Information, Contract Design, and Unsecured Credit Supply: Evidence from Credit Card Mailings*

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Abstract

How do lenders of unsecured credit use screening and contract design to mitigate the risks of information asymmetry and limited commitment issues in the absence of collateral? We take advantage of a unique data set of over 200,000 credit card mail solicitations to a representative sample of households over the recent credit cycle—a period including the implementation of the CARD Act—to address this question. We find that while lenders use credit scores as their central screening device, they take into account a substantial array of other information on borrowers' credit histories and financial and demographic characteristics. For instance, the likelihood of offer receipt is sensitive to the exact timing of a prior bankruptcy filing. Credit market conditions affect the marginal information used in lenders' offer decisions, as lenders sharply reduced credit supplied to subprime borrowers during the crisis and in response to the CARD Act. Finally, we document that lenders extend multiple distinct offers to the same consumers over a relatively short period, designed such that consumers are likely to reveal private information in their choice of contract.

JEL Classifications: J22, K35

Key words: credit supply, information asymmetry, credit cards, mail solicitation, personal bankruptcy, CARD Act, household finance

1 Introduction

Household debt of every type expanded substantially during the credit boom of the 2000s. Previous studies have documented that the growth in secured credit markets, such as mortgages and auto loans, was driven in large part by expanding access to risky or "subprime" borrowers (Adams, Einav and Levin, 2009; Mian and Sufi, 2009; Keys, Mukherjee, Seru and Vig, 2010). By contrast, there has been considerably less empirical analysis of unsecured consumer credit, where growth was as dramatic as secured credit. For example, credit card debt outstanding grew more than 40 percent in real terms between 1997 and 2008, a period when median household income saw little increase.[1]

The rapid expansion of unsecured consumer credit is especially remarkable because of the information challenges, incentives, and market environment of unsecured consumer lending. First, it is well-known that the market for unsecured credit is a classic setting where information asymmetry may lead to market failure (Stiglitz and Weiss, 1981; Riley, 1987; De Meza and Webb, 1987; Hellwig, 1987). Furthermore, even in the absence of severe information asymmetry, the limited commitment issue remains (Athreya and Janicki, 2006). Because unsecured claims are often wiped out in the event of personal bankruptcy filing, U.S. bankruptcy law does not necessarily provide strong incentives for households to repay their unsecured debt (Fay, Hurst and White, 2002; Agarwal, Liu and Mielnicki, 2003). Indeed, such credit risk has heightened substantially over the past three decades as personal bankruptcy filings increased fivefold, from fewer than 300,000 filings in 1980 to over 1.5 million filings in 2010.[2] Last but not least, the profitability of unsecured lending, like most financial transactions, may be constrained by evolving regulation and is not immune to the fluctuations of credit and business cycles.

In this paper, we use a unique sample of over 200,000 credit card mail solicitations linked

[1]Taking a longer perspective, the growth of credit card debt has been even more spectacular: While secured consumer debt grew by 130 percent (in real terms) between 1980 and 2010, credit card debt grew 475 percent over this same period. Source: Federal Reserve.

[2]Source: The Administrative Office of the U.S. Courts.

to consumer credit records to provide novel quantitative evidence on what information credit card lenders use in screening borrowers and designing credit contracts to address information and limited commitment issues in an evolving regulatory and economic environment. Specifically, guided by existing theory, we focus our empirical analysis on the following four questions: First, what information do lenders use to select and screen potential borrowers and to design credit card offer terms? Second, how does unsecured credit supply change over credit cycles and respond to regulatory reforms? [3] Third, how do lenders react to conspicuous indicators of default risk such as bankruptcy flags? And finally, do credit card lenders adopt strategies to facilitate separating equilibria, where borrowers with different credit risks are sorted into different credit contracts?

Our main results are summarized as follows: First, as expected, credit scores play a central role in unsecured lenders' screening of borrowers. However, lenders appear to take a large array of other information, such as the precise timing of personal bankruptcy filing, into account beyond the extent to which this information affects consumers' credit scores. Thus, the credit score is not a "sufficient statistic" when analyzing the determinants of unsecured credit supply. Further, exploring the geographic heterogeneity of unsecured credit supply, we find that lenders also factor local economic conditions (such as unemployment) into their determination of credit supply, a result that is broadly consistent with the findings of Hsu, Masta and Melzer (2014), who document regional heterogeneity in equilibrium credit outcomes.

Second, we find credit supply changed substantially over the past credit cycle. Consumers with "nonprime" credit scores received *more* credit card offers than prime consumers during the boom, while after the financial crisis these consumers experienced the largest reduction in access to credit, a contraction that persists six years later. Furthermore, we find that the Credit Card Accountability Reliability and Disclosure (CARD) Act of 2009 has further limited the supply of unsecured credit to borrowers with greater credit risks. Note that

[3] In Section 3 below, we discuss whether credit offers themselves can be taken as a direct measure of "credit supply," and argue that they are a reasonable (though imperfect) proxy.

because the implementation of the CARD Act was followed by a stabilization and recovery of the broad economy and credit markets, the net effects of the Act on the supply of credit can be hard to discern. That said, we find that consumers with the lowest credit scores—those who the Act was arguably most intended to protect—have not received any increase in credit card offers during the prolonged recovery. Moreover, reflecting the broad credit market recovery, the Mintel data show that offers of auto loans (not targeted by the CARD Act) increased evenly across the credit score distribution in the post-crisis period. This contrasting experience across types of credit suggests that the CARD Act may have differentially reduced the supply of unsecured credit to consumers with the greaterest credit risks.

Our results on credit card offers, at both extensive and intensive margins of credit supply, provide a new angle on the effects of the CARD Act, complementing Agarwal, Chomsisengphet, Mahoney and Stroebel (2015), who examine a large set of existing credit card accounts and argue that the CARD Act effectively reduced fees levied by credit card lenders. Our analysis focuses on the Act's impact on the supply of credit through card offers.[4] Hence, the two studies jointly suggest that borrowers became more selective in accepting credit card offers, the substantial reduction in credit card mail volume notwithstanding. Such a heightened selectiveness is broadly consistent with the well-documented phenomenon of household balance sheet deleveraging in the wake of the housing bust (see, e.g. Mian, Rao and Sufi (2013)).

Third, the impact of the most conspicuous indicator of a consumer's credit risk, a bankruptcy flag, on lenders' credit supply decisions is surprisingly ambiguous and depends crucially on when the bankruptcy was filed. Consumers who filed for bankruptcy fewer than two years earlier are just as likely to receive an offer as comparable nonfilers. In contrast, those who filed for bankruptcy more than five years earlier receive significantly fewer offers, suggesting that lenders are wary of re-filing risk. Furthermore, despite relatively small differences in the probability of receiving a credit card offer, offers to filers are more restrictive,

[4]See also Debbaut, Ghent and Kudlyak (2014) on the impact of the CARD Act on young borrowers, and Ronen and Pinheiro (2014) for a theoretical exploration of the CARD Act's limitations on re-pricing.

more expensive, and provide fewer take-up incentives than offers to their nonfiler counterparts. Notably, even in the aftermath of the most severe financial crisis in recent history, even the riskiest consumers are not excluded outright from the unsecured credit market. This sophisticated approach to lending to bankruptcy filers underscores our overall findings that unsecured lenders take into consideration extensive and dynamic information in their decision-making.

Finally, we present novel evidence that lenders actively use offers with different terms as a device to facilitate achieving separating equilibria. In particular, lenders not only send different offers to consumers of different credit risk characteristics, but also send offers of different terms to the *same* consumer over a short period of time. Such a strategy is consistent with search models (as in Butters (1977)) and helps to explain the dispersion of borrowing costs among individuals of similar credit attributes as documented in Stango and Zinman (2013). This separating strategy is more commonly used to target higher credit-score individuals, whose credit score alone may provide less information on their "type," or who may be more valuable customers to lenders in light of the CARD Act's restrictions on re-pricing and fees.

The key innovation of our approach is our use of a unique proprietary survey data set of credit card mail offers that is administratively linked to offer recipients' credit records to better separate variation in credit supply from credit demand. Through a household survey we also observe extensive demographic information, which is generally impossible when using credit data due to fair lending restrictions. Existing studies largely focus on borrowers' behaviors such as their incentives to default (Fay et al., 2002), the equilibrium quantity and price of credit following major credit events (Han and Li, 2011; Musto, 2004; Cohen-Cole, Duygan-Bump and Montoriol-Garriga, 2009), or how equilibrium loan pricing reflects credit risk (Edelberg, 2006). Due partly to data limitations, these studies are not able to identify how credit supply changes with lenders' information sets or relevant regulatory and economic conditions.[5] Importantly, our data cover the time period that overlaps with the latest credit cycle and the implementation of the CARD Act, allowing us to study how unsecured credit supply has evolved over the credit cycle and reacted to increases in legislative oversight.

Our paper contributes to a growing literature on information asymmetry and credit markets. Recent studies have underscored the critical importance of credit scores in overcoming information asymmetry, particularly in unsecured credit markets (Athreya, Brown, Tam and Young, 2013; Chatterjee, Corbae and Rios-Rull, 2011). Our findings suggest that credit scores alone are "insufficient statistics" in the credit card market, as lenders use an extensive set of consumer characteristics to differentiate between good and bad risks. These results support the view that innovation in information technology has played a crucial role in the expansion of unsecured credit to risky borrowers (Narajabad, 2012; Sanchez, 2010). Finally, our findings in the credit card market enrich our understanding of information asymmetries in consumer credit markets, as explored in other credit markets by Einav, Jenkins and Levin (2012), Karlan and Zinman (2009), and Dobbie and Skiba (2013), who explore related issues in auto lending, microcredit, and payday loans, respectively, as well as in the credit card market by Agarwal, Chomsisengphet and Liu (2010).

The rest of the paper is organized as follows. Section 2 briefly reviews the legislative and institutional background related to the U.S. credit card market, then discusses the related theoretical literature and how our results inform this broad research agenda. Section 3 describes the data and presents summary statistics. Section 4 explores what information lenders employ in screening potential borrowers. Sections 5 and 6 discuss how credit supply has evolved over the recent credit cycle and how bankruptcy flags may affect the supply of unsecured credit, respectively; Section 7 presents results on the dispersion of offer terms and lenders' distinct mail offers to the same household, and we conclude in Section 8.

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

2 Legislative Background and Conceptual Framework

2.1 Legal Background

Three areas of regulation—the U.S. bankruptcy code, the Fair Credit Reporting Act (FCRA), and the CARD Act—are most relevant to the unsecured credit market. As discussed before, a key feature of unsecured credit is that the debt owed can be substantially reduced or even discharged outright through a bankruptcy filing. A debtor can file under Chapter 7 of the bankruptcy code to obtain a discharge of unsecured debts.[6] Alternatively, the debtor can file under Chapter 13, thereby obtaining 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 filing. Specifically, a debtor is prohibited from obtaining another bankruptcy discharge (Chapter 7) until eight years after a previous debt discharge.[7] The empirical implications of such re-filing restrictions on credit supply are explored in detail later in the paper.

The supply of unsecured credit is also affected by how credit scores are derived and how credit information is reported, particularly for borrowers with damaged credit histories. To comply with the FCRA (and the Equal Credit Opportunity Act, or ECOA), credit scoring algorithms may use only the information on one's credit history and cannot use information such as race, gender, and income. In addition, the FCRA permits a bankruptcy record to stay on credit reports furnished by the credit bureaus for at most 10 years after the date of relief or the date of adjudication (FCRA 605 (a)(1)), and all other non-bankruptcy defaults for up to seven years (FCRA 605 (a)(5)). If credit reports are lenders' only source for borrowers' default histories, then lenders cannot distinguish between 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

[6]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).

[7]The restriction on repeated Chapter 7 filing was six years prior to the 2005 Bankruptcy Abuse Prevention and Consumer Protection Act.

removed, inducing greater access to and subsequent use of 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, a hypothesis we explore below.[8]

2.2 Theoretical Motivation and Empirical Hypotheses

We now present a stylized model of credit card offering (very much along the lines of Einav et al. (2012)) as the conceptual framework that guides our empirical analysis. Recent research has generated a great deal of insights on how lenders use contract design and modern technology, including credit scoring, to mitigate information asymmetry and limited commitment issues. We will use this framework to develop several specific hypotheses to be tested using the credit card offer data.

2.2.1 Credit Card Offers with Information Asymmetry

Consider a two-period model, $t = 0, 1$. At $t = 1$, after learning his earnings y_1, a consumer with credit card balance L and rate of interest R decides whether to pay off this debt. He has only limited commitment to the debt repayment because the legal environment gives borrowers options to default on their debt obligations by either filing for bankruptcy or

[8] For more details, see Consumer Financial Protection Bureau (2013).

choosing "informal" bankruptcy (Rea, 1984; Fay et al., 2002; Athreya and Janicki, 2006).[9] Denote his utility by $v(y_1)$ at $t = 1$ if he defaults, where v reflects costs of default, including the possibility of being excluded from the credit market, social stigma, efforts of avoiding collection, or legal expenses related to court filing (Athreya, Tam and Young, 2009). Thus, the consumer will pay off the debt if and only if

$$u(y_1 - L(1+R)) \geq v(y_1). \tag{1}$$

Under fairly general conditions, this simple setup implies that the borrower is more likely to default on loans with a higher interest rate or a larger balance. This result is an important insight by the classic credit rationing literature: credit terms affect the risk of default (Stiglitz and Weiss, 1981).

At $t = 0$, if the consumer receives a credit card offer, ϕ, consisting of credit limit L^u and interest rate R, he determines the optimal balance L^* according to:

$$W(L^*; \phi, Z) = \max_{0<L\leq L^u} \left[u(y_0 + L) + \beta \mathbf{E} \left(\max(u(y_1 - L(1+R)), v(y_1) | Z \right) \right], \tag{2}$$

where the distribution of y_1 depends on household and economic conditions, Z.

In this context, information asymmetry occurs if the lender observes only a subset of variables Z. Let X indicate the set of information known to both the consumer and the lender, such as payment history and debt balance, and θ information private to the borrower, such as time preference or default stigma. That is, $Z = (X, \theta)$. For a given credit offer ϕ, the set of borrowers who would take it up is given by:

$$\widehat{\Theta}(\phi, X) = \{\theta : W(L^*; \phi, X, \theta) \geq \overline{W}\}, \tag{3}$$

[9] The term "informal bankruptcy" refers to a scenario where a borrower chooses to default but not to file for formal bankruptcy (Ausubel and Dawsey, 2004). In such a scenario, state laws govern the extent of debtor liability and creditor collection rights, typically allowing creditors to pursue repayment more aggressively using methods such as wage garnishment.

where $\overline{W} = u(y_0) + \beta \mathbf{E} u(y_1)$, utility in the financial autarky state.

It is clear from (3) that the offer terms affect the riskiness of the borrower pool, that is, the distribution of $\widehat{\Theta}$. To illustrate how this endogenous riskiness may affect a lender's offer decision, we follow Einav et al. (2012) to first consider a pooling equilibrium. That is, given observable characteristics X, the lender chooses ϕ from the permissible contract set, Φ, to maximize her expected profits:

$$\Lambda(X; \Phi, r) = \max_{\phi \in \Phi} P(\widehat{\Theta}; \phi, X) \cdot \int_{\theta \in \Theta(\phi, X)} \pi(L^*, \phi, X, \theta, r) dF(\theta) - C(\phi, X). \tag{4}$$

The above problem illustrates how contract design and information asymmetry may interact to affect a lender's expected profits. In particular, the lender chooses optimally the offer terms by taking into account loan the demand schedule L^* and the effect of ϕ on the take-up pool $\widehat{\Theta}$. First, ϕ affects the borrower pool $\widehat{\Theta}$ and the probability of consumers with X taking up the credit offer, $P(\widehat{\Theta}; \phi, X)$. Second, ϕ affects the lender's expected profit, net of funding cost r, denoted by $\pi(L^*, \phi, X, \theta, r)$ on the loan to a consumer with (X, θ).[10] Third, the nature of information asymmetry affects how the riskiness of the pool $\widehat{\Theta}$, and in turn, expected profits $\int_{\widehat{\Theta}} \pi dF(\theta)$, changes with ϕ.

Finally, the term C captures the cost of processing information and designing and mailing the offers—which may depend in part on the complexity of information and contract terms. With all of these considerations, the lender mails an offer to the set of consumers with observable characteristics X such that $\Lambda(X, r) \geq 0$.

2.2.2 Credit Scores, Bankruptcy Flags, and Other Borrower Information

Within the above framework, a classic result is that, under certain conditions, adverse selection may occur because unfavorable terms may drive out "good" prospective borrowers, leaving a gradually riskier pool of applicants. When the adverse selection risk is severe, the

[10] As an example, denote a default by $D = 1$ and 0 otherwise, the charge-off rate upon default by g, and the lender's funding costs by r. Then, $\pi(L^*, \phi, X, \theta) = \big((1 - \mathbb{I}^D)(1 + R) + \mathbb{I}^D(1 - g) - (1 + r)\big) L^*$.

credit market equilibrium may exhibit quantity rationing.

Lenders may address the information issue by collecting more information about borrower quality to better classify risk types and improve the pricing of credit risks. Indeed, the practice of using credit scores as a summary statistic of certain borrower characteristics (such as the length of credit history, lines of credit capacity, and prior use of credit) has become lenders' most important tool in credit underwriting and pricing (Pagano and Jappelli, 1993; Edelberg, 2006). In the context of the stylized model introduced above, credit scores can be interpreted as a statistic for a subset of observable consumer characteristics, X. Recent studies suggest that the use of credit scores reduces the level of asymmetric information in the unsecured lending market, leading to an increase in the amount of credit provided, and greater dispersion in loan terms (Athreya et al., 2013; Chatterjee et al., 2011; Einav, Jenkins and Levin, 2013).

Importantly, various types of information are not used in credit scoring. For example, by law, credit scores cannot use information on race, national origin, sex, and marital status. Further, credit scores may not use age, assets, or employment history. Thus, certain information beyond a credit score may be important as well for underwriting unsecured credit (Sanchez, 2010; Livshits, MacGee and Tertilt, 2010; Chatterjee et al., 2011; Narajabad, 2012).[11] Empirically, we test the importance of credit scores and other borrower characteristics on both extensive (offer likelihood) and intensive (offer terms) margins of lenders' credit card offer decisions.

While credit scores are designed to predict the likelihood of default over the subsequent period across a range of credit markets, some direct indicators of creditworthiness may be

[11] Narajabad (2012) and Sanchez (2010) focus on the impact of improvements in information technology on the quality of signals received by lenders. Intuitively, when credit rating technology is weak, the market cannot distinguish across risk types, and a pooling equilibrium arises. In contrast, if rating technology improves, then this information provides lenders with enough guidance to separate types. Narajabad (2012) shows that this improvement in screening leads to a large expansion of credit to low-risk borrowers, and a relatively smaller decrease of credit to higher-risk borrowers. Alternatively, Livshits et al. (2010) argue that financial innovation lowered the fixed cost of offering new contracts and helped spur growth in the market for unsecured credit. These improvements in credit rating technologies have a bigger impact on the extensive margin, as new lending contracts can target riskier borrowers. The expansion on the extensive margin leads to both increased borrowing and increased default.

valuable to unsecured lenders beyond their power in predicting default. For instance, theory suggests that making bankruptcy and debt discharge history information broadly available to the credit market may mitigate both adverse selection and moral hazard issues (Pagano and Jappelli, 1993; Padilla and Pagano, 2000; Ordonez, Perez-Reyna and Yogo, 2014). The main premise is that bankruptcy filers can be penalized by being denied for future access to credit markets for a long period of time or forever, increasing the costs of filing for personal bankruptcy.

From a lender's perspective in practice, however, a bankrupt consumer presents both a risk and an opportunity. On the one hand, bankruptcy records generally send a negative signal to lenders regarding consumers' risk and time preferences, their ability to manage debt, and the uncertainty of their income.[12] On the other hand, because bankruptcy allows for the discharge of most unsecured consumer debt, filers emerge from their bankruptcy proceedings with cleaner balance sheets than prior to filing. Moreover, the law's refiling restriction described earlier effectively prevents recent filers from repeatedly filing.

Thus, access to credit for borrowers with a default history presents an interesting subject for empirical analysis. Our estimates below of the dynamic impact of bankruptcy filing on credit card access can serve to provide sophisticated models of unsecured credit and default (e.g. Chatterjee, Corbae, Nakajima and Rios-Rull (2007) and Livshits, MacGee and Tertilt (2007)) with new moment conditions for additional calibration. More broadly, understanding the information set used by lenders allows for more accurate modeling of the partition between X and θ in the above framework, and establishes the scope for information asymmetry in light of the rapidly expanding use of "big data" in credit risk analysis.

[12] Bankruptcy not only signals borrowers' default risks, it may also alter borrowers' demand for credit, to which the terms of credit supply may react. Ex ante, information sharing affects debtors' default incentive in that $v(y_1)$ in eq. (1) depends on bankruptcy filing status. Ex post, like other consumers, bankruptcy filers need credit for smoothing consumption and facilitating transactions.

2.2.3 Credit Cycles and the CARD Act

Notably, how the quantity and terms of credit vary with borrowers' characteristics may also evolve over the credit cycle. Within the theoretical framework discussed above, credit cycles may manifest themselves through systematic changes in lenders' funding costs, r (see, e.g., Arnold and Riley (2009)) and the permissible contract sets, Φ, in that the bust of a credit cycle leads to increased cost of funds, and in turn reduces the set of non-negative NPV contracts. Accordingly, we hypothesize that the offer likelihood is more sensitive to marginal consumers during the bust of the credit cycle. Higher funding costs affect the intensive margin of credit contracts as well. For example, as shown in Arnold and Riley (2009) and Han (2004), equilibrium loan amounts tend to decrease and loan rates increase with the costs of funding. Therefore, we hypothesize that during the bust we should observe lower credit limits L^u and higher interest rate spreads R.

Regulation of the credit card industry is another key factor that influences the supply of credit. For example, regulation limiting the feasible contract space may reduce lenders' ability to design contracts with the nuance to separate types in the presence of information asymmetry. For instance, certain fees or interest charges may be designed to compensate for taking on heightened default risk or greater funding costs. Furthermore, regulation may also affect operating cost and capital costs.

In this context, we study the impact of the CARD Act on the supply of unsecured credit through changes in credit card offers. The CARD Act's impact on credit card lending has attracted a great deal of attention from both policymakers and academics. Our unique data on credit offers helps achieve better identification of the supply effect of the Act without relying on instrumental approaches to separate supply and demand. Because the CARD Act was implemented at a time when both the macroeconomy and unsecured credit market began to recover from the aftermath of the financial crisis, discerning the restrictive effects of the Act can be challenging. We therefore focus on a "difference-in-differences" thought experiment to compare the changes in credit card offers received by consumers across the credit score distribution and ask whether the CARD Act had a disproportionate effect on consumers with different levels of creditworthiness. We also use data on auto loan offers to provide a contrast (or "triple-difference" thought experiment) for the CARD Act's impact on the unsecured lending market, as the Act did not affect the regulatory environment of the auto lending industry.

2.2.4 Lenders' Strategies for Facilitating Separating Equilibria

Arguably, even with the most advanced information collection and screening technologies, unsecured lenders still face challenges related to information asymmetry and unobservable consumer risk. Lenders may further mitigate the adverse selection problem through more sophisticated contract designs. The key insight from the literature is that there has to be some costly and credible signaling device that low-risk types of borrowers are willing to pay, but high-risk types are not, resulting in endogenous separation by risk types in the equilibrium. Importantly, some commonly used screening devices, such as collateral (Bester, 1985), are not available for unsecured lending. Instead, unsecured lenders have to rely on alternative mechanisms to solve the information and limited commitment issues. These mechanisms may include various forms of exclusion on defaulted borrowers (e.g., Athreya and Janicki (2006) and Ordonez et al. (2014)), social stigma attached to loss of creditworthiness (Athreya, 2004; Livshits et al., 2010), and implicit collateral.[13]

Our empirical analysis focuses on a largely unexplored aspect of credit card lenders' contracting effort for achieving separating equilibria. Specifically, we exploit the panel structure of a subset of our data (discussed below) and examine the common strategy of sequentially sending distinct offers to the same consumer over time. If consumers only engage in a limited search for the best offers, such offer strategies will lead to a dispersed interest rate distribution even among consumers with similar characteristics, a pattern documented by Stango and Zinman (2013). One interpretation is that the extensive set of contract features

[13]For instance, most student loans are non-dischargeable in bankruptcy filing, effectively converting human capital into collateral in student lending.

in the permissible contract set Φ allows for sufficient dimensionality to allow borrowers with different types or different private information to self-select into their preferred contracts. Alternatively, credit card contracts are notoriously complex, and most consumers, even the most sophisticated ones, do not take the time to read the entirety of the credit card offers they accept (Agarwal, Chomsisengphet, Liu and Souleles, 2006; Agarwal, Driscoll, Gabaix and Laibson, 2011), instead focusing on the most salient aspects of the contract (Gabaix and Laibson, 2006; DellaVigna and Malmendier, 2004). Our panel data on card offers from the same lender to the same consumer provide an unprecedented look into how banks conduct screening to identify profitable borrower-contract matches in a market with information asymmetries.

3 Data and Summary Statistics

3.1 Data Description

Our main data source is Mintel Comperemedia's (henceforth "Mintel") proprietary survey on credit offers to U.S. consumers.[14] Our data span from January 2007 to June 2014, covering three distinct phases of the most recent credit cycle. The period between January 2007 to March 2008 largely covers the final episode of the credit boom.[15] The period between April 2008 and February 2010 covers the credit bust and early recovery prior to the full implementation of the CARD Act. Finally, the remainder of our sample (March 2010 to June 2014) covers the recovery period under the CARD Act.

On average, about 2,500 households participate in the Mintel survey each month by forwarding all incoming marketing mail, including offers for credit cards and auto loans, to Mintel and completing an extensive demographic questionnaire. After processing the

[14] 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.

[15] We choose March 2008 as the end of the boom because Bear Stearns was bailed out that month and the decline of credit card mail volume accelerated after that month. Our results are robust to alternative choices of the end of the credit boom.

forwarded mail offers, Mintel sends the database to TransUnion, one of the three major credit reporting agencies, where credit history information, including credit scores, of the individual consumers of the participating households is merged in. Thus, our data provide a unique combination of detailed information about credit card offer terms, credit history, and demographic and socioeconomic characteristics, which is rarely available in other data sources.

Prior to July 2011, the data consisted of a cross-section of households surveyed in each month. After that date, a longitudinal sample of 600 consumers on average replaced a portion of the cross-sectional sample.[16] Unlike the cross-sectional sample, however, we have only limited demographic and socioeconomic information—age, income, and homeownership—as of the month joining the panel for the consumers in the longitudinal sample. Therefore, the summary statistics and baseline analysis we present use only the cross-sectional sample. Meanwhile, we use the longitudinal sample to examine lenders' offer strategies, particularly contract dispersion, in offers made to the same borrower from the same lender.

To obtain a consistent sample, we restrict the cross-sectional sample to individuals who have a valid credit history, whose household income was between $10,000 and $200,000 (trimming the top and bottom 2.5 percent of the sample household income distribution), and who are between 20 and 60 years old. The final cross-sectional sample contains about 219,700 credit card offers that were sent to about 170,000 individuals in more than 105,000 households.

Columns (1) and (2) of Table 1 compare the demographics of the Mintel cross-sectional sample with those of the households in the 2007, 2010, and 2013 waves of the Survey of Consumer Finances (SCF) who meet the same income and age restrictions.[17] We find that Mintel sample households are broadly comparable with the SCF respondents, with the Mintel sample being, on average, somewhat older, having higher educational attainment and income, and more likely to be white, married, and homeowners. These differences are due partly to

[16]The panel is unbalanced, with more households added to the longitudinal sample over time.

[17]All statistics are estimated using the weights provided by Mintel and the SCF, respectively.

our sample restriction to only those Mintel respondents who have a valid credit history. Because the credit records are merged in using survey participants' names and addresses, homeowners, who tend to have more stable addresses, are more likely to have a successful merge.

The data merged by TransUnion contain rich information about Mintel respondents' debt balances and credit histories. Columns (3) and (4) of Table 1 compare selected attributes of the credit history in the Mintel data with those in the FRBNY CCP/Equifax data (a five percent random sample of U.S. consumers who have a valid credit history) between 2007 and 2013.[18] As the table shows, the liability and credit history characteristics of the consumers in the Mintel sample are broadly consistent with those in the FRBNY CCP/Equifax data, with the former having somewhat lower amounts of debt but more lines of revolving credit. The two samples are similar regarding the frequency of personal bankruptcy, serious delinquencies, and other derogatory records. Thus, on balance, the Mintel sample of participating consumers is fairly representative of U.S. consumers in terms of demographic and credit characteristics.

Finally, the TransUnion credit history data contain a credit score measure, the VantageScore.[19] Over the last 30 years, credit scores have become an increasingly prominent factor in consumer lending (see, for example, Federal Reserve Board (2007)). The VantageScore, which ranges from 500 to 990, is a product developed by the three major consumer credit reporting agencies. Consumers whose VantageScores are greater than 700 are often labelled as prime or superprime consumers, while those with a VantageScore below this level are typically referred to as nonprime or subprime consumers. The credit record information that is provided through the Mintel-TranUnion merge is similar to what a lender would receive through a "soft pull" of the credit record, a close approximation of the lenders' information set in the absence of an existing relationship with a consumer.

[18] See, for example, Lee and van der Klaauw (2010) for a more detailed description of the FRBNY CCP/Equifax data and a discussion of the data's statistical properties.

[19] Specifically, our data subscription includes scores based on the VantageScore 2.0 credit scoring model.

3.2 Mail Offers as a Measure of Credit Supply

Credit card offers in the Mintel data represent not only lenders' marketing efforts, but also their desired supply of credit given the information available and the economic conditions at the time of mailing. First, because it is costly to design and send an offer, it would inefficient for a lender not to provide credit unless the application reveals new information that lowers the expected profits below the lender's break-even point. Indeed, our conversations with lenders revealed that they typically conduct a complicated, multi-stage screening process, very similar to credit underwriting, in selecting credit card offer recipients. This costly process implies that, ex-ante, lenders treat offers as their committed supply of credit. See also our discussion in Section 2.2 on the lender's decision to extend a credit offer.

In addition, both the level and the change in the aggregate volume of mail offers are highly correlated with other indicators of the aggregate supply of unsecured credit. Specifically, total credit card mail volume (as estimated by Mintel) is highly correlated with the aggregate number of credit card accounts opened (estimated using data from the FRBNY CCP/Equifax). As shown in the upper panel of Figure 1, the two time series track each other very closely over the last ten years, with a correlation coefficient of about 0.9. Moreover, as indicated in the lower panel, the quarter-to-quarter change in credit card offer mail volume and the net-easing of credit card lending conditions reported in the Federal Reserve's Senior Loan Officer Opinion Survey on Bank Lending Practices (SLOOS)—a widely-used gauge of aggregate credit supply—are strongly positively correlated.[20]

That said, we caution that credit card offers are not exactly equivalent to credit supply in various aspects. Offers generally contain clauses to allow lenders to react to any new information provided by applicants or changing economic conditions. Thus, lenders have the option of not approving an application responding to an outstanding offer, even if these are so-called "pre-approved" offers. Even for an approved offer, the credit limit ultimately

[20]Note that the metric available in the SLOOS is the share of banks reporting a tightening or loosening of lending standards, which only roughly maps into direct measures of changes in mail volume. The two series have a statistically significant correlation coefficient of 0.45.

extended is not necessarily identical to the amount specified in the offer. In addition, discussions with various major credit card lenders suggest that the volume of mail offers is also affected by lenders' marketing strategies and budget limitations, which may not always reflect changes in willingness-to-lend.[21]

The Mintel database 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 our baseline analysis, we examine five key parameters of an offer—interest rates, credit limits, annual fees, promotional interest rates, and reward programs. Depending on whether charging annual fees and offering reward programs, a credit card can be categorized into one of the four types of card according to industry practice: plain vanilla (no fee, no reward), credit building (charging a fee, no reward), general market (no fee, having reward programs), and premium rewards (charging a fee, having reward programs).

To measure the price of credit, we focus on the so-called "go-to" interest rate—the regular non-promotional interest rate for purchases.[22] Regarding 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. Examining offers sent in 2007 that specified both a minimum and maximum credit limit, we find the two limits are positively correlated, with a Spearman rank-order correlation coefficient above 0.5.

Table 2 summarizes these characteristics of credit card offers in the Mintel sample. As

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[21]For example, the sharp decline of mail volume in the first quarter of 2012 was primarily due to the reduction in solicitations sent by two major credit card lenders that market participants attributed to shifts in marketing channels at these lenders.

[22]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 nonfilers and dynamics over the credit cycle. For more on interest rate pricing, see Ausubel (1991), Stango (2000), and Knittel and Stango (2003).

column (1) of the table indicates, on average, 50 percent of consumers receive at least one credit card offer in a given month.[23] Moreover, nearly 40 percent of consumers receive at least one general market (no fee but with rewards) offer while only 7.5 percent of consumers receive a credit building (with a fee but no rewards) offer. The offers on average have a regular purchase interest rate (the go-to rate) of 13.7 percent and a minimum credit limit of $1,158. In addition, roughly two-thirds of these solicitations offer introductory interest rates and rewards programs, whereas about 20 percent of the offers require an annual fee.

Columns (2) and (3) of Table 2 compare the offers received by prime (VantageScore$\geq$ 700) and nonprime (VantageScore$<$ 700) consumers. Prime consumers are more likely to receive an offer and the offers they receive are more likely to be general market and premium rewards (with a fee and rewards programs) offers, whereas nonprime consumers are much more likely to receive a credit building offer. Furthermore, offers received by prime consumers on average have lower interest rates, higher credit limits, and are more likely to offer introductory rates and rewards programs, but less likely to charge an annual fee. This simple split of the data suggests that credit score alone is a strong predictor of both the frequency and characteristics of credit offers; In the next section we explore these relationships in greater detail.

4 Screening in the Unsecured Credit Market

4.1 Baseline Model of Offer Likelihood

We begin our analysis with an exploratory model that examines what characteristics influence a consumer's chances of receiving an offer in a given month and the terms contained in the offers received. The stylized framework in Section 2.2 suggests that lenders' offer decisions depend on consumers' characteristics (including their credit scores), macroeconomic conditions, and the regulatory and legal environment. We estimate the following model for

[23]Not shown in the table, among those consumers who received offers, the average number of offers is 2.5 per month.

the likelihood of receiving an offer (using a probit specification) and for the offer terms conditional on offer receipt (using OLS and probit where applicable) for consumer i in state j in month t:

$$Y_{ijt} = f\left(VS_{it}, Flag_{it}, Attr_{it}, Demo_{it}, Law_{jt}, Econ_{jt}, \delta_t \right) + \epsilon_i \tag{5}$$

To allow for nonlinear effects of credit scores on the supply of unsecured credit, we specify the effects of credit scores VS_{it} nonparametrically by including dummy variables for 50-point bins in VantageScore. A prominent question is if lenders use credit scores alone in screening borrowers or also take into account other factors both in and out of a consumer's credit report. To keep our model parsimonious, we include a relatively small set of key credit attributes in the model. Of note, such variables are also likely used for estimating the VantageScore. Because we control for the effects of the VantageScore in a highly flexible way, we argue that the effects estimated reflect the additional weight lenders put on these credit history variables on top of their impact on the VantageScore.

Specifically, we include a set of dummies, $Flag_{it}$, indicating flags of adverse credit events—personal bankruptcy, severe derogatory records (e.g. debt collection or foreclosure), deep debt delinquencies (90 days and longer), and recent debt delinquencies within the previous 24 months. In addition, we include a set of credit attributes, $Attr_{it}$: the total debt-to-income ratio to reflect general indebtedness (Johnson and Li, 2010), a dummy for having credit cards, a dummy for high credit card utilization (the ratio between outstanding balances and credit limits over 80 percent), and the number of credit inquiries over the past six months. Including the number of credit inquiries, usually associated with a loan application, helps shed light on whether lenders' actions respond to variations in credit demand.

Furthermore, we explore whether consumers' demographic and financial characteristics, $Demo_{it}$, affect lenders' decisions by including age, marital status, family size, race, educational attainment, homeowner status, and income.[24] We are also interested in whether

[24]These characteristics are collected and made available to us by Mintel. Some of these characteristics,

lenders' credit card mailing decisions are influenced by the legal conditions (such whether state law is more favorable to borrowers in the event of default), Law_{jt}, and economic environment, $Econ_{jt}$, of the consumer's state of residence. Specifically, we include in the model state-level property and homestead bankruptcy exemptions, and state unemployment rates. Finally, we include year and month fixed effects, δ_t, to control for aggregate macroeconomic and credit market conditions and potential seasonal effects.

4.2 Baseline Model Results

In column (1) of Table 3, we report the estimated marginal effects of the probit model of offer likelihood covering the full sample period (2007–2014). First, as expected, consumers with higher credit scores are, on balance, more likely to receive a credit card offer in a given month. Consumers in the highest VantageScore bin (> 950) are 26 percentage points more likely to receive an offer than consumers in the lowest score bin (< 550). Also, we note that the relationship between the VantageScore and the likelihood of receiving an offer is nonlinear and non-monotonic, as consumers with VantageScores between 750 and 850 are most likely to receive an offer.

In general, unsecured credit is more plentifully offered to higher credit score individuals. However, it is interesting to note that the VantageScore effects on the likelihood of receiving an auto credit offer are substantially different from those for credit card offers. Estimating a similar model of auto credit offers using the Mintel data, we find that consumers with VantageScores greater than 750 are less likely to receive an offer and consumers with VantageScores between 600 and 650 (subprime consumers) are most likely to receive an auto credit offer (shown by time period in Figure 3). The differences likely reflect, in part, that credit card loans are unsecured and credit risk represents a more important factor in the offer decision relative to auto loans, which are secured by the car purchased. This dependency

such as race and gender, are prohibited by law (ECOA) from being used by lenders in credit transactions. The estimated effects of these characteristics may reveal the degree to which lenders use these variables directly, or legitimate variables that are correlated with them in determining credit card mailing strategies.

on credit risk highlights a unique feature of the unsecured lending market relative to other secured lending markets.

Despite the fact that we allow for a very flexible specification of the effect of credit scores on offer probabilities, other credit history variables nonetheless have a significant impact on the likelihood of receiving an offer. In particular, consumers with personal bankruptcy flags or other severe derogatory records are about six percentage points less likely to receive an offer. In addition, consumers with severely delinquent accounts are three percentage points less likely to received an offer, while having a recent delinquent account also has a small but statistically significant negative effect. On net, lenders are more likely to extend offers to consumers who have existing credit card accounts but less likely to extend offers to those who have high utilization rates (higher than 80 percent) on existing cards. Moreover, recent credit inquiries appear to have a small positive effect, suggesting that lenders may be more likely to extend offers to consumers who have actively applied for credit in recent months.

Interestingly, several socioeconomic characteristics also appear to influence lenders' offer decisions, even after controlling for credit histories. Notably, white consumers are almost three percentage points more likely to receive an offer than otherwise identical nonwhite consumers. In addition, homeownership, college education, and higher household income all boost the likelihood of receiving an offer. Indeed, our finding motivated Firestone (2014) to explore possible explanations for this disparity, including, but not limited to, the existence of omitted variables, model misspecification, or disparate impact in lenders' marketing strategies. Therefore, while the use of some socioeconomic variables, such as race, is prohibited, the driving factors behind these results warrant further research.

Finally, state laws and local economic conditions appear to have significant effects on lenders' credit card mailing decisions. For example, our estimates indicate that a one percentage point increase in a state's unemployment rate implies a 1.6 percentage point reduction in the likelihood of receiving an offer. This result is broadly consistent with Hsu et al. (2014) who find a higher volume of credit card mailings in states with more generous unemployment benefits. In addition, we find that a $100,000 increase in homestead and property exemptions in personal bankruptcy filings imply a 0.3 and 3.5 percentage points reduction in the chances of receiving an offer, respectively. These estimates provide new support to an extensive literature on the impact of the bankruptcy option on credit availability (see, e.g. Gropp, Scholz and White (1997)).

4.3 Results on Offer Terms

We now turn our analysis to the factors lenders potentially take into account when deciding the terms in their credit card offers. We examine how the same set of credit, demographic, and financial characteristics, as well as state-level legislative and economic conditions, affect the quantity and price of credit and other features of the offer. Specifically, we consider the following terms in the offer—minimum credit limits, interest rate spreads, and whether the contract includes an introductory teaser interest rate, an annual fee, or a rewards program.[25] The minimum credit limits and interest rate spreads models are estimated using OLS regressions, while models of whether having teaser rates, annual fees, and rewards programs are estimated using probit regressions.[26]

As shown in columns (2) through (6) in Table 3, offer terms are generally improving as credit scores increase. Although the relationships are not monotone, in part because of the presence of "premium rewards" cards that charge an annual fee, the pattern over the score distribution is consistent across offer terms. The estimated coefficients of other variables are broadly consistent with those in column (1). For example, conditional on credit scores, offers to consumers with bankruptcy flags and derogatory public records have lower credit limits, while offers to consumers who are white, have higher educational attainment or higher

[25] As discussed in Section 3, the vast majority of credit card offers mailed during our sample period specify only a minimum credit limit. Moreover, we consider interest rate spreads (relative to the two-year Treasury yield) instead of interest rate levels to take into account variation in risk-free rates.

[26] Because the distribution of minimum credit limit and interest rate spread is bounded at zero, we also estimated these specifications using Tobit models, which yielded results similar to the OLS estimates (not shown).

income have higher credit limits.[27] The results with respect to the pricing variables reveal a similar pattern. Offers to consumers with credit scores between 550 and 600 seem to have the least favorable terms—higher interest rate spreads, greater likelihood of having an annual fee, but lower likelihood of having a teaser rate or rewards program.

Notably, despite our extensive set of explanatory variables and flexible specifications, our models explain only a relatively small portion of the overall variation in contract terms. For instance, the largest R-squared we obtain in the model is for the interest rate spread, where we can explain only 35% of the variation using observable borrower and geographic characteristics (and time fixed effects). Our low R-squareds are remarkable because the amount of information we use is similar to what a lender would have at its disposal in screening a consumer without a prior business relationship. This large amount of unexplained cross-sectional variation in offer prices may reflect the practice of lenders varying contract terms to induce borrowers to reveal private information through self-sorting, a hypothesis that we test later using our longitudinal sample.

4.4 Evidence from the Longitudinal Sample

So far we have demonstrated that credit scores are one of the most important indicators that lenders use in determining credit card offers for a cross-section of borrowers. Do lenders also monitor a borrower's credit score over time and dynamically adjust their offers accordingly? In answering this question, we explore the longitudinal sample of the Mintel data, containing 13,800 offers to more than 600 households over a three-year period (July 2011 to June 2014). Compared to the cross-sectional sample, which we used in Table 3 above, the longitudinal sample has very limited socioeconomic information. However, the advantage of the panel data is that we can include consumer fixed effects in our specifications, which negates the need for time-invariant household characteristics.

[27] The notable exception is the coefficient of personal property exemption level in bankruptcy filings. Our results indicate that offers to consumers living in states with higher exemption levels are less likely to receive an offer, but conditional on receiving an offer, these consumers tend to receive offers with higher credit limits.

Accordingly, we estimate a panel regression model of how changes in a consumer's credit score affects his likelihood of receiving credit card offers and the terms therein, controlling for consumer fixed effects. The results are reported in Table 4. Our estimates indicate that lenders monitor borrowers' credit scores and use the new information for credit card offer decisions. In particular, for the same consumer, a 100 point increase in credit score implies the probability of receiving an offer in a given month to be higher by 4 percentage points, the minimum credit limit higher by almost $240, and interest rate spread narrower by nearly 100 basis points. In addition, improved credit scores also boost the chances of receiving credit card offers with reward programs. However, changes in credit scores do not appear to influence other offer terms such as introductory interest rate promotions and annual fees. Overall, these results suggest that lenders respond to changes in consumers' credit positions, and indeed adjust their offers accordingly. In Section 7, we further explore the longitudinal patterns in lender screening by examining multiple distinct offers made by the same lender to the same borrower.

5 Lenders' Responses to the Credit Cycle and the CARD Act

We now examine how the supply of unsecured credit responds to credit cycles and the CARD Act by taking advantage of three distinct periods covered by our Mintel data. Figure 2 presents the changes in the likelihood of receiving a credit card offer in a given month by VantageScore bin over the three phases (boom, crisis/pre-CARD Act, post-CARD Act). The figure shows that the VantageScore gradient in the likelihood during the boom period of January 2007–March 2008 (the solid blue line) was remarkably flat. Indeed, 40 percent of consumers with the worst credit scores (VantageScore below 550) received a credit offer in a given month, compared to 60 percent of consumers with the best credit scores (VantageScore above 950). If anything, consumers in the subprime and near-prime range of the

VantageScore distribution, between 600 and 750, were *more* likely to receive an offer 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, a trend also shown in other credit markets (Adams et al., 2009; Mian and Sufi, 2009).

In the wake of the crisis, April 2008–February 2010, access to unsecured credit dropped precipitously, as lenders cut existing lines and significantly curtailed credit card mail offers. The overall likelihood of a consumer receiving an offer in a given month fell from 60 to 35 percent, but this decrease was not felt evenly over the credit score distribution. As shown in the figure, the VantageScore gradient steepened sharply during this time period, the orange line, with consumers at the top of the VantageScore distribution becoming about five times more likely to receive an offer than those at the bottom.

The overall volume of credit card mail offers has steadily recovered since early 2010, but the recovery has been uneven across the credit score distribution. As indicated by the purple line, following the implementation of the CARD Act (March 2010–June 2014), the likelihood of receiving an offer increased for consumers with credit scores above 650. However, those located in the bottom of the credit score distribution did not see any improvement in their odds of receiving an offer. In addition, the improvement for consumers with credit scores between 650 and 750 is more subdued relative to those with higher credit scores. On balance, compared to the orange line, the purple line represents a steeper credit score gradient, implying a wider gap in the likelihood of receiving an offer between the most and the least creditworthy consumers. The trends shown in this figure provide new evidence of the uneven patterns of access to unsecured credit during the boom and bust.

Notably, the lack of growth in credit card offers to consumers with greater credit risks after the CARD Act suggests that the Act may have reduced the supply of credit. Such an inference may be complicated by the concurrent broad credit market recovery. As a parsimonious approach to "control" for the broad market effect, we use our Mintel data to examine offers of auto loans, a type of consumer credit that is not covered by the CARD

Act, but may move with the aggregate improvements in credit markets over this period. As shown in Figure 3, the likelihood of receiving an auto loan offer improved after 2010 across almost the entire credit score spectrum. Moreover, consumers with subprime credit scores (between 600 and 650) consistently have the *best* chance of receiving an auto loan offer through the entire credit cycle. This contrast with auto lending underscores that the supply of unsecured consumer credit is more dependent on evaluation of credit risk, which is likely more sensitive to credit cycles, and highlights the isolated effects of the CARD Act on the credit card industry.

Not only the odds of receiving an offer but also the price of offered credit changed substantially across the credit score distribution over the credit cycle. Figure 4 presents the spreads of offered regular purchase interest rates over the yield on two-year Treasury securities. We find that spreads widened significantly during the financial crisis and the early phase of recovery before the CARD Act, with larger increases for consumers with lower credit scores. Such a shift in offered interest rates likely reflects the tighter credit supply during this period, in particular for consumers with less-than-pristine credit records. Furthermore, despite the ensuing general improvements in financing conditions, spreads widened even more after the implementation of the CARD Act over the entire credit score distribution, with the increases being particularly pronounced for consumers with lower credit scores. This result is largely consistent with the hypothesis that lenders raised interest rates on new credit card contracts in part responding to provisions of the Act that made such lending more restrictive and unsecured debt more difficult to subsequently re-price.

In related work, Agarwal et al. (2015) examine a large set of credit card accounts and do not find that interest rates increased following the implementation of the CARD Act, despite the reduction in lenders' fee revenues. Notably, our analysis focuses on credit card offers while Agarwal et al. (2015) focus on existing accounts. Hence, one way to interpret the complementary findings is that the two studies jointly suggest that borrowers became more selective in accepting credit card offers, the substantial reduction in credit card mail offer volume notwithstanding. A heightened selectiveness by consumers during this time period is in turn broadly consistent with the well-documented phenomenon of household balance sheet deleveraging (Mian et al., 2013).

Apart from wider interest rate spreads, other terms in credit card offers extended after the financial crisis, before or after the CARD Act, did not appear to be more stringent than those in the offers sent during the era of credit boom. Indeed, as shown in the upper left panel of Figure 5, the average credit limit in the offers sent during the credit bust and recovery period before the CARD Act (the red curve) was almost identical to that in the offers sent during the credit boom (the blue curve) except for a moderate reduction among consumers with VantageScore higher than 850. Furthermore, credit limits increased across the credit score distribution after the CARD Act.

In addition, the other panels of Figure 5 show no evidence that the offers sent after the credit boom ended had worse terms, including introductory interest rates, annual fees, or rewards programs, either before or after the implementation of the CARD Act. For example, the lower left panel indicates that the share of credit card offers with an annual fee did not increase during our sample period. Consistent with Agarwal et al. (2015), this share declined significantly for consumers with VantageScores below 650 after the implementation of the CARD Act. In addition, the post-CARD Act offers were more likely to contain introductory teaser interest rates and rewards programs than the pre-CARD Act offers, with the changes being more pronounced for consumers with a lower VantageScore.

In sum, our results suggest that lenders' responses to the credit crunch appear to primarily focus on whether to extend an offer and the regular purchase interest rate. In contrast, credit offers mailed during the bust became somewhat more favorable regarding credit limits and other salient terms. This finding is consistent with the notion that during this period, lenders' main concern was borrowers' elevated default risk, which led lenders to sharply reduce the volume credit card offers. However, for consumers deemed as creditworthy based on observables, lenders appeared to have sent them more attractive offers, potentially reflecting both heightened competition for low-risk customers and responses to the requirements of the CARD Act.

6 Conspicuous Credit History: The Case of Bankruptcy Flags

Our credit card offer data reveal that lenders take into account borrowers' credit history information in a sophisticated way when making offer decisions. We further illustrate this practice by examining how consumers' personal bankruptcy flags affect the offers they receive. To the extent that bankruptcy flags are generally interpreted as signaling heightened default risks, examining credit card offers to personal bankruptcy filers presents a unique perspective for understanding the supply of unsecured credit, in particular to high-risk borrowers. Furthermore, such an analysis sheds light on the economic costs of filing for personal bankruptcy, which should include not only the expenses related to the filing itself but also the costs associated with any limited accessibility to credit markets post-filing. In this regard, our results inform the literature that examines the household bankruptcy decision and provides useful summary measures and moment conditions for calibrating dynamic general equilibrium models developed in recent years for studying unsecured credit markets.[28]

We first document that consumers are not excluded outright from the unsecured credit market after filing for bankruptcy, even in the aftermath of the most severe financial crisis in recent history. The Mintel data suggest that, on average, nearly 40 percent of consumers with a history of personal bankruptcy receive at least one credit card offer in a given month. We find both anecdotal and statistical evidence that offers to consumers with a bankruptcy history are not the result of a non-discriminatory "blanket campaign." Rather, some lenders design their offers specifically to such consumers, further demonstrating that lenders take

[28]See, e.g., Fay et al. (2002), Gross and Souleles (2002*b*), Keys (2010), Dick and Lehnert (2010) for empirical work on personal bankruptcy, and Li and Sarte (2006), Chatterjee et al. (2007), and Livshits et al. (2007) on theoretical advances in this area.

information on borrowers' credit history besides their credit scores into account.[29] As the estimates in Table 3 suggest, the likelihood of a filer receiving an offer is, on average, only moderately (six percentage points) lower than a non-filer with comparable observable characteristics, including credit scores. That said, despite relatively small differences in the probability of receiving a credit card offer, offers to filers tend to have lower credit limits, higher interest rates, and fewer take-up incentives than offers to their non-filer counterparts.

Lenders' use of bankruptcy filing status in screening consumers not only focuses on whether a consumer has a bankruptcy history, but also the time elapsed since the previous filing. As discussed in Section 2, U.S. bankruptcy law (BAPCPA) prohibits repeated debt discharge within eight years after the previous Chapter 7 filing. Therefore, while in general a filer's credit score gradually recovers after bankruptcy filing, such a borrower potentially represents a greater default risk as time elapses and he approaches discharge re-eligibility. To explore how time since previous filing influences lenders' credit card offer decisions, we modify equation (5), replacing the filer dummy with a vector of three dummies—"recent" filer (filer within the last two years), "seasoned" filers (filed two to five years ago), and "remote" filers (filed more than five years ago). The estimated coefficients of these three dummies regarding each of the six outcome variables are reported in Table 5.

The results regarding the likelihood of receiving an offer (column 1) show that, consistent with the implications of the restrictions on repeated debt discharge, lenders appear to view recent filers as carrying lower credit risk. Borrowers who filed for personal bankruptcy within the previous two years are no less likely than similar nonfilers to receive an offer in a given month, while those who filed more than five years ago are 12 percentage points less likely to receive an offer. Nonetheless, conditional on receiving an offer, the offers to remote filers are more favorable than those to recent filers (though they are mostly worse than offers to nonfilers). For example, comparing the estimated marginal effects of a recent bankruptcy filer with those of a remote filer in columns (2)–(5) of Table 5, we find that offers to remote

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

filers have interest rate spreads that are, on average, about 130 basis points lower, are more than 10 percentage points less likely to impose an annual fee, and are about 20 percentage points more likely to include a rewards program.

We further contrast how the filer-nonfiler disparity evolved over the credit cycle by estimating the above model separately for the three distinct episodes of time in our sample. We present the results of the likelihood of receiving a credit card offer in Table 6. Column (1) repeats the same result shown in Table 5 as a reference point. As shown in columns (2)–(4), recent filers were 8 percentage points *more* likely to receive an offer than otherwise comparable nonfilers during the credit boom, whereas remote filers were 5 percentage points less likely. The favorable treatment of recent filers largely persisted even during the depths of the credit crunch (April 2008–February 2010). However, the pattern appears to have changed substantially during the post-CARD Act era, when recent filers lost their edge in receiving credit card offers relative to nonfilers, while the gap between remote filers' likelihood of receiving an offer and that of comparable nonfilers became ever larger. This result suggests that the CARD Act made lenders more concerned about the credit risks born by bankruptcy filers, even those who filed very recently and are not eligible for debt discharge in the near future, possibly due to limitations on re-pricing debt. These findings highlight one example of how information on a conspicuous credit risk may influence lenders' offer decisions, and support the view that credit underwriting in the unsecured market changed sharply during the Great Recession to reduce the supply of unsecured credit for risky households.[30]

7 Lenders' Sophisticated Screening Efforts

Although lenders observe detailed credit histories of potential borrowers (as in our data), and therefore can infer a great deal about borrowers' likely demand for and use of unsecured credit, the unobserved heterogeneity among potential borrowers remains substantial. Our

[30]In results not shown, we find that after the implementation of the CARD Act, credit card offers to filers have interest rates spreads nearly 300 basis points higher than nonfilers with similar credit profiles, and are 20 percentage points more likely to require an annual fee.

analysis indicates that lenders commonly send the same consumer credit offers that contain distinct terms so that consumers with unobserved characteristics may sort themselves into different contracts. Our results suggest that lenders may use this approach as a strategy to facilitate achieving separating equilibria.

We first focus on the monthly cross-sectional sample of consumers, which we used above in our baseline analysis. We define two offers as "distinct" if they have different specifications regarding at least one of the following five contractual terms: regular purchase interest rate, minimum credit limit, annual fee, introductory interest rate, or rewards program. As shown in columns (1) and (2) in Table 7, 22 percent of consumers receive distinct offers in a given month. Notably, 11 percent of consumers received distinct offers extended by the *same lender* in the same month.

The difference in credit terms across offers to the same consumer are substantial, corroborating the results of Stango and Zinman (2013). For example, among all distinct offers a consumer receives in a given month, the average max-min difference is 370 basis points for regular purchase interest rates, and nearly $1,200 for minimum credit limits. Even among the distinct offers sent from the same lender, such differentials remain significant, at 210 basis points and $1,126 respectively. Moreover, 30 percent of consumers received offers sent by the same lender that contain different terms regarding introductory interest rates, 19 percent with different annual fees (including $0), and 45 percent with differences in the availability of reward programs.

Exploiting Mintel's longitudinal sample of consumers, we further study how the practice of sending distinct offers to the same consumer plays out over a longer time period. As shown in column (3) of Table 7, more than half of consumers in the longitudinal sample received distinct offers from the same lender within six months. The differences in credit terms widens among offers received over a longer period, with the max-min differences of regular purchase interest rates and minimum credit limits reaching 540 basis points and $1,400 on average, respectively. Notably, almost none ($< 1\%$) of the increase in the dispersion of credit terms can be accounted for by within-borrower variation in credit scores over the six-month time period, suggesting that lenders are sequentially experimenting with distinct offers to search for potential borrowers' revelation of private information.

Finally, we examine how the likelihood of receiving distinct offers extended by the same lender and the offered term dispersions vary with borrower characteristics—their credit scores in particular. Specifically, for each consumer in the longitudinal sample, we calculate his six-month average credit score. We then estimate models that associate the odds of receiving distinct offers and term dispersions with average credit scores. The results are reported in Table 8. We find that consumers with higher credit scores are more likely to be the target of distinct offers. As shown in column (1), a probit regression indicates that a one-standard deviation increase in credit scores implies a 67 percent higher chance of receiving distinct offers sent by the same lender within six months. That said, conditional on receiving distinct offers, the dispersion of credit terms, on balance, is smaller among offers extended to consumers with higher credit scores. For example, as shown in column (2), the max-min difference in offered regular purchase interest rates narrows by 1.75 percent for consumers with credit scores 100 points higher.

For discrete offer term variables (such as whether the offer includes a promotional introductory rate, annual fee, or rewards program), we construct a Herfindahl index to measure offer term dispersion. Specifically, if λ is the fraction of the offers sent by the same lender containing a certain term, then the Herfindahl index is calculated as $\lambda^2 + (1-\lambda)^2$. A higher Herfindahl index indicates more similar offers regarding this particular term. As shown in columns (5) and (6), higher credit scores are associated with higher Herfindahl index regarding annual fees and reward programs, with the effect being statistically significant. The only exception is that consumers with higher credit scores appear to receive offers with more dispersed minimum credit limits (column 2).

On balance, our results are consistent with the notion that consumers with higher credit scores are more likely to be the targets of competition among lenders. These consumers may have more unobserved heterogeneity with respect to profitability that lenders are trying to separate using more dispersed terms in their offered credit card contracts. The restrictions of the CARD Act may also have heightened competition for these lower-risk borrowers. These findings provide an unprecedented look into how lenders conduct sophisticated screening to identify profitable borrower-contract matches in a market with information asymmetries. By varying contract features, sometimes substantially, over a relatively short period of time, lenders effectively create a "menu" of contracts into which consumers self-select.[31]

8 Conclusion

Lenders of unsecured credit face the challenges of information asymmetry and limited commitment without the luxury of collateral as a screening device or protection against default. Characterizing how credit card lenders use screening and contract design to mitigate these challenges, particularly in a changing economic and regulatory environment, advances our understanding of credit markets and potentially provides policy guidance regarding regulation of the credit card industry. In this paper, we take advantage of a unique new dataset of over 200,000 credit card mail solicitations to directly observe credit card access and offer terms. The administrative linkage of these credit offers to borrower credit histories allows us to examine effectively the same set of creditworthiness characteristics that a lender (without a pre-existing relationship) would obtain on a "soft pull" of a consumer's credit record. Although it is generally quite difficult to identify credit supply *per se* from observed variation in equilibrium prices and quantities, this dataset provides an unprecedented proxy for credit supply in the credit card market.

While we confirm the conventional wisdom that credit card lenders use credit scores as their central screening device, we also provide new evidence that lenders also take into account a substantial array of other information on borrowers' credit histories and financial

[31] An alternative view is that consumers may not be especially attentive to the details of the contract, and lenders thus alter contract features in order to adjust the salient aspects of the contract, while "shrouding" other costly contract features (Gabaix and Laibson, 2006; Bordalo, Gennaioli and Shleifer, 2013).

and demographic characteristics beyond their effects on the calculation of the credit score. For instance, lenders use a dynamic measure of the recency of bankruptcy filing to influence the contract offers they mail to consumers. We also find that lenders extend multiple, distinct offers to the same consumers over a relatively short period, consistent with the predictions of search theory or endogenous separation in a sorting equilibrium with information asymmetry.

The recent credit cycle had an enormous impact on the volume of credit card offers, which peaked at nearly 2 billion per quarter in 2007 and fell by a factor of four by mid-2008. We find that subprime offers were prevalent during the peak years of credit expansion, but that this segment of the market contracted most sharply during the downturn. Thus the balance-sheet recession and need for deleveraging has not been felt evenly across the credit score distribution. Despite this contraction, however, even the riskiest households maintained some access to new credit offers in the midst of the Great Recession.

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 likely affected the supply of unsecured credit to increasingly risky borrowers. Understanding the impacts of these specific drivers of cyclical dynamics remains a promising area of future research.

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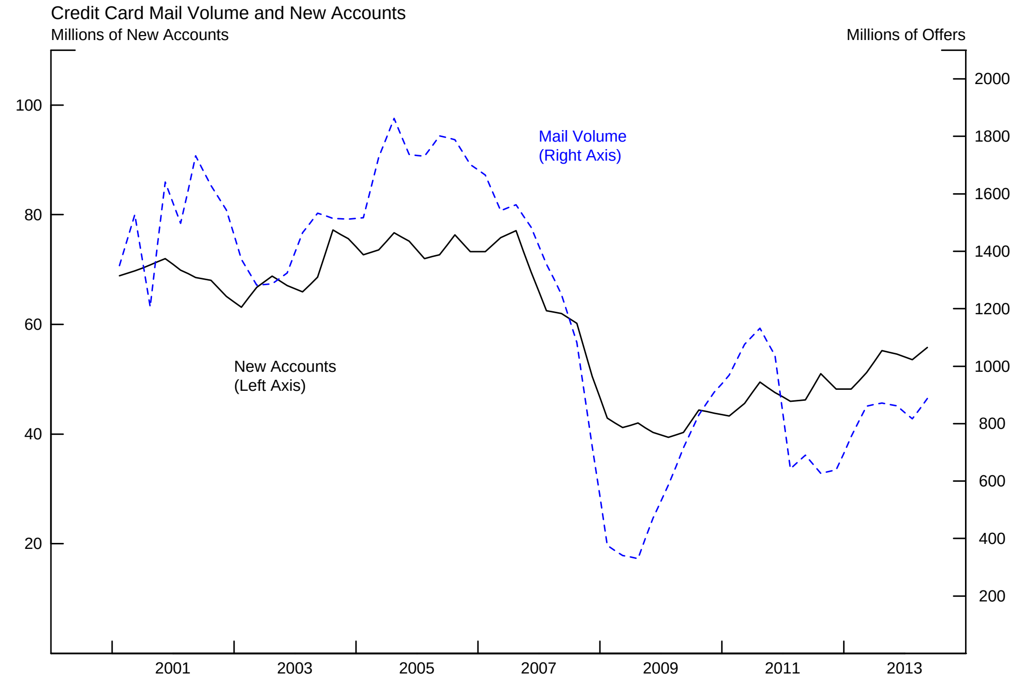
Figure 1: **Credit Card Solicitation Volume, New Accounts Opened, and Lending Standards**

The figure shows how credit card solicitation volume tracks other measures of credit access. The top panel shows the time series of total credit card solicitation mail volume in the U.S. from 2001:Q1 through 2014:Q2 using the Mintel data and the number of new credit card accounts opened estimated using the FRB/NY Equifax Consumer Credit Panel. The two time-series show a strong common pattern, with a correlation coefficient of 0.9. The bottom panel shows the quarter-over-quarter change in credit card solicitation volume and bank-reported changes in lending standards from the Senior Loan Officer Opinion Survey (SLOOS). The two series are again highly correlated.



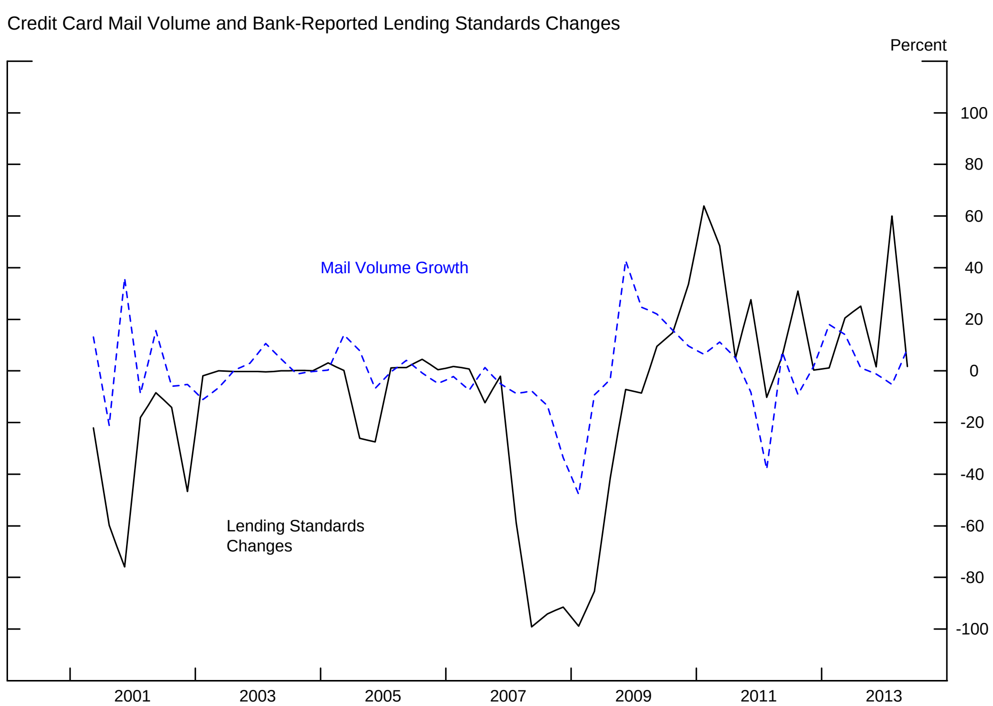


Figure 2: **Likelihood of Receiving an Credit Card Offer by VantageScore over the Recent Credit Cycle**
The figure presents the relationship between the likelihood of receiving a credit card offer (in a given month) and credit scores, separately for three time periods. The blue line shows the relationship during the boom period (January 2007–March 2008), which was flat over the distribution of credit scores, and if anything peaked among subprime borrowers. The yellow line shows the "offer curve" for the post-crisis period but before the CARD Act was implemented, April 2008–February 2010. In this period, the likelihood of receiving an offer became increasingly correlated with credit score. In the final post-CARD Act period (March 2010–June 2014), the association between creditworthiness and credit access as measured by the likelihood of receiving a credit card offer only strengthened. Consumers with the lowest credit scores were even less likely to receive an offer in this most recent period. Shaded bands represent 95 percent confidence intervals.

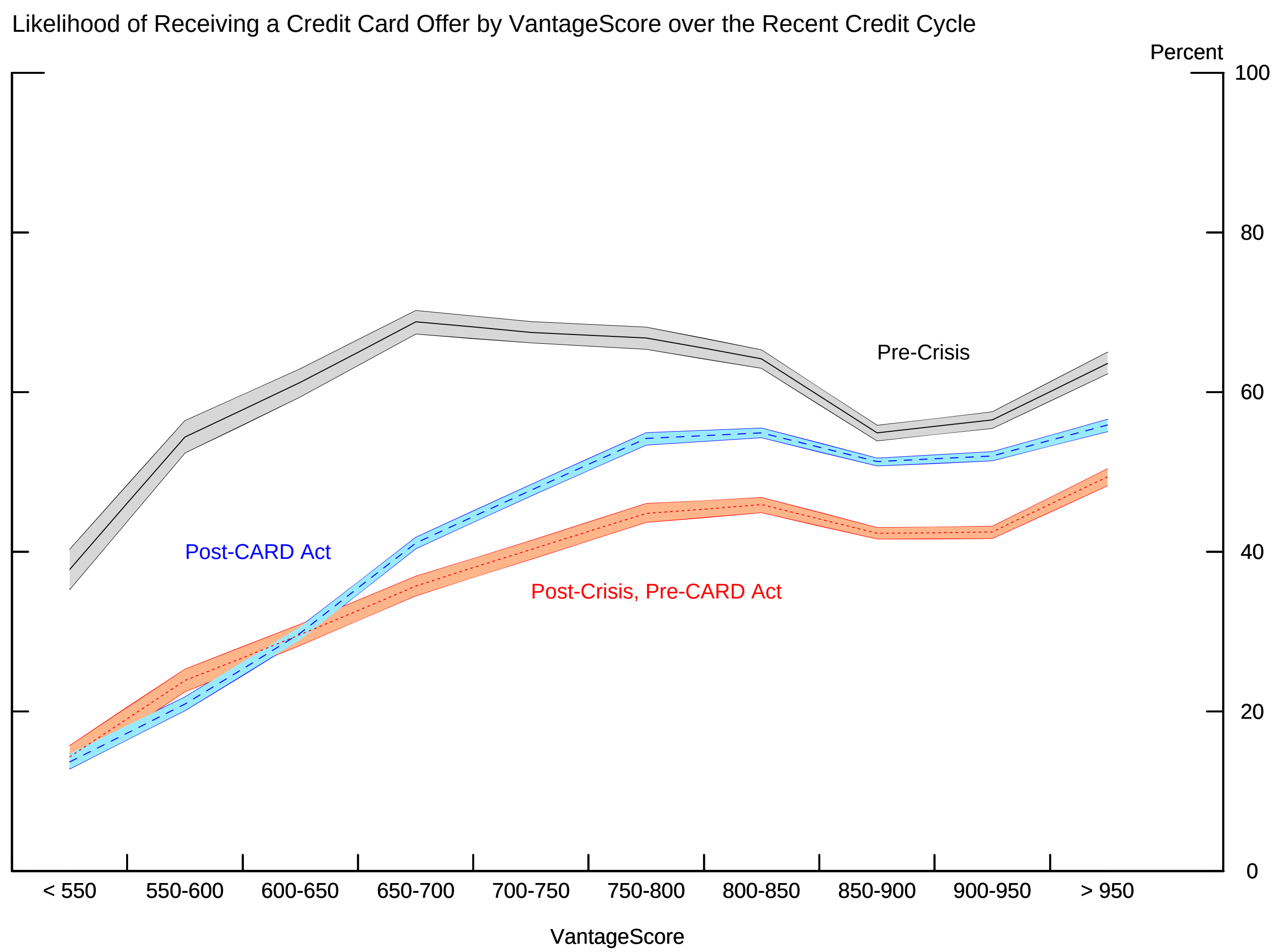


Figure 3: **Likelihood of Receiving an Auto Loan Offer by VantageScore over the Recent Credit Cycle**

The figure presents the relationship between the likelihood of receiving an auto loan offer (in a given month) and credit scores, separately for three time periods. The three time periods represent the credit boom (January 2007–March 2008), the credit crunch period prior to the implementation of the CARD Act (April 2008–February 2010), and the post-CARD Act period (March 2010–June 2014). In contrast to the unsecured credit market, auto loans are more commonly targeted at subprime borrowers, as lenders can rely on repossession of the collateral backing the loan. The pattern in the figure suggests that the auto loan market improved for all consumers between the depths of the crisis and the recovery period.

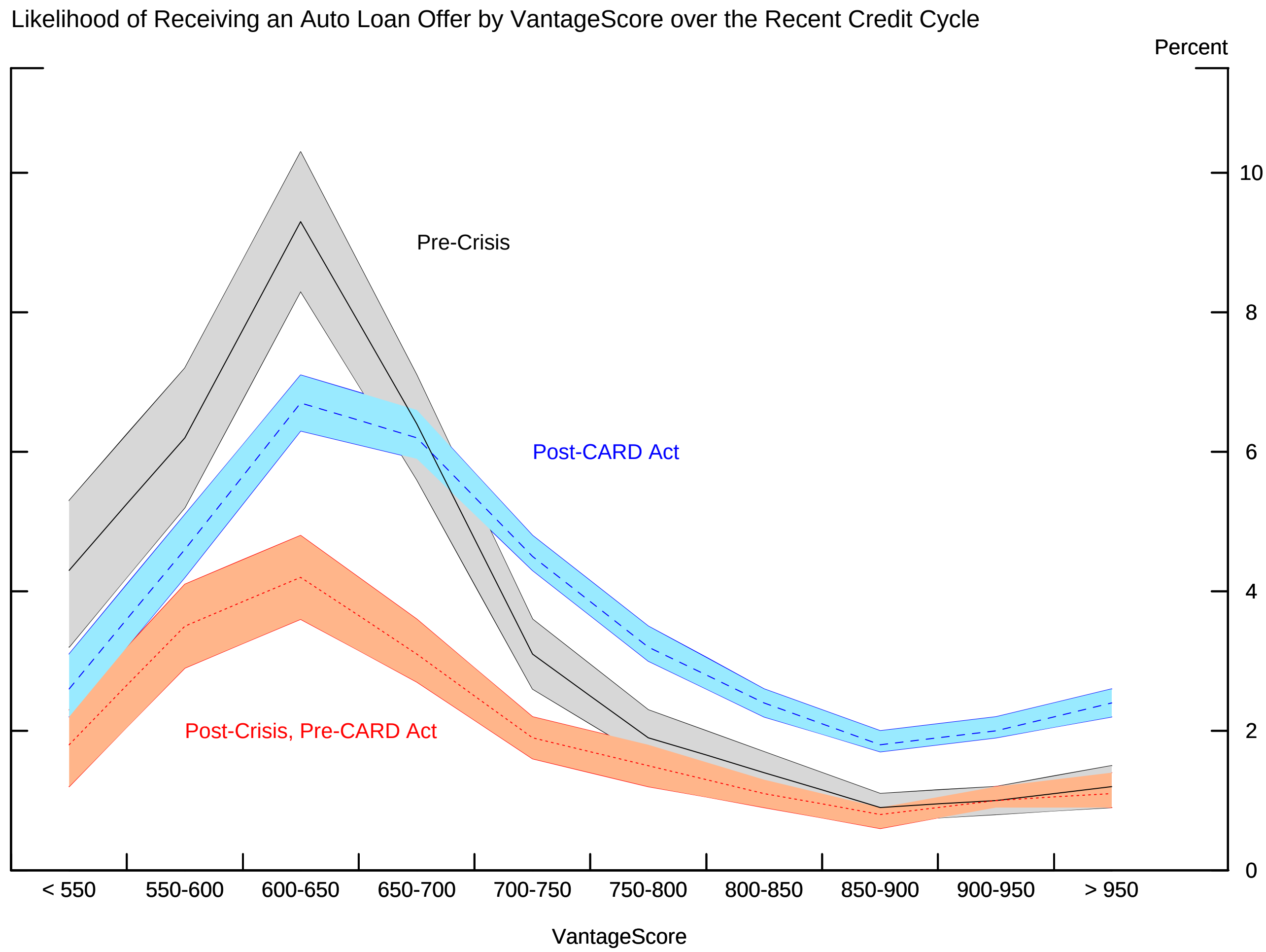


Figure 4: **Spreads of Interest Rates Offered by VantageScore over the Recent Credit Cycle**
The figure presents the relationship between interest rate spreads on credit card offers and credit score, separately for three time periods. The three time periods represent the credit boom (January 2007–March 2008), the credit crunch period prior to the implementation of the CARD Act (April 2008–February 2010), and the post-CARD Act period (March 2010–June 2014). The figure shows that interest rates have risen for all types of consumers in the post-CARD Act period, but that rates have risen more sharply for subprime consumers relative to prime consumers.

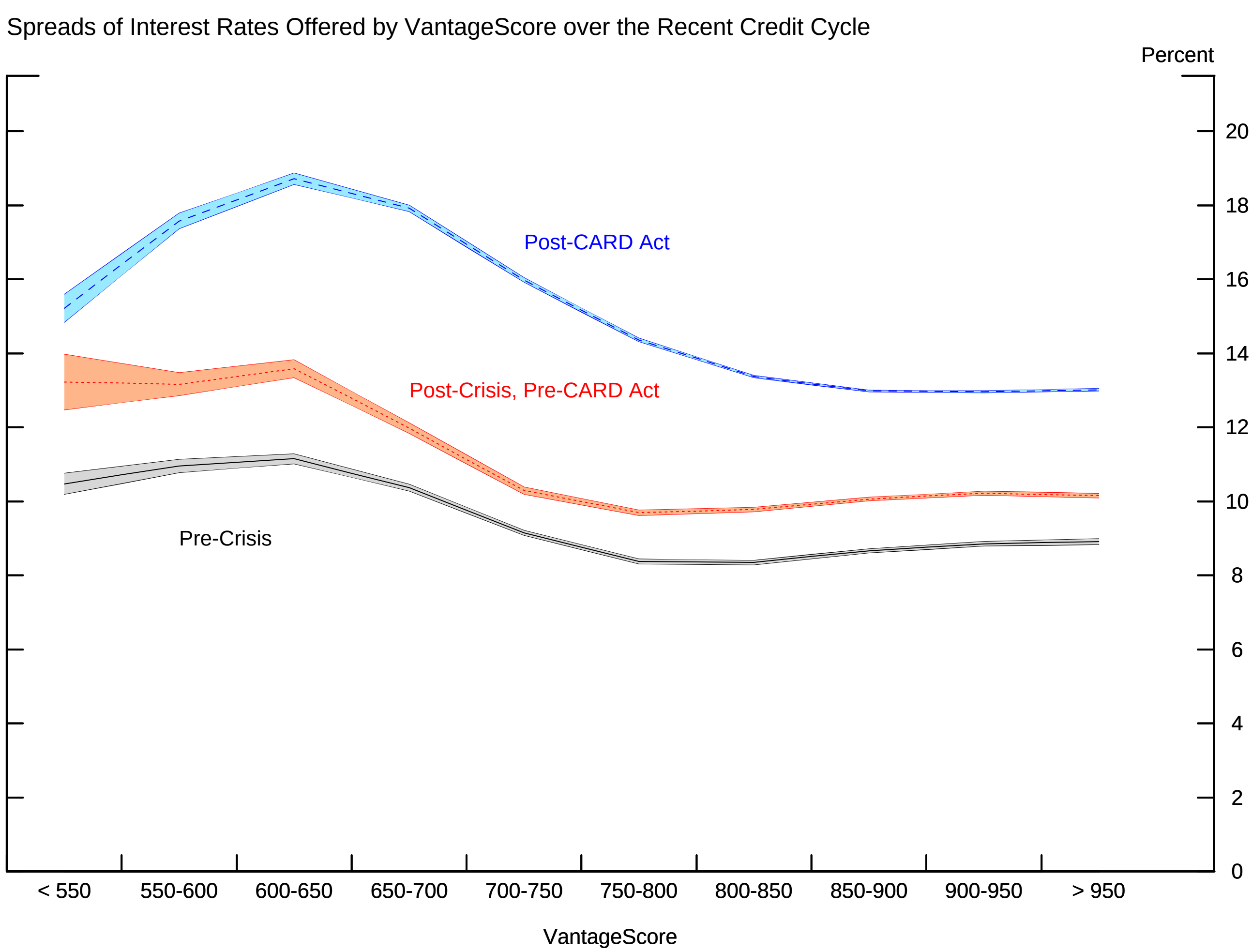


Figure 5: **Other Terms Offered by VantageScore over the Recent Credit Cycle**
The figure presents the relationship between other terms on credit card offers and credit score, separately for three time periods. The three time periods represent the credit boom (January 2007–March 2008), the credit crunch period prior to the implementation of the CARD Act (April 2008–February 2010), and the post-CARD Act period (March 2010–June 2014). The top left panel shows the pattern for minimum credit limits, which increased for consumers of all creditworthiness levels in the post-CARD Act period. The top right panel shows the prevalence of promotional introductory teaser rates, which have become increasing common for less creditworthy consumers. The bottom left panel shows the use of annual fees, which have fallen among subprime consumers after the implementation of the CARD Act. The bottom right panel suggests an increase in the use of rewards programs as a contract feature among subprime consumers.

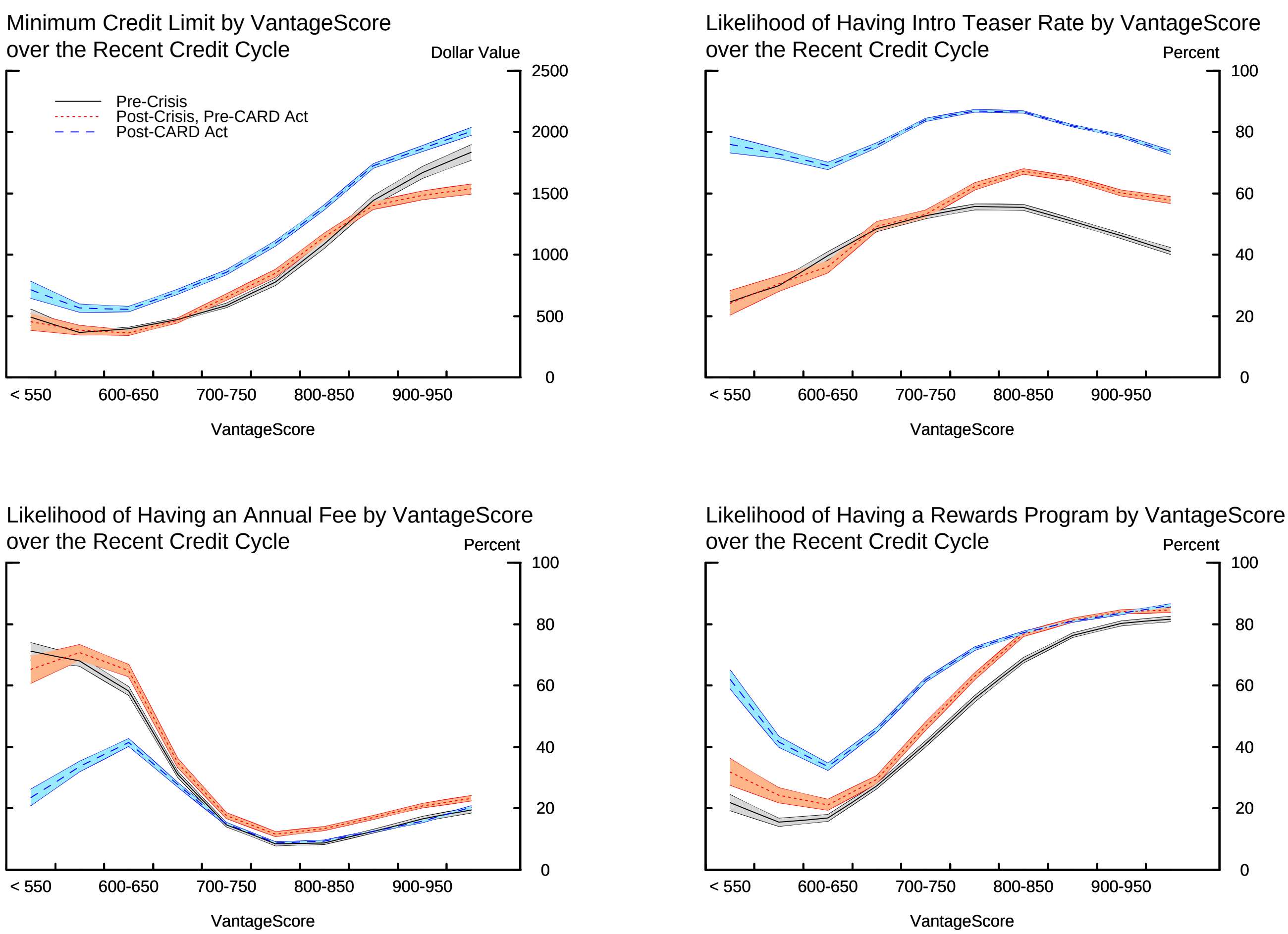


Figure 6: **Likelihood of Receiving Multiple Distinct Offers Extended by the Same Lender**

The figure presents the relationship between the likelihood of receiving multiple distinct offers from the same lender over a six-month period and credit score. The shaded band represents a 95 percent confidence interval. This figure uses the longitudinal sample collected by Mintel from July 2011-June 2014. The figure shows that while relatively few subprime consumers receive multiple offers from the same lender, there is a strong positive relationship up to a credit score of roughly 700, where the relationship flattens out. Over 70% of consumers with credit scores above 700 receive multiple distinct offers from the same lender over a six-month period, suggesting that lenders are intensively searching for low-risk consumers to reveal private information by offering different contracts.

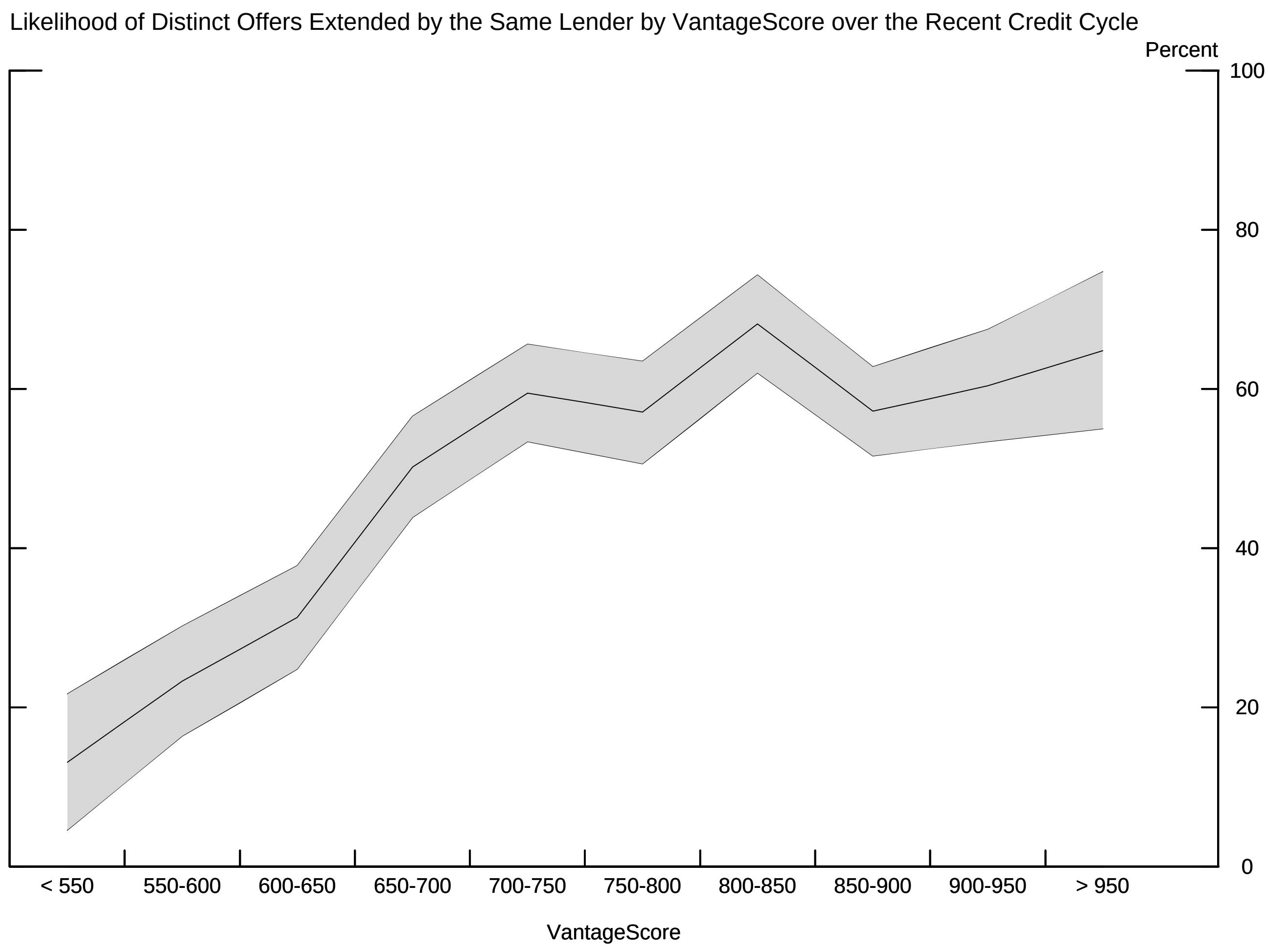


Table 1: **Demographic and Credit Characteristics of the Mintel Cross-Sectional Sample**

The table presents summary statistics of key demographic and socioeconomic characteristics for the heads of households in the Mintel monthly cross-sectional sample and compares our sample to two representative samples of U.S. consumers. We restrict Mintel the sample to be the households whose heads aged between 20 and 60 and household annual income between $10,000 and $200,000. The final cross-sectional Mintel sample contains about 222,900 credit card offers that were sent to about 173,300 individuals in more than 107,700 households. For comparison, we also include corresponding statistics estimated using the 2007, 2010, and 2013 SCF sample, subject to the same criteria and weighted accordingly, in column (2), and corresponding statistics from the FRBNY/Equifax Consumer Credit Panel in column (4).

Demographics	Mintel (1)	SCF (2)	Liability and credit history	Mintel (3)	Equifax (4)
Mean age	45.3	41.7	Total debt (2013$)	100,065	108,101
Mean household size	2.7	2.9	Rev. debt (2013$)	10,680	12,556
High School (%)	29.8	31.9	Rev. credit limit ($)	42,620	36,375
Some College (%)	23.3	20.4	Utilization rate	0.25	0.33
College (%)	40.6	37.6	Have credit cards	0.75	0.64
Homeowner (%)	70.5	61.1	Number of credit cards	1.88	1.85
White (%)	85.0	80.2	Bankruptcy	0.08	0.07
Married (%)	55.4	50.2	Other derog.	0.07	0.10
Income (2013$)	72,139	66,383	Deep delinquency	0.06	0.07

Table 2: **Credit Card Offers by Credit Status**

The table presents summary statistics of credit card offers by credit status (prime vs. nonprime) for the full Mintel cross-sectional sample. Prime consumers refer to those with a VantageScore greater than 700, while and nonprime consumers refer to those with VantageScores below this threshold. The average number of offers is calculated conditional on receiving at least one credit card offer. Mean values are reported, with median values shown in brackets below (where applicable). 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 offers 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.

	All (1)	Prime (2)	Nonprime (3)
Number of consumers	169,692	127,197	42,495
Received at least one offer (%)	50.4	55.8	36.1
Received at least one			
credit building offer (%)	7.5	3.2	18.7
plain vanilla offer (%)	20.7	22.8	15.2
general market offer (%)	38.8	47.7	15.3
premium reward offer (%)	14.6	18.0	5.5
Among consumers receiving offers			
Avg. num. of offers received (monthly)	2.5	2.6	2.2
	[2]	[2]	[1]
Number of offers	219,707	185,962	33,745
Avg. interest rate (%)	13.7	13.2	16.1
	[13.0]	[13.0]	[15.0]
Avg. min credit limit ($)	1,158	1,313	518
	[500]	[500]	[300]
Have introductory rate (%)	68.3	71.3	53.9
Have annual fee (%)	18.9	13.9	43.4
Have rewards program (%)	67.0	74.3	31.2

Table 3: **Determinants of Credit Card Offers**

	Having an offer	Credit limit	Spread	Intro rate	Annual fees	Rewards
VantageScore bins						
550-600	0.100***	-208.749***	1.229***	0.034**	0.051***	-0.169***
	(0.009)	(34.383)	(0.181)	(0.016)	(0.013)	(0.016)
600-650	0.155***	-251.378***	2.249***	0.069***	0.052***	-0.234***
	(0.010)	(34.182)	(0.186)	(0.019)	(0.013)	(0.016)
650-700	0.223***	-208.157***	1.693***	0.146***	-0.070***	-0.143***
	(0.011)	(32.610)	(0.203)	(0.016)	(0.009)	(0.016)
700-750	0.252***	-100.237***	0.436**	0.187***	-0.136***	-0.014
	(0.011)	(33.416)	(0.188)	(0.016)	(0.006)	(0.014)
750-800	0.285***	102.084***	-0.367*	0.214***	-0.162***	0.064***
	(0.011)	(31.987)	(0.191)	(0.014)	(0.006)	(0.013)
800-850	0.292***	326.984***	-0.871***	0.220***	-0.164***	0.119***
	(0.012)	(35.524)	(0.190)	(0.014)	(0.006)	(0.012)
850-900	0.264***	577.903***	-0.969***	0.197***	-0.150***	0.147***
	(0.012)	(31.360)	(0.185)	(0.017)	(0.007)	(0.011)
900-950	0.254***	714.265***	-0.865***	0.168***	-0.124***	0.169***
	(0.011)	(33.499)	(0.192)	(0.017)	(0.007)	(0.010)
> 950	0.267***	809.787***	-0.770***	0.141***	-0.106***	0.176***
	(0.010)	(40.664)	(0.178)	(0.016)	(0.007)	(0.009)
Credit hist. attr.						
Bankruptcy filer	-0.068***	-238.100***	0.834***	-0.128***	0.107***	-0.296***
	(0.008)	(14.106)	(0.111)	(0.009)	(0.010)	(0.010)
Other derog rec.	-0.065***	-130.100***	0.153	-0.071***	0.060***	-0.082***
	(0.009)	(13.166)	(0.106)	(0.009)	(0.009)	(0.008)
Deep del.	-0.027***	-26.073	0.091	0.065***	-0.008	0.007
	(0.010)	(19.841)	(0.113)	(0.013)	(0.008)	(0.014)
Recent del.	-0.004***	-31.710***	0.124***	-0.004***	0.015***	-0.023***
	(0.001)	(2.115)	(0.015)	(0.001)	(0.001)	(0.002)
Num inquiries	0.001	-20.461***	0.011	-0.008***	0.008***	-0.011***
	(0.001)	(2.610)	(0.011)	(0.001)	(0.001)	(0.001)
Debt-income ratio	-0.001	-9.194***	-0.030***	-0.002***	-0.000	-0.001
	(0.001)	(2.715)	(0.007)	(0.001)	(0.001)	(0.001)
Have credit card	0.065***	47.819***	-0.536***	-0.019***	-0.033***	0.032***
	(0.004)	(12.860)	(0.044)	(0.003)	(0.004)	(0.004)
High util	-0.022***	-13.200	0.454***	0.008	0.012***	-0.010
	(0.006)	(16.002)	(0.043)	(0.006)	(0.004)	(0.007)
Household char.						
Head age	-0.001	5.551	-0.018	-0.002	-0.000	0.002**
	(0.001)	(4.609)	(0.012)	(0.002)	(0.001)	(0.001)
Head age^2/100	0.001	-5.231	0.019	0.002	-0.000	-0.002**

Continued on next page

Table 3 – *Continued*

	Having an offer	Credit limit	Spread	Intro rate	Annual fees	Rewards
	(0.002)	(5.291)	(0.014)	(0.002)	(0.002)	(0.001)
Married	0.007	33.262***	-0.077	0.013***	-0.007*	-0.005
	(0.005)	(10.691)	(0.046)	(0.004)	(0.004)	(0.004)
Household size	0.007***	-12.111***	0.049***	0.011***	-0.009***	-0.006***
	(0.001)	(3.818)	(0.011)	(0.001)	(0.001)	(0.001)
White	0.034***	19.181	-0.049	0.022***	-0.025***	0.021***
	(0.007)	(15.554)	(0.040)	(0.006)	(0.006)	(0.004)
High school	0.012*	-8.502	-0.135	0.006	-0.021***	0.021**
	(0.007)	(16.729)	(0.084)	(0.006)	(0.007)	(0.009)
Some college	-0.006	26.578	-0.192**	-0.026***	0.002	0.030***
	(0.008)	(23.713)	(0.080)	(0.007)	(0.008)	(0.007)
College	0.011	137.328***	-0.128	-0.067***	0.041***	0.059***
	(0.008)	(19.567)	(0.076)	(0.006)	(0.007)	(0.008)
Homeowner	0.014***	-1.546	-0.177***	0.030***	-0.036***	-0.009**
	(0.005)	(13.039)	(0.058)	(0.007)	(0.004)	(0.004)
Log(income)	0.042***	96.004***	-0.027	-0.051***	0.039***	0.048***
	(0.005)	(8.667)	(0.030)	(0.003)	(0.003)	(0.003)
Legal & econ. cond.						
Unemp	-0.016***	-1.300	0.213***	0.004	0.010***	0.003***
	(0.002)	(4.943)	(0.037)	(0.003)	(0.003)	(0.001)
Homestead exempt	-0.003***	-2.104	0.026**	-0.001	0.002***	-0.001*
	(0.001)	(2.759)	(0.012)	(0.001)	(0.001)	(0.001)
Property exempt	-0.035**	72.618	0.273	-0.053*	0.075***	0.002
	(0.018)	(50.175)	(0.292)	(0.028)	(0.014)	(0.014)
Yearly fixed-effects	yes	yes	yes	yes	yes	yes
Monthly fixed-effects	yes	yes	yes	yes	yes	yes
R2 / pseudo R2	0.061	0.115	0.341	0.095	0.115	0.149
N	169,692	148,656	217,920	219,707	219,707	219,707

Note: The table presents estimates of probit (offer, has intro rate, has annual fee, has reward program) and OLS (credit limit, spread) regressions to explore the determinants of credit card offers and their features. Standard errors in parentheses are clustered by state. *, **, and *** indicate that the estimated coefficients are statistically significant at the 90-, 95-, and 99-percent level, respectively.

Table 4: **Do Lenders Monitor Credit Scores of an Individual over Time?**

The table presents estimates of probit (offer, has intro rate, has annual fee, has reward program) and OLS (credit limit, spread) regressions to explore the relationship between individual credit scores and credit card access. The regressions are fixed-effects panel regressions that control for individual consumers, thus the identification comes solely from within-consumer variation in credit scores over time. These specifications use the longitudinal sample of Mintel respondents, covering July 2011-June 2014. Heteroskedasticity-robust standard errors in parentheses. *, **, and *** indicate that the estimated coefficients are statistically significant at the 90-, 95-, and 99-percent level, respectively.

	Having an offer	Credit limit	Spread	Intro rate	Annual fees	Rewards
VantageScore/100	0.061***	236***	-1.056***	-0.008	0.001	0.072***
	(0.015)	(41.0)	(0.010)	(0.011)	(0.010)	(0.013)
Number of consumers	631	493	527	533	533	533
Number of observations	10,149	10,259	13,251	13,786	13,786	13,786

Table 5: **Effect of Bankruptcy on Credit Access**

The table presents estimates of probit (offer, has intro rate, has annual fee, has reward program) and OLS (credit limit, spread) regressions of the relationship between the recency of bankruptcy filing and credit card offers and their features. The specifications are identical to those presented in Table 3, except the dummy variable for bankruptcy flag has been replaced with three measures of the time since filing. "Recent" filers are those who have filed for personal bankruptcy within the last two years, "seasoned" filers are those who filed between three and five years prior, and "remote" filers are those who filed more than five years earlier and are approaching re-filing eligibility (after 8 years). The table shows that recent filers are as likely as similar nonfilers to obtain a credit card offer, but their offers have decidedly less favorable terms. Remote filers are substantially less likely to receive offers, reflective of their re-filing risk. Thus, a simple bankruptcy flag masks considerable heterogeneity in how lenders treat this information. Standard errors in parentheses are clustered by state. *, **, and *** indicate that the estimated coefficients are statistically significant at the 90-, 95-, and 99-percent level, respectively.

	Having an offer	Credit limit	Spread	Intro rate	Annual fees	Rewards
Recent	-0.004	-266.151***	1.790***	-0.066***	0.152***	-0.403***
	(0.015)	(21.820)	(0.350)	(0.015)	(0.016)	(0.017)
Seasoned	-0.069***	-238.458***	1.530***	-0.138***	0.143***	-0.372***
	(0.015)	(21.836)	(0.153)	(0.014)	(0.016)	(0.017)
Remote	-0.117***	-282.646***	0.459***	-0.132***	0.057***	-0.203***
	(0.010)	(15.691)	(0.112)	(0.014)	(0.012)	(0.016)
Controlled for						
VantageScore bins	yes	yes	yes	yes	yes	yes
Credit history attributes	yes	yes	yes	yes	yes	yes
Household characteristics	yes	yes	yes	yes	yes	yes
State fixed-effects	yes	yes	yes	yes	yes	yes
Yearly fixed-effects	yes	yes	yes	yes	yes	yes
Monthly fixed-effects	yes	yes	yes	yes	yes	yes
R2 / pseudo R2	0.065	0.116	0.407	0.105	0.118	0.150
N	169,692	148,656	217,920	219,707	219,707	219,707

Table 6: **How Did Bankruptcy Flags' Impact Evolve over the Credit Cycle?**
The table presents estimates of probit (offer, has intro rate, has annual fee, has reward program) and OLS (credit limit, spread) regressions to relationship between bankruptcy filing status and credit card offers and their features over three time periods. The three time periods represent the credit boom (January 2007–March 2008), the credit crunch period prior to the implementation of the CARD Act (April 2008–February 2010), and the post-CARD Act period (March 2010–June 2014). Column (1) repeats the same result shown in Table 5 as a reference point. As shown in columns (2)–(4), recent filers were 8 percentage points *more* likely to receive an offer than otherwise comparable nonfilers during the credit boom, whereas remote filers were 5 percentage points less likely. The favorable treatment of recent filers largely persisted even during the depths of the credit crunch. However, the pattern appears to have changed substantially during the post-CARD Act era, where recent filers lost their edge in receiving credit card offers relative to nonfilers, while the gap between remote filers' likelihood of receiving an offer and that of comparable nonfilers became ever larger. Standard errors in parentheses are clustered by state. *, **, and *** indicate that the estimated coefficients are statistically significant at the 90-, 95-, and 99-percent level, respectively.

	(1)	(2)	(3)	(4)
	Whole sample	Pre-crisis	Post-crisis pre-CARD Act	Post-CARD Act
Recent	-0.004	0.046*	0.064**	-0.031*
	(0.015)	(0.025)	(0.032)	(0.016)
Seasoned	-0.069***	-0.044**	-0.046***	-0.100***
	(0.015)	(0.022)	(0.017)	(0.017)
Remote	-0.117***	-0.056***	-0.088***	-0.152***
	(0.010)	(0.018)	(0.016)	(0.013)
Controlled for				
VantageScore bins	yes	yes	yes	yes
Credit history attributes	yes	yes	yes	yes
Household characteristics	yes	yes	yes	yes
State fixed-effects	yes	yes	yes	yes
Yearly fixed-effects	yes	yes	yes	yes
Monthly fixed-effects	yes	yes	yes	yes
R2 / pseudo R2	0.065	0.022	0.075	0.059
N	169,692	29,701	44,520	95,471

Table 7: **Multiple Offers to the Same Consumer**

The table presents results based on analyzing distinct credit offers sent to the same consumer. The first two columns use data from the Mintel cross-sectional sample, while the last column uses six-month intervals from the Mintel longitudinal sample. The summary statistics here suggest that the majority of consumers receive multiple offers from the same lender over a six-month period, with dramatic dispersion in contract characteristics. The average difference in interest rates between the minimum and maximum credit offer over the six-month period from the same lender is 310 basis points, and the average difference in minimum credit limits is $1,401.

	Cross-sectional sample (In a given month)		Longitudinal sample (6-month intervals)
	(1)	(2)	(3)
	All lenders	Same lender	Same lender
% received distinct offers	26.1	13.5	51.1
Number of distinct offers			
(conditional on receiving)	3.1	2.3	3.1
Max-Min Differences in			
Interest rates (percent)	3.9	2.2	5.6
Minimum credit limits ($)	1,143	1,044	1,386
Share of consumers received offers			
with different terms regarding (%)			
Whether having introductory rates	46.7	30.9	47.8
Whether having annual fees	30.7	19.0	41.4
Whether offering rewards	46.8	45.1	55.0

Table 8: **Multiple Offers and Credit Scores**

The table uses the Mintel longitudinal sample to explore the relationship between credit scores, the prevalence of multiple offers, and the dispersion in those offers. The specifications are collapsed to the level of the respondent in the longitudinal sample. Dispersion in having teaser rate, annual fees, and rewards is measured using the Herfindahl index, see text for details. The table shows that consumers with higher credit scores are more likely to receive multiple distinct offers extended by the same lender, with less dispersion in their interest rates but more dispersion in credit limits and other features (annual fee and rewards program). Heteroskedasticity-robust standard errors in parentheses. *, **, and *** indicate that the estimated coefficients are statistically significant at the 90-, 95-, and 99-percent level, respectively.

	Received > 1 offer	Dispersion in Contract Terms				
		Max-Min		Herfindahl Index		
	(1)	(2)	(3)	(4)	(5)	(6)
		Reg. int. rate	Min. limits	Have intro. rate	Have annual fee	Rewards
VantageScore/100	0.445***	-1.661***	477***	-0.004	0.012**	0.033***
	(0.044)	(0.146)	(60)	(0.005)	(0.005)	(0.004)
	[1.690]					
N	1,682	938	694	480	431	563