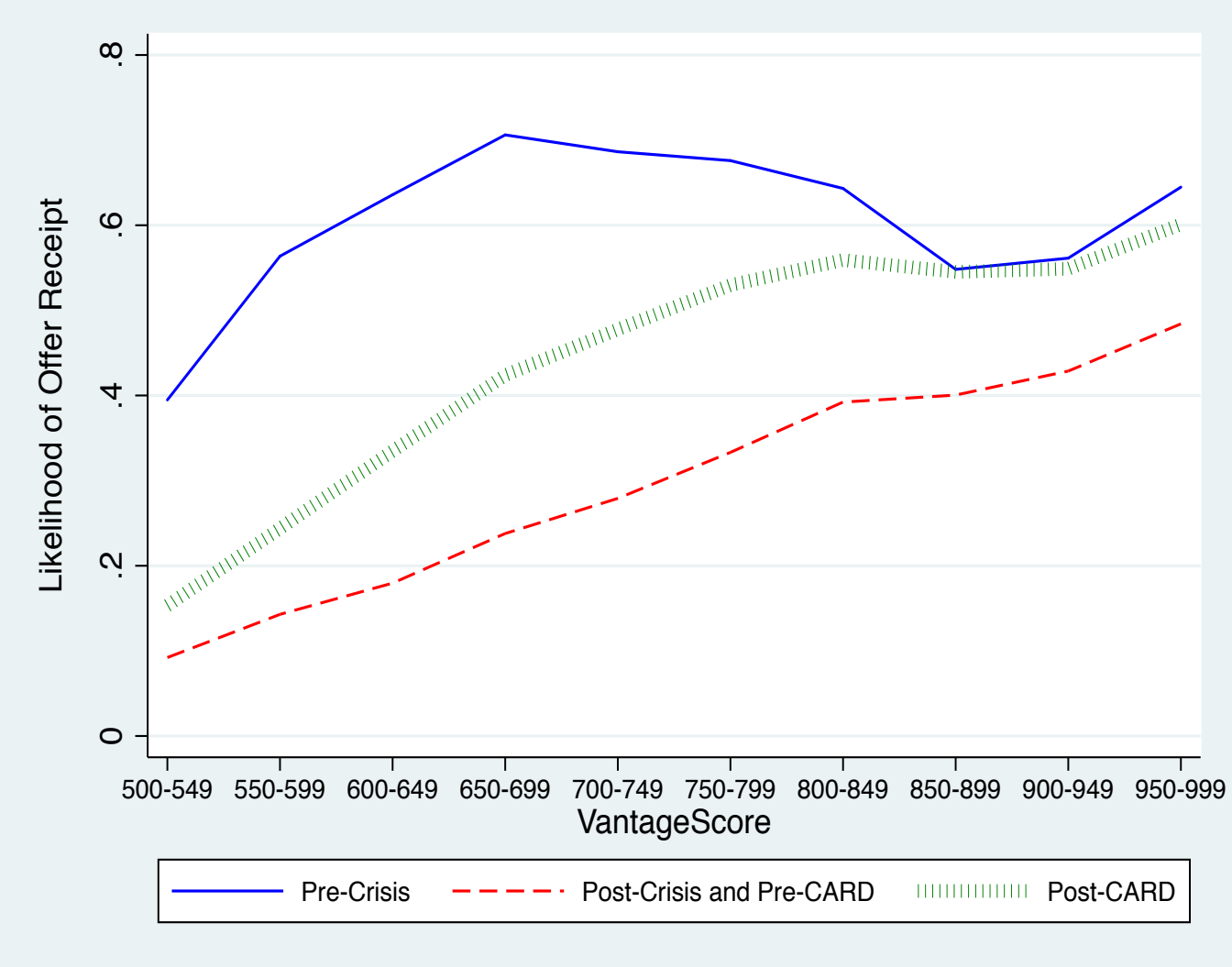
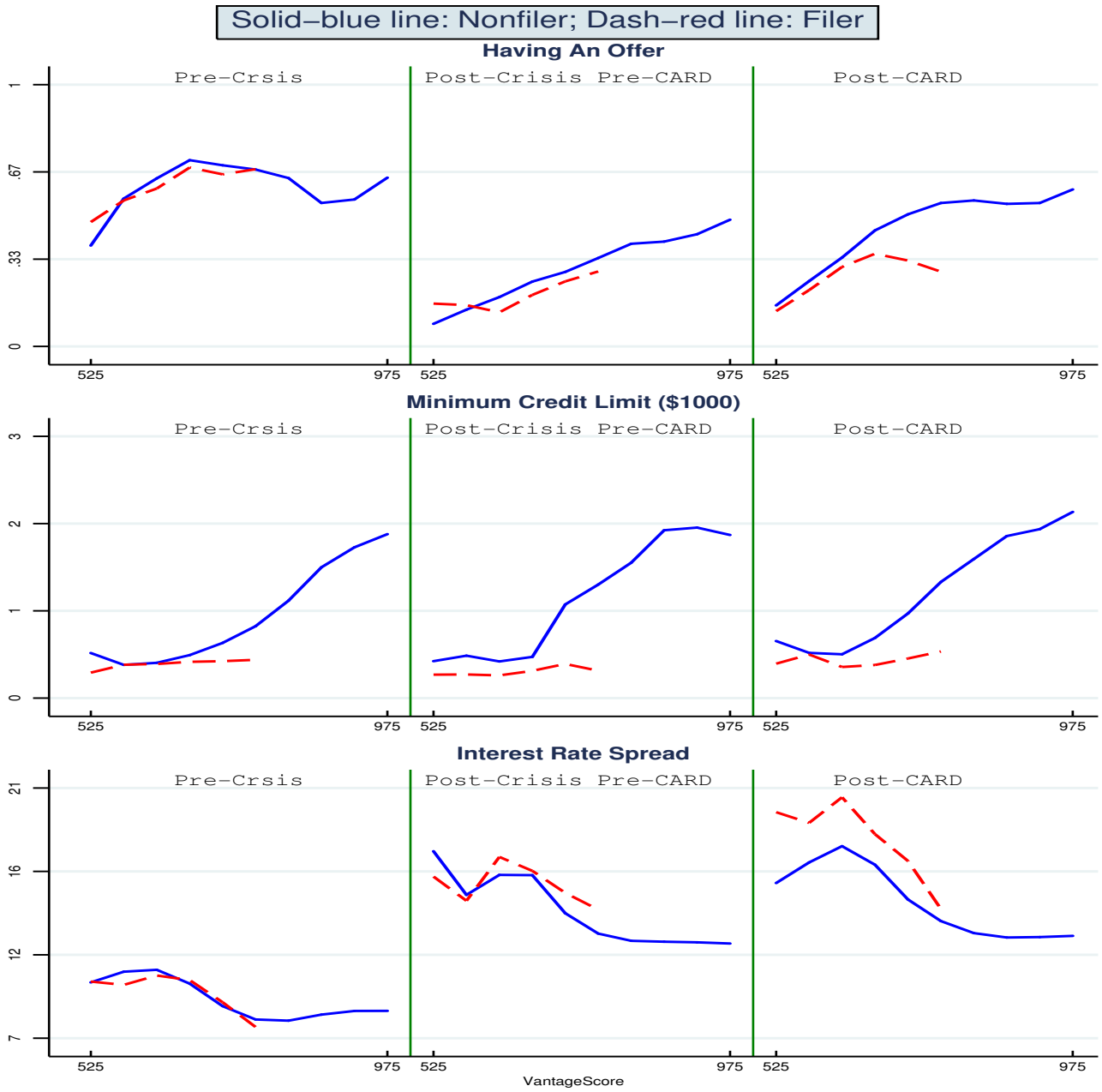


Figure 5: Credit Card O ers by Vantage Scores and Filing Status I

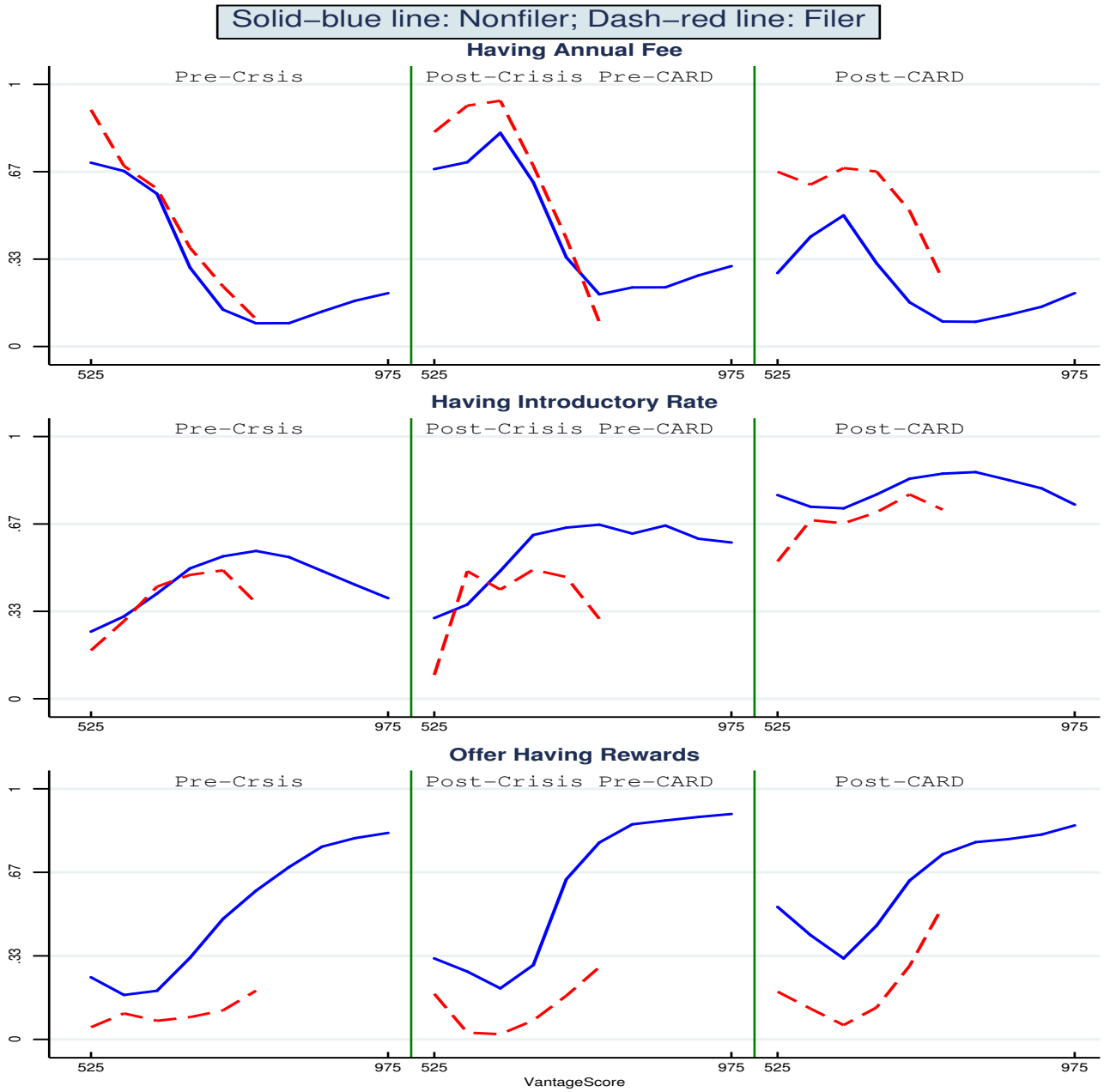
This gure shows how the likelihood of receiving an o er and, conditional on having an o er, the minimum credit limit and interest rate spread vary with a consumer's Vantage Score by the consumer's bankruptcy ling status. Bankruptcy lers are shown in dotted red lines, non-bankrupt consumers in solid blue lines. The panels in the left column present results of the pre-crisis period (January 2007 to December 2007), the middle column the post-crisis pre-CARD-Act period (August 2009 to February 2010), and the right column the post-CARD-Act period (March 2010 to December 2011). In the pre-crisis period, bankrupt consumers were equally likely to get an o er, conditional on credit score, and o ers had similar interest rates but signi cantly lower credit limits. In the post-crisis, post-CARD Act period, bankrupt consumers receive fewer o ers and their o ers have both higher interest rates and lower credit limits.



Data source: Compiled by authors using Mintel data.

Figure 6: Credit Card O ers by Vantage Scores and Filing Status II

This gure shows how, conditional on having a credit card o er, the likelihood of having annual fees, having an introductory interest rate, and having rewards vary with a consumer's Vantage Score by the consumer's bankruptcy ling status. Bankruptcy lers are shown in dotted red lines, non-bankrupt consumers in solid blue lines. The panels in the left column present results of the pre-crisis period (January 2007 to December 2007), the middle column the post-crisis pre-CARD-Act period (August 2009 to February 2010), and the right column the post-CARD-Act period (March 2010 to December 2011). In the post-crisis, post-CARD Act period, o ers to bankrupt consumers are much more likely to have an annual fee, but less likely to have either an introductory interest rate period or a rewards program.



Data source: Compiled by authors using Mintel data.

Table 1: Demographics by Bankruptcy Filing Status and Timing

This table presents descriptive statistics on key demographic and socioeconomic characteristics by bankruptcy ling status and the time elapsed since ling. For comparison, on the two far-right columns, we also include corresponding statistics on lers based on the 2007 SCF. All statistics, except the number of consumers in each column, are computed using the weights provided by Mintel and the SCF. Individuals in the Mintel sample are broadly similar to those in the SCF, but are somewhat more likely to be homeowners and less likely to be African-American.

	Mintel					SCF	
			Number of years since last ling				
	Non lers	Filers	0-2 years	3-5 years	6-10 years	Non lers	Filers
Mean age	53.4	50.8	49.5	50.2	51.7	50.1	49.2
Mean household size	2.6	2.7	2.9	2.7	2.6	2.5	2.7
High School (%)	31.2	37.2	34.7	38.3	37.7	32.0	39.1
Some College (%)	21.0	23.8	23.8	25.2	23.0	17.7	23.4
College (%)	34.9	21.2	23.1	19.2	21.5	36.9	23.4
Homeowner (%)	77.6	57.4	63.0	52.9	57.5	62.5	51.4
Black (%)	5.9	8.5	8.7	9.1	8.1	12.2	15.3
Married (%)	58.3	50.3	56.9	48.8	48.2	59.5	54.1
Number of consumers	145,095	8,183	1,776	2,203	4,204	3,982	436

Source: Mintel/Comperemedia data and the Survey of Consumer Finances (SCF).

Table 2: Liabilities Statistics by Bankruptcy Filing Status

This table presents summary statistics of liabilities by bankruptcy status and the time elapsed since last filing. For each variable, we report mean values with median values shown in the brackets below. Number of delinquent account refers to the accounts that were 30 or more days past due during the last 12 months. All statistics are computed using the weights provided by Mintel.

			Filed		
	Non filers	Filers	0-2 years	3-5 years	6-10 years
Total debt ($)	82,035	45,417	37,328	33,290	55,416
	[22,789]	[9,868]	[3,352]	[7,443]	[14,543]
Nonmortgage debt ($)	20,361	13,530	9,592	11,744	16,154
	[6,642]	[5,509]	[1,077]	[4,462]	[8,149]
Revolving debt ($)	9,603	3,538	1,756	2,443	4,882
	[1,519]	[592]	[0]	[483]	[1,794]
Revolving credit limit ($)	41,211	8,217	5,597	5,867	10,596
	[24,900]	[2,800]	[500]	[1,800]	[5,500]
Number of revolving accounts	6.2	3.9	2.6	3.8	4.5
	[5]	[3]	[2]	[3]	[4]
Installment debt ($)	10,265	9,858	7,765	9,237	11,074
	[0]	[0]	[0]	[0]	[986]
Income ($)	75,076	52,792	55,454	47,174	54,738
	[55,000]	[42,500]	[47,500]	[37,500]	[42,500]
Number of del. accounts	0.35	0.68	0.97	0.53	0.64
	[0]	[0]	[0]	[0]	[0]

Table 3: New Accounts Opened and Inquiries Made on Credit History

This table shows the number of new accounts opened by lers and non lers. Statistics referring to the previous M months do not include the consumers who led for personal bankruptcy within this period. The average number of trades open is calculated conditional on having at least one such trade opened. All statistics are computed using the weights provided by Mintel.

		All trades		Bank cards	
	Timing	Non lers	Filers	Non lers	Filers
Percent of consumers opened trades(%)	previous 3 months	18.2	19.3	7.3	8.8
Avg. num. of trades opened	previous 3 months	1.3	1.3	1.1	1.2
Percent of consumers opened trades(%)	previous 6 months	31.6	31.9	13.3	15.2
Avg. num. of trades opened	previous 6 months	1.5	1.6	1.2	1.3
Percent of consumers opened trades(%)	previous 12 months	50.3	50.2	23.7	25.7
Avg. num. of trades opened	previous 12 months	1.9	2.1	1.4	1.5
Percent of consumers opened trades(%)	previous 24 months	70.9	70.9	40.5	42.8
Avg. num. of trades opened	previous 24 months	2.9	3.2	1.7	1.9

		Non lers	Filers
Percent of consumers with credit inquiry	previous 6 months	29.6	41.6
Avg. num. of credit inquiry	previous 6 months	1.9	2.3

Table 4: Credit Card O ers by Bankruptcy Filing Status

This table presents the summary statistics of credit card o erings by bankruptcy ling status for the full sample. The average number of o ers is calculated conditional on receiving at least one credit card o er. Mean values are reported, with median values shown in brackets below. All statistics are computed using the weights provided by Mintel. Plain vanilla, credit building, general market, and premium rewards are four types of credit card o ers that, in this order, charge no annual fee and carry no rewards program, charge an annual fee and carry no rewards program, charge no annual fee and carry rewards programs, and charge an annual fee and carry rewards programs, respectively.

			Filed		
	Non lers	Filers	0-2 years	3-5 years	6-10 years
Received at least one o er (%)	51.4	38.9	43.0	41.2	35.9
Avg. num. of o ers received (monthly)	2.6	2.8	3.0	3.0	2.7
	[2]	[2]	[2]	[2]	[2]
Avg. min credit limit ($)	1,368	407	381	417	415
	[500]	[300]	[300]	[300]	[300]
Avg. interest rate (%)	13.7	15.6	17.1	15.5	14.9
	[13.0]	[14.9]	[16.9]	[15.0]	[14.0]
Have introductory rate (%)	68.7	53.1	56.8	51.7	52.2
Have annual fee (%)	19.1	44.7	57.6	47.9	35.2
Have rewards program (%)	69.9	14.4	6.5	8.7	22.9
Plain vanilla (%)	22.5	42.5	36.6	44.5	44.4
Credit building (%)	7.6	43.2	56.9	46.8	32.7
General market (%)	58.5	12.8	5.8	7.6	20.4
Premium rewards (%)	11.4	1.6	0.7	1.1	2.5

Table 5: Empirical Results Estimated Using the Pre-Financial-Crisis Sample (January 2007 – December 2007)

This table reports the estimated effects of bankruptcy filing status on the likelihood of receiving a credit card offer and, conditional on receipt, offer terms, for the pre-crisis period (January 2007–December 2007). State-cluster-corrected standard errors are reported in parentheses. Statistical significance at the 10, 5, and 1 percent levels is indicated by *, **, and ***, respectively. "Recent," "Seasoned," and "Remote" filers refer to consumers who filed for bankruptcy 0-2 years, 3-5 years, and 6-10 years prior to the surveys, respectively.

	Have an offer	Min. credit limit	Spreads	Annual fee	Have intro rate	Rewards
	Probit	OLS	OLS	Probit	Probit	Probit
	(1)	(2)	(3)	(4)	(5)	(6)
Filer	-0.028***	-93.631***	-0.015	0.057***	-0.054***	-0.342***
	(0.010)	(16.892)	(0.120)	(0.013)	(0.011)	(0.009)
Debt ratio	0.003***	-1.633	-0.023**	-0.001	0.000	0.001
	(0.001)	(3.127)	(0.010)	(0.001)	(0.001)	(0.001)
Have rev. credit	0.110***	67.269***	-0.651***	-0.099***	0.006	0.084***
	(0.010)	(19.444)	(0.107)	(0.020)	(0.015)	(0.015)
Mort. curr. 90+ del.	0.253***	-136.200**	0.343	-0.095*	0.327***	0.130
	(0.055)	(65.138)	(0.676)	(0.050)	(0.065)	(0.103)
90+ del. in pre. 24 mo.	0.001	-8.353**	0.094***	0.034***	-0.012***	-0.030***
	(0.004)	(4.124)	(0.029)	(0.003)	(0.003)	(0.004)
30+ del. ever	0.018**	-193.123***	0.190***	0.029***	-0.010	-0.092***
	(0.007)	(20.787)	(0.052)	(0.007)	(0.007)	(0.007)
Log(income)	0.037***	123.947***	0.047	0.018***	-0.031***	0.051***
	(0.004)	(13.266)	(0.029)	(0.003)	(0.004)	(0.004)
Controlling for						
Demographics?	Yes	Yes	Yes	Yes	Yes	Yes
VantageScore bin?	Yes	Yes	Yes	Yes	Yes	Yes
Monthly fixed effects?	Yes	Yes	Yes	Yes	Yes	Yes
State fixed effects?	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.036	0.141	0.100	0.156	0.022	0.199
N	40,241	44,718	68,889	68,894	68,894	68,894
Recent filer	0.071***	-29.020	0.233	0.090***	0.011	-0.366***
	(0.027)	(23.693)	(0.168)	(0.022)	(0.024)	(0.020)
Seasoned filer	-0.024	-59.958**	0.290**	0.098***	-0.032	-0.376***
	(0.021)	(22.545)	(0.124)	(0.015)	(0.021)	(0.011)
Remote filer	-0.062***	-151.499***	-0.387***	0.006	-0.103***	-0.304***
	(0.016)	(19.170)	(0.133)	(0.015)	(0.011)	(0.013)

Table 6: Empirical Results Estimated Using the Post-Crisis, Pre-CARD-Act Sample (August 2009{February 2010)

This table reports the estimated e ects of bankruptcy ling status on the likelihood of receiving a credit card o er and, conditional on receipt, o er terms, for the post-crisis and pre-CARD-Act period (August 2009-February 2010). State-cluster-corrected standard errors are reported in parentheses. Statistical signi cance at the 10, 5, and 1 percent levels is indicated by *, **, and ***, respectively. \Recent," \Seasoned," and \Remote" lers refer to consumers who led for bankruptcy 0-2 years, 3-5 years, and 6-10 years prior to the surveys, respectively.

Table 7: Empirical Results Estimated Using the Post-CARD-Act Sample (March 2010{December 2011)

This table reports the estimated e ects of bankruptcy ling status on the likelihood of receiving a credit card o er and, conditional on receipt, o er terms, for the post-CARD-Act period (March 2010-December 2011). State-cluster-corrected standard errors are reported in parentheses. Statistical signi cance at the 10, 5, and 1 percent levels is indicated by *, **, and ***, respectively. \Recent," \Seasoned," and \Remote" lers refer to consumers who led for bankruptcy 0-2 years, 3-5 years, and 6-10 years prior to the surveys, respectively.

	Have an o er	Min. credit limit	Spreads	Annual fee	Have intro rate	Rewards
	Probit	OLS	OLS	Probit	Probit	Probit
	(1)	(2)	(3)	(4)	(5)	(6)
Filer	-0.130***	-365.824***	1.787***	0.267***	-0.076***	-0.333***
	(0.008)	(27.252)	(0.181)	(0.021)	(0.011)	(0.024)
Debt ratio	-0.000	-1.841	-0.006	0.001	-0.001	0.001
	(0.001)	(2.948)	(0.005)	(0.001)	(0.001)	(0.001)
Have rev. credit	0.102***	65.376**	-0.682***	-0.006	-0.023**	0.003
	(0.009)	(31.834)	(0.113)	(0.009)	(0.010)	(0.009)
Mort. curr. 90+ del.	-0.122	-124.830	0.401	-0.083***	0.099***	-0.010
	(0.084)	(108.888)	(1.034)	(0.023)	(0.034)	(0.078)
90+ del. in pre. 24 mo.	-0.006**	-35.498***	0.188***	0.020***	-0.010***	-0.028***
	(0.002)	(5.463)	(0.047)	(0.002)	(0.002)	(0.004)
30+ del. ever	-0.023***	-272.507***	0.611***	0.038***	-0.006	-0.074***
	(0.008)	(17.536)	(0.062)	(0.006)	(0.005)	(0.006)
Log(income)	0.036***	84.136***	-0.080***	0.033***	-0.041***	0.035***
	(0.003)	(20.876)	(0.018)	(0.003)	(0.003)	(0.004)
Controlling for						
Demographics?	Yes	Yes	Yes	Yes	Yes	Yes
VantageScore bin?	Yes	Yes	Yes	Yes	Yes	Yes
Yearly-monthly xed e ects?	Yes	Yes	Yes	Yes	Yes	Yes
State xed e ects?	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.053	0.084	0.219	0.117	0.040	0.112
N	81,396	65,291	102,629	102,688	102,688	102,688
Recent ler	-0.033	-321.416***	2.688***	0.297***	-0.055***	-0.519***
	(0.020)	(28.202)	(0.347)	(0.032)	(0.018)	(0.035)
Seasoned ler	-0.116***	-307.806***	2.056***	0.348***	-0.113***	-0.476***
	(0.018)	(57.342)	(0.237)	(0.034)	(0.024)	(0.037)
Remote ler	-0.181***	-431.099***	1.016***	0.211***	-0.074***	-0.195***
	(0.009)	(34.882)	(0.225)	(0.026)	(0.013)	(0.028)

Table 8: Marginal E ects of Macroeconomic and Legal Factors on the Likelihood of Receiving Credit Card O ers

This table reports the estimated e ects of macroeconomic and legal factors (at the state level) on the likelihood of receiving a credit card o er using the whole sample (2007, August 2009-December 2011). The regression includes as additional controls the full set of variables, except the state xed e ects, shown in Table 7. State-cluster-corrected standard errors are reported in parentheses. Statistical signi cance at the 10, 5, and 1 percent levels is indicated by *, **, and ***, respectively. Both macroeconomic factors such as unemployment and house price growth a ect the likelihood of receiving an o er. State regulatory environments related to bankruptcy and foreclosure law are also important determinants of receiving an o er.

Property exempt / 100,000	House exempt / 100,000	Pro-lender foreclosure	Unemployment	Lagged HPI
-0.026	-0.002*	0.012**	-0.008***	0.132***
(0.020)	(0.001)	(0.007)	(0.002)	(0.054)

Table 9: Bankruptcy Filing E ects on the Likelihood of Credit Card O ers Estimated Using a Propensity Score Matching Method

This table reports the bankruptcy ling e ects on the the likelihood of credit card o ers estimated using a propensity score matching method. Coe cients are average treatment e ects on the treated, that is, for those who have led for bankruptcy, the di erence between their observed likelihood of credit o ers and the would-be likelihood of credit o ers if they had not led. The control sample for all estimations consists of consumers who have never led for bankruptcy. Standard errors estimated using a bootstrapping method with the state-level clustering are reported in parentheses. Statistical signi cance at the 10, 5, and 1 percent levels is indicated by *, **, and ***, respectively. \Recent," \Seasoned," and \Remote" lers refer to consumers who led for bankruptcy 0-2 years, 3-5 years, and 6-10 years prior to the surveys, respectively,

	All Filers	Recent	Seasoned	Remote
Pre-crisis				
	-0.027**	0.055*	-0.030	-0.054***
	(0.01)	(0.03)	(0.02)	(0.02)
Post-crisis & pre-CARD				
	-0.039**	0.027	-0.018	-0.072***
	(0.02)	(0.04)	(0.03)	(0.02)
Post-CARD				
	-0.118***	-0.036	-0.104***	-0.163***
	(0.01)	(0.02)	(0.02)	(0.01)

Table 10: Additional Costs and Hidden Fees

This table reports the estimated effects of bankruptcy filing status on additional costs and "hidden" fees. Pre-crisis refers to January 2007-December 2007; post-crisis, pre-CARD-Act refers to August 2009-February 2010; and post-CARD-Act refers to March 2010-December 2011. All regressions include the full set of controls shown in Table 7. State-cluster-corrected standard errors are reported in parentheses. Statistical significance at the 10, 5, and 1 percent levels is indicated by *, **, and ***, respectively. The cells labeled "N.A." have too few observations across groups to report meaningful results.

	Dependent variables:		
Sample Period	Waived annual fee Probit (1)	Min. finance charges OLS (2)	Have other fees Probit (3)
Pre-Crisis	-0.048***	0.174***	N.A.
	(0.004)	(0.013)	
Post-Crisis, Pre-CARD-Act	N.A.	0.233***	0.230***
		(0.045)	(0.081)
Post-CARD-Act	-0.002	-0.028**	0.118***
	(0.007)	(0.011)	(0.017)