Forgive and Forget: Who Gets Credit after Bankruptcy and Why?*

Ethan Cohen-Cole

University of Maryland - College Park Robert H Smith School of Business Burcu Duygan-Bump Federal Reserve Bank of Boston

Judit Montoriol-Garriga Federal Reserve Bank of Boston

1 November 2009

Abstract

Conventional wisdom holds that individuals are excluded from credit markets post-bankruptcy. Using credit bureau data we show that bankrupts are indeed penalized, but only for a short time: ninety percent receive credit within 18 months. Interestingly, individuals with good credit prior to filing have much lower availability after filing, while more than 60% of individuals at the bottom of the credit quality spectrum receive more credit. We illustrate that this pattern is consistent with a lender that segments borrowers by observable credit quality and bankruptcy status. Finally, we show that our findings depend heavily on the aggregate credit environment.

JEL Classification Codes: D14, I30, K45 **Keywords:** Post-bankruptcy credit

^{*}Ethan Cohen-Cole: Robert H School of Business. University of Maryland College-Park. 4420 Van Munching Hall. College Park, MD 20742. Phone: +1 301 541 7227. E-mail: ecohencole@rhsmith.umd.edu. Burcu Duygan-Bump: Federal Reserve Bank of Boston. 600 Atlantic Ave. Boston, MA 02210. Phone: +1 (617) 973-3475. E-mail: burcu.duygan-bump@bos.frb.org. Judit Montoriol-Garriga: Federal Reserve Bank of Boston. 600 Atlantic Ave. Boston, MA 02210. Phone: +1 (617) 973-3191. Email: judit.montoriol-garriga@bos.frb.org. We also acknowledge the excellent research assistance provided by Nicholas Kraninger, Jonathan Larson, and Jonathan Morse. We are grateful for feedback from Sumit Agarwal, Jeff Brown, John Campbell, Chris Carroll, Dean Corbae, Jane Dokko, Bob Hunt, Howell Jackson, Jan Krahnen, Victor Rios-Rull, Nick Souleles, Peter Tufano and seminar participants at the NBER Summer Institute, the Consumer Finance Research Group Workshop at Harvard, Federal Reserve System Applied Micro Conference, the 2009 European Finance Association, the Federal Reserve Banks of Dallas and San Francisco and the University of Illinois - Champaign Urbana. Finally, we are particularly grateful to the variety of analysts and executives at Transunion, Portfolio Recovery Associates, the Runci Group, NCO and many others that provided their knowledge of industry. All remaining errors are ours alone. The views expressed in this paper do not necessarily reflect those of the Federal Reserve Bank of Boston or the Federal Reserve System.

1 Introduction

This paper presents an empirical portrait of consumers' access to credit after bankruptcy. Understanding this access is important for two reasons. One, as the growing literature on consumer finance has acknowledged,¹ bankruptcy carries widespread social and financial costs. Increased access to credit after a filing lends itself naturally to an increased incentive to file; more credit access ex-post implies more filings and consequently higher cost of borrowing for the full market. Two, the private sector provision of credit after bankruptcy emerges at least partially as a function of lender optimization. The patterns of post-bankruptcy lending can provide insight into whether bankruptcy signals an increased propensity to default on new debt or, on the contrary, it leads to improved credit quality. Indeed, as corporations can benefit from a cleaning of balance sheets, so can individuals.²

Accordingly, this paper makes two contributions. First, we present what we believe to be the most comprehensive empirical analysis of post-bankruptcy consumer credit to date. Second, we provide a very simple theoretical framework that both illustrates why lenders differentiate borrowers by bankruptcy status and explains the empirical patterns we uncover.

We find that available consumer credit does decline some after bankruptcy but this decline becomes insignificant within 18 months. Within this period, 90% of individuals have access to some sort of credit and 75% have access to revolving credit. More importantly, we find that the lowest quality borrowers, on average, see an increase in credit: our data shows that 65% of individuals in the lowest credit score bracket receive more credit after bankruptcy.³ Finally, we show that the impact of bankruptcy filing on credit access is closely tied to the credit cycle. We find that low credit quality borrowers have both the greatest relative increase in credit post bankruptcy and the largest difference in access between high and low credit supply periods; that is, when credit tightens, it has a relatively larger impact on low-credit quality individuals.⁴

We interpret these empirical findings as evidence that profitability calculations lead lenders to differentiate credit supply both as a function of credit quality and bankruptcy status. Bankruptcy leads to a shift in

¹See Cambpell (2006) for a discussion of the consumer finance literature broadly writ.

²For the seminal reference on debt overhang see Myers (1977).

³Another paper that discusses the impact of bankruptcy laws on the distribution of available credit is Gropp, Scholz, and White (1997). They find that exemption laws redistribute credit prior to bankruptcy from borrowers with few assets to those with many. Berkowitz and White (2004) also discuss the role of homestead exemptions in the personal bankruptcy code on the access to unincorporated firm credit prior to bankruptcy.

⁴More specifically, we show that as credit supply tightened by the end 2007, access to credit after bankruptcy decreased, reducing the ex-ante incentives to file. A long literature has linked changes in lending that resulted from bank deregulation and technological innovation. See for example Black and Strahan (2002). A recent paper (Dick and Lehnert, 2009) directly links the expansion of lending due to deregulation to rising bankruptcy rates. We refine the latter story by suggesting that the link between expansion of credit and bankruptcy may operate principally through extension of credit to low credit quality borrowers rather than to all borrower types.

risk profiles, revealing both new information about borrowers' characteristics but also signaling a fresh-start such that certain individuals become more profitable to lenders after they file for bankruptcy.

We point to three types of evidence to support this interpretation. First, it is consistent with survey evidence provided by legal studies (see Section 2) showing that lenders quickly offer credit even to low credit quality borrowers after bankruptcy. A recent *NY Times* article also provides anecdotal discussion of how the credit card industry has relied on riskier households as a significant source of revenue through penalty interest rates and fees.⁵

Second, our interpretation is supported by internal industry marketing materials that illustrate how lenders segment borrowers in the way mentioned. Lenders use separate measures of risk ('scorecards') for individuals who have filed for bankruptcy versus those who have not. This allows lenders to isolate profitable bankrupt borrowers; suggesting that a borrower who was not profitable prior to bankruptcy may be profitable afterwards.

Our third type of evidence is based on the bankruptcy process itself. Note that the goal of a Chapter 7 bankruptcy proceeding is to obtain a discharge of debts. As a result, individuals emerge from bankruptcy with a cleaner balance sheet than similarly troubled individuals that have not filed. In that sense, bankruptcy positively affects their ability to repay newly incurred debt as compared to non-bankrupt individuals with similar risk profile. Furthermore, bankruptcy enables the new lenders to file legal proceedings on new debt without fear of repeated bankruptcy because of legal restrictions on repeat Chapter 7 filings in a 7 year period. Indeed, lenders account for the option to file for bankruptcy in their lending decisions.

To illustrate these mechanisms, we present a simple theoretical framework to help understand lenders' decision to extend credit to different types of borrowers. The framework breaks down borrowers into four types, a simplified representation of industry segmentation practices. By doing so, the framework helps illustrate why lenders may increase lending post bankruptcy to certain segments of borrowers, as the data indicate.

The framework produces a number of useful insights that explain the industry practice of segmentation by type and bankruptcy status. First, lenders have no incentive to reduce borrowers' credit limit unless bankruptcy reveals a change in a borrower's likelihood of repayment in the future or changes recovery rates post default. Second, lenders acknowledge that the credit score is not a sufficient statistic for calculating repayment probability post bankruptcy, but that the bankruptcy filing itself provides information on the propensity to repay. In fact, as we show below, there is a differential change in default behavior after

⁵"Credit Card Industry Aims to Profit From Sterling Payers," May 19, 2009, Andrew Martin, The New York Times. (http://www.nytimes.com/2009/05/19/business/19credit.html)

bankruptcy that depends on ex-ante credit score: individuals with high ex-ante credit scores exhibit a large change in their default probabilities, while the delinquency rates of those who are at the low-end of the credit quality spectrum remain relatively constant after a bankruptcy filing. This helps explain why lending to low quality borrowers remains constant or increases after filing, as we observe in the data.

This framework also helps understand the observed changes in credit provision throughout the business and credit cycle. We argue that in a credit crunch the repayment ability of the low quality borrowers is highly impaired, especially after bankruptcy. Additionally, since the credit cycle is closely related to the business cycle, recovery rates on defaulted debt tend to decrease in a downturn. As a consequence, lending to low quality borrowers who have filed for bankruptcy in downturns is not as profitable as in booms. This is supported by our empirical findings that show that by the end of 2007 bankrupt subprime borrowers faced more difficulties accessing the credit market than in 2004, while access to credit for bankrupt prime borrowers was largely unchanged in the same period.

The remainder of the paper is organized as follows. In Section 2 we provide a short summary of the economics and legal literature on personal bankruptcy. Both of these brief literature reviews are intended to provide a baseline for our discussion. In Section 3 we provide a simple model of lender decisions. Section 4 describes our dataset, and Section 5 presents the methodology we use to assess credit availability post bankruptcy together with our results. We follow this with a short section discussing some potential caveats to the analysis in Section 6. Section 7 concludes the paper.

2 Literature on Bankruptcy and Access to Credit

Bankruptcy has potentially two sets of impacts on credit access. The first of these is the legal option that individuals hold to file for bankruptcy. This operates similarly to a put option: a chapter 7 filing provides the ability to discharge many forms of unsecured credit. A chapter 13 filing allows borrowers to restructure debt and in some cases discharge debt.⁶ This option to file impacts individual decisions (Cohen-Cole, 2009) and leads to differences in lending incentives. Gropp, Scholz, and White (1997) and Berkowitz and White (2004) both highlight that differences in homestead exemptions lead to differences in lending prior to bankruptcy.⁷ The former finds that differences in homestead exemptions changes the availability of credit by re-allocating from asset poor to asset rich individuals. The latter find that high homestead exemptions

⁶An example of a Chapter 13 'discharge' is the ability to strip-off non-secondary leins from owned property. This is an effective discharge of home equity loans and home equity lines of credit.

⁷Homestead exemptions are state laws that allow individuals in Chapter 7 bankruptcy proceedings to keep accumulated equity in their houses while discharging unsecured debt. States have varying levels of permitted exemptions, including a subset that allow unlimited home equity at the time of filing.

limit credit availability to unincorporated small businesses that rely on the owner's individual credit history.

The second impact on credit availability is the presence of an exclusion period after filing. Individuals that file for Chapter 7 bankruptcy cannot file for Chapter 7 again for seven years from the date of the original filing. The law is intended to protect lenders from serial bankruptcies and to punish borrowers for the initial filing. The punishment in principle is that the knowledge of a prior bankruptcy will lead to an exclusion from credit markets. This is implemented by leaving the record of the bankruptcy filing on the individual's credit report for 7-10 years or more.⁸ The impact of these exclusions on both access to credit and the initial filing decision is complex, as we highlight in this paper.

Musto (2004) and Fisher, Filer and Lyons (2000) provide other evidence in support of an exclusion period.⁹ Musto (2004) analyzes the impact of the removal of the bankruptcy record from an individual's credit record and shows that especially the credit-worthy individuals get more cards and see big jumps in their credit limits. Indeed, such a finding is consistent with our results in that the high-credit individuals here see a relatively larger 'penalty' in the form of reduced credit lines and can thus have larger increases at the time the bankruptcy flag is removed from the record. Using a panel study of households, Fisher, Filer, and Lyons (2000) show that consumption of the bankrupt households depict higher sensitivity to their incomes than in the period preceding the filing, which is consistent with binding borrowing constraints in the post-bankruptcy period.

A wide quantitative macroeconomic literature, including Athreya (2002), Chatterjee et al. (2007), and Livshits, MacGee and Tertilt (2007) assume the presence of a market exclusion following default. The existence of such an exclusion penalty facilitates these quantitative macro models in a number of ways. Most importantly, by imposing the presence of a non-renegotiable ex-ante exclusion, the models rule out moral hazard problems. Agents cannot accumulate assets with the explicit intention of expunging debt and then acquiring new debt. Of course, debt renegotiation does occur and nothing prevents a credit issuer from providing credit to a bankrupt ex-post. Because these models largely do not treat debt overhang nor lender incentives post-bankruptcy, they do not lead to results that match our empirical patterns.¹⁰

These reasons for access are closely linked to the decision to file. Domowitz and Sartain (1999) find both that the scale of dischargeable credit card and medical debt is a key factor and that homestead exemptions

⁸The standard amount of time differs by jurisdiction. In addition, lenders can apply exception to keep bankruptcy information present for borrowers that have high income levels.

⁹A very recent study by Han and Li (2009) also analyze this question using data from the Survey of Consumer Finances and a different methodology attempting to understand the equilibrium dynamics and disentangling changes in demand and supply.

¹⁰More recently, however, there has been increased discussion about whether these assumptions are realistic, followed by a move away from reliance on such assumptions. For example, Athreya and Janicki (2006) evaluate "the commonly used (but rarely justified) assumption" that bankrupt individuals get excluded from unsecured credit markets. They conclude that such an assumption is hard to justify from a theoretical perspective.

are important in the decision between Chapter 7 and Chapter 13. Gross and Souleles (2002) and Fay, Hurst and White (2002) find that the benefit to filing, in terms of the scale of dischargeable debt, is a primary determinant of filing. These papers however, do not directly treat the question of access after bankruptcy and its potential influence on the filing decision.

So why do lenders provide credit after bankruptcy?

The open question that we address is why lenders would provide credit to borrowers post-bankruptcy.¹¹ We point to two facts. The first is the well known debt overhang problem. All else equal, borrowers with high debt are worse credit risks than borrowers with lower debt. As is well understood, firms (and individuals) are constrained from recovering from the debt burden precisely due to the cash flow constraints imposed by the debt itself.¹² In our case, we focus on how removing the overhang problem post-bankruptcy can improve the prospects of an individual. As a result, lenders may now find this borrower a more attractive one.

The second reason is central to our model below. The legal restriction against refiling has the effect of providing lenders greater access to existing assets than borrowers that maintain the Chapter 7 option. Recall from above that the presence of homestead exemptions led to differences in lending and in filing. The expost absence of this issue will result in a change in lending. Consistent with the Berkowitz and White (2004) finding that pre-bankruptcy lending redistributes credit from low asset holders to high asset holders, we find that post-bankruptcy lending for low credit quality individuals, who are likely also to be low asset holders, receive a disproportionately large increase in the access to credit.¹³

Legal Literature

Legal studies on post-bankruptcy rely primarily on available survey data to describe the exclusion patterns, and have produced a wide range of work on bankruptcy. Among others Block-Lieb and Janger (2006), Sullivan, Warren and Westbrook (2006) and Weiner et al. (2005) find support for an unexpected event explanation for most bankruptcy filings. A comprehensive overview is available in Porter and Thorne (2006) and Porter (2008).

In a seminal study that preceded the large 1973 change in the US bankruptcy code, Stanley and Girth (1971) interviewed a small sample of people, and, found that credit was relatively easy to obtain post bankruptcy. Among the literature that has found evidence of access on post 1973 data, Porter (2008) finds that

¹¹Indeed Stavins (2000) finds that individuals with prior bankruptcies have higher delinquency rates than the rest of the population.

¹²This logic has been applied to sovereign debt relief (Bulow, 1991; Fernandez-Ruiz, 2000, Arslanalp and Henry, 2005) as well.

¹³Chatterjee, Corbae, & Rios-Rull (2009) also make the debt overhang argument. They argue that individuals with discharged debt are better risks, particularly if the bankruptcy was caused by a temporary shock. Our empirical finding of a limited exogenous exclusion period supports their framework and suggests that lenders do indeed use current repayment and bankruptcy status to infer future probabilities of default when deciding whether to lend and to whom to lend.

a very high percentage of individuals being offered unsecured lines of credit within a year of going bankrupt. As well, she finds support for the 'adverse event' theory of bankruptcy. She also notes that little prior empirical work has been done, but that a number of authors have cited the need for more data and evidence on the topic (see Braucher (2004) and Jacoby (2005)). In other work, Staten (1993) looks at the role of post-bankruptcy credit on the number of bankruptcies. He draws his data from a survey as well, and finds that one year post bankruptcy, 16.2 percent got new credit. Three years after, 38.6 percent obtained credit. About half of each came in installment and revolving debt. However, highlighting the problems with surveys and sample size, these numbers are quite different from the Porter (2008) results.

The background to the literature directly on post-bankruptcy lending is the work that has found that the changes in the bankruptcy code enacted in 2005 made consumer bankruptcy more difficult to obtain, and more expensive for the filer both in terms of filing costs and time allocation (Mann 2007, Sommer 2005).

Our question is about lending to consumers who have already filed for bankruptcy. Porter (2008) describes the criteria that should apply, "If even a modest proportion of bankruptcy debtors are untrustworthy deadbeats who behave in immoral or strategic ways, the credit industry should be reluctant to lend to these families." Indeed, individuals with low credit scores, defined as those individuals who have been unreliable in repayment of debts, should not typically be a target of credit issuance. In a story that is consistent with our findings, Porter (2008), using a longitudinal study of bankrupt individuals, finds evidence that consumers are 'bombarded' with credit offers, including from the very issuers that have just had debts expunged. Overlain with this motive is evidence that more than a third of families post bankruptcy had worsening financial conditions, even accounting for the bankruptcy discharge (Porter and Thorne, 2006).

While these results are based on surveys alone, the patterns are largely consistent with our findings. The remaining two thirds of families that have improved financial condition post discharge are a good prospect for increased lending.

3 A Simple Model of Creditor Decisions

3.1 Model Setup

To gain insight into why credit issuance may increase for some bankrupt borrowers, we draw on a stylized model of debt valuation and lenders' decisions. The framework starts with a simple definition of debt from a lender's perspective. The value of debt can be obtained as the weighted average, by the probability of default, of two terms. The first is the stream of risk free cash flows and second the recovery value in case of default. In other words, the first term is the value of debt when lenders know that individuals will repay their

debt for certain, so it can be valued as simply the discounted future value of payments using the risk-free rate. The second term is the value of debt in case of default and can be obtained by multiplying the face value of debt by the recovery rate and the exposure at default. Accordingly, the value of a debt to a lender can be expressed as:

$$V = (1 - PD)FV + PD(1 - LGD)(EAD)B$$
(1)

where FV is the discounted future value of payments in the non-default scenario, PD is the probability of default i.e. the likelihood of non-payment, LGD is the loss given default i.e. the percentage of losses conditional on default, EAD is the exposure at default i.e. the percentage of the face value of debt owed at time of default, and B is the face value of debt. While the FV can have a complex form depending on the type of debt, for our purposes we treat FV to reflect the full credit line rather than the amount borrowed. This allows us to simplify the assumptions regarding the EAD and abstract from credit line utilization rates. Realistically, the exposure at default might vary depending on credit lines and consumer types. We focus on total credit limit available and assume that the exposure at default is 100% in all cases. Given that many debtors increase utilization rates prior to default, we believe this to be a reasonable assumption. Furthermore, we are interested in analyzing credit supply and therefore credit limit is more relevant than balance for our purpose.

With this broad framework in place, our goal is to uncover differences in profitability by type of borrower and by bankruptcy status. In other words, suppose there are four types of borrowers defined along two dimensions, bankruptcy status and repayment behavior: prime borrowers who have never gone bankrupt, ex-ante prime borrowers who went bankrupt, ex-ante subprime borrowers who have never gone bankrupt, and subprime borrowers who filed for bankruptcy. Note that the most straightforward way to think about prime vs. subprime borrowers within our empirical framework above is looking at the spectrum of highto-low credit scores, which mainly reflect a borrower's debt holding and historical repayment behavior. Accordingly, a lender considers the following four versions of equation 1:

$$V = \left[V_{NB}^P, V_B^P, V_{NB}^{SP}, V_B^{SP}\right]$$

where the superscripts P, SP refer to prime and subprime borrowers, and the subscripts NB and B refer to not-bankrupt and bankrupt, respectively. It is important to note that an individual can be in default of payment but not bankrupt. What this model implies is that lenders use distinct score cards by type of borrower and by bankruptcy status.

3.2 Lender Practice

We base our model on extensive conversations with lenders and is built around the notion that lenders provide credit based on the profitability of each set of borrowers. Because it is difficult to predict the behavior of any given individual, lenders use credit scores to group borrowers. Credit scores are rank ordering of default probability that are based on population (or sub-population) average behavior. A generic credit score is one that applies to a wide population. Such a score could be created by regressing the incidence of non-payment (default) on a linear combination of predictive variables, including credit utilization rates, total available credit, number of cards, etc. As lenders discovered that the factor loadings on these variables changed by sub-population of borrowers, they changed from using generic scores to customized ones. These custom scores are a function of the same variables, but are calculated on a subset of the population only.¹⁴ As an example, VantageScore, a credit score product developed by the three large credit reporting agencies, indicates the following on its website: "VantageScore was developed using a combination of key attribute and score-based segmentation methodology, resulting in 12 scorecards, including previous bankruptcy, thin file and thick file."

Figure 1 shows an example of marketing materials from VantageScore that indicate the custom scores available. Our emphasis in this paper is on previous bankruptcy high risk, previous bankruptcy low risk, no previous bankruptcy high risk, and no previous bankruptcy low risk. For simplicity, we only segment individuals with no previous bankruptcy into two categories.

3.3 Model Implications

To distinguish between these four types of borrowers and to understand the profitability of each type, we now analyze each of the components of equation 1 in turn. We will show that the probability of default (PD)and loss percentage conditional on defualt (LGD) are the key variables of interest. Default probabilities will nicely differentiate ex-ante good and bad borrowers. Losses given default will be key to understanding post-bankruptcy decision. Lenders both have increased expectation of debt recovery given the reduction in borrower debt levels and borrowers have less ability of file for Chapter 7. As both of these can increase recoveries, the model will show that lending will increase.

Table 1 below presents a catalog of our assumptions regarding each of these components. Recall that we assume exposure at deafult (EAD) to be 100% for all types. On the other hand, FV and B vary

¹⁴Of course, subdividing the population and re-running a linear regression is tantamount to running a regression on the full population with the appropriate combination of interaction terms. Nonetheless, in part because some lenders provide credit to specific subpopulations, the simplicity of a custom score appears to outweight the advantages of a single estimation process.

across these four types of borrowers. However, we can assume these terms to be equivalent across each type without loss of generality as part of a normalization assumption. After all, the *risk-free* component of one dollar of riskless lending has equal future value for all types of borrower. This claim is based on two assumptions which we think reasonable given the institutional features of the credit card market. One, the length of contract loan is equivalent for each borrower. This ensures that the discounted value of a \$1 risk free loan is equivalent across types. Two, we assume that there is a one-to-one mapping from probability of default to interest rate. This ensure that lenders choosing a particular interest rate for a loan associates that loan with a particular default probability. Once individuals are segregated into the four groups by observables, the loan rates are associated with type alone.

This leaves us with only the probability of default (PD) and loss given default (LGD). By signing the relationships between each of these parameters for all four types, we can make some claims and derive inference on the profitability of lenders and thus potentially gain insight into the observed patterns. Note that, for each of these cases we consider the lender's decision at the margin for a single marginal dollar of lending.

 Table 1: Summary of Assumptions

 Prime borrower (P)
 Subprime borrower (S)

| | Buoprinie bonower (b) |
|----------------------------------|--------------------------------|
| $PD_{NB}^P << PD_B^P$ | $PD_{NB}^{SP} \le PD_B^{SP}$ |
| $LGD_{NB}^{P} > LGD_{B}^{P}$ | $LGD_{NB}^{SP} > LGD_B^{SP}$ |
| $EAD_{NB}^{P} = EAD_{NB}^{SP} =$ | $EAD_B^P = EAD_B^{SP} = 100\%$ |

The key component that distinguishes ex-ante prime vs. ex-ante subprime borrowers who have gone into bankruptcy is the change in the probability of default. This change in probability will result both from the shock that led to the bankruptcy (e.g. unemployment, health changes, divorce, etc.) as well as the impact of the change in the budget constraint from removing the debt overhang problem. In our simple model, we assume that ex-ante subprime borrowers move marginally from high to higher default probability postbankruptcy, while ex-ante prime borrowers show a significant increase in default probabilities on average. In other words, ex-ante prime borrowers who file for bankruptcy look a lot more like a subprime borrower after they have filed for bankruptcy.

This assumption is strongly backed by evidence from our data as shown in Figure 2, which shows the 90-day delinquency rate for non-bankrupt and bankrupt borrowers in each of 5 credit categories where the

90 day delinquency rate is used as a proxy for non-bankruptcy default. Note that the credit scores listed on the x-axis correspond to the credit score of the bankrupt borrowers before their bankruptcy filing.¹⁵

As for ex-ante subprime borrowers, the data shows that these borrowers' delinquency / default rates are largely unchanged after bankruptcy. These are, largely speaking, borrowers that were already at the bottom of the credit quality spectrum. The data shows that the combination of the nature of shocks that led to bankruptcy and the relaxation of the budget constraint largely offset to produce similar default rates: $PD_B^{SP} \ge PD_{NB}^{SP}$. For prime borrowers, however, the same data shows a very large increase in default rates. This is due both to the shocks and to the fact that changes in debt burden may have less impact on high credit quality individuals. If they have been able to make payments in the past with the high debt levels, reductions in debt level on its own may be essential to describing ex-post default probabilities. As a result, we can write: $PD_B^P >> PD_{NB}^P$. In fact, it is these large average changes and differences in post-bankruptcy probability of default which help explain the relative decline in access to credit for prime-borrowers post-bankruptcy that we observe in the data. This finding is also in-line with our prior belief that bankruptcy is likely to carry a stronger signal about the post-bankruptcy repayment ability of ex-ante prime borrowers: it is very likely that individuals who had higher ex-ante credit scores ended up in bankruptcy due to a permanent shock, while those who are consistently around the low-end of the credit quality spectrum might be more prone to frequent, transitory shocks. Similarly, low-credit quality individuals are those most likely to benefit from a reduction in debt burdens.

The comparison of loss given default across borrower types is straightforward. Once a borrower enters bankruptcy, the creditor has two primary reasons to lend more to the individual that if they had not declared. The first is that once a borrower files for Chapter 7 bankruptcy, individuals cannot file for Chapter 7 bankruptcy again within 7 years. This means that legal avenues to recover debt cannot be avoided through a bankruptcy filing. The second is the the debt overhang story. A lender's expectation of recovery at the time of a new loan will be higher for an individual with lower existing obligations, ceteris paribus. Accordingly, we can also assume $LGD_{NB}^{SP} > LGD_{B}^{SP}$ and $LGD_{NB}^{P} > LGD_{B}^{P}$. While we have validated these assumptions with industry analysts, there is no readily available empirical evidence. Accordingly, in the next Section we carry-out a simple simulation exercise to better capture the effects of changes in LGD across our borrower types on lender's profits.

Following these assumptions, we can now evaluate the relationship between debt values for each group and make some claims about lenders' decisions to supply credit to these different groups.

¹⁵The 90-day delinquency rate for bankrupt borrowers is computed for individuals that filed for bankruptcy at least six months before the observation period in order to capture delinquencies after bankruptcy.

Claim 1 From a lender's perspective, the value of an extra dollar lent to a subprime borrower who has gone bankrupt is greater than one that is lent to a subprime borrower who has never gone bankrupt: $V_{NB}^{SP} < V_{B}^{SP}$.

To see this, we can re-write the debt value equation above for subprime borrowers who have never filed for bankruptcy:

$$V_{NB}^{SP} = (1 - PD_{NB}^{SP}) + PD_{NB}^{SP} \left(1 - LGD_{NB}^{SP}\right)$$
(2)

Recalling our assumptions that $LGD_{NB}^{SP} > LGD_{B}^{SP}$ and $PD_{B}^{SP} \ge PD_{NB}^{SP}$, we can evaluate how equation 2 changes when this borrower becomes bankrupt. Breaking the equation into two parts, we can see that the first term decreases as individuals move to bankruptcy. However, this change is rather small because the probability of default only slightly increases for these subprime borrowers as discussed above and as shown in Figure 2:

$$(1 - PD_{NB}^{SP}) \ge (1 - PD_B^{SP})$$

However, the second term increases as both the probability of default modestly increases and the loss given default decreases:

$$PD_{NB}^{SP}\left(1 - LGD_{NB}^{SP}\right) < PD_{B}^{SP}\left(1 - LGD_{B}^{SP}\right)$$

Accordingly, which of the two terms has a larger effect on V as subprime borrowers move to bankruptcy depends on the magnitude of change in each sub-component. We do know from data (as shown in Figure 2) that the change in PD is relatively small, and therefore, the change in V will be determined by the change in LGD. When the loss given default for bankrupts is sufficiently small compared to the loss given default for non-bankrupts we can conclude that $V_{NB}^{SP} < V_{B}^{SP}$. We discuss this LGD relationship in more detail in Section 3.2.

Claim 2 Contrary to the case of subprime borrowers, the value of an extra dollar lent to a prime borrower who has gone bankrupt is much smaller than one that is lent to a prime borrower who has never gone bankrupt: $V_{NB}^P > V_B^P$

To see this, we can again start from the debt value equation for prime borrowers who have never filed for bankruptcy:

$$V_{NB}^{P} = (1 - PD_{NB}^{P}) + PD_{NB}^{P} \left(1 - LGD_{NB}^{P}\right)$$

Given our assumptions and what we observe in the data, we can see that the first term $(1 - PD_{NB}^{P})$ decreases significantly when a prime borrower enters bankruptcy as their post-bankruptcy probability of default

increases. On the other hand, the latter term, $PD_{NB}^{P}(1 - LGD_{NB}^{P})$, increases as probability of default increases and loss given default declines. Again, we need to determine which one of the two terms has a larger effect on V as prime borrowers move to bankruptcy. We can see in Figure 2 that the change in PD_{NB}^{P} to PD_{B}^{P} is a very large one—on the order of 20%. So, we conjecture that V^{P} will fall as prime borrowers enter bankruptcy unless LGD changes on a very large magnitude.

3.4 A short simulation

We conduct two short simulation exercises to test the two conjectures seen above. As mentioned, the conclusions drawn rest on assumptions about the nature of loss given default for each type. In the prime case, we posited that $V_{NB}^P > V_B^P$ unless LGD changes by a large amount. In the subprime case, we claimed that $V_{NB}^{SP} < V_B^{SP}$ based on the assumption that $LGD_{NB}^{SP} > LGD_B^{SP}$.

To illustrate these assumptions, we solve equation 1 for each of the four types based on known values for probability of default (see Figure 2) and for all possible values of LGD. We can then determine what range of values of LGD are needed to confirm the conjectures above. Figure 3 shows the results of two simulations.

In the prime case, our exercise shows that there are no values of LGD that permit in increase in V^P as borrowers move to bankruptcy (Panel A). There is a negligible black region meaning that Claim 1 is invalidated only in the very unlikely situation where $LGD_B^P = 0$, i.e. recovery rates on defaulted debt of prime bankrupt individuals are close to 100%. This is strongly contradicted by industry experience; credit cards writeoffs are well above 0%!

In the subprime case, there is a range of LGD combinations before and after bankruptcy that are consistent with the conjecture above (Panel B). The shaded region is composed of LGD combinations that have post bankruptcy recoveries increase with respect to pre-bankruptcy. It is this region that is consistent with the concept that lenders have increased ability to collect on new debt after bankruptcy, either through enhanced ability to pursue legal action or through reduced competition with other lenders for the same assets. This invokes the law of unintended consequences: bankruptcy is intended to shield assets from creditors, and indeed it does. However, the trade-off is that lenders have increased ability to claim assets on new lending as borrowers cannot file again for a period of time.

This model, together with the results of our simulation exercise provides support for our findings regarding the differential supply of credit post-bankruptcy to prime and subprime borrowers. The framework presented helps us illustrate why the value of lending may be higher for subprime borrowers after they have filed for bankruptcy as opposed to lending to prime borrowers, especially since the latter become more like a "subprime" borrower once they enter bankruptcy.

In the subsequent sections, we present data on credit availability pre and post bankruptcy for each type of borrower. These empirical analyses support the post-bankruptcy conjectures discussed above. We find that while prime borrowers receive less credit after bankruptcy, subprime borrowers may indeed receive more. Both of these are consistent with the value changes in the lender models above.

4 Data

Our analysis is based on a unique, very large proprietary data set provided by one of the three major credit bureaus in the US. The data are drawn from geographically stratified random samples of individuals and include information on variables commonly available in a personal credit report. In particular, the file includes age, a variety of account and credit quality information such as the number of open accounts, defaulted accounts, current and past delinquencies, size of missed payments, credit lines, credit balances, etc. The information spans all credit lines, including mortgages, bank cards, installment loans and department store accounts. The credit bureau also provides a summary measure of default risk—a generic credit score. As is customary, account files have been purged of names, social security numbers, and addresses to ensure individual confidentiality.

The primary data were drawn from two periods in time with an 18 month interval—June 2003 and December 2004—comprising a very large repeated panel with about 270,000 individuals. For each individual, the data provider a generic credit score. Credit scores, in general, are inverse ordinal rankings of risk. That is, an individual with a credit score of 200 is viewed to have higher risk of default than an individual of score 201. However, the difference in risk between 200 and 201 may or may not be equal to the change from 201 to 202. Having information on credit quality allows us to answer some of the outstanding questions more accurately than has been done to date. Importantly, the data set also includes information on individual public bankruptcy filings.

Our key variable of interest is revolving credit line limits.¹⁶ We focus on revolving credit because unsecured credit is discharged during bankruptcy, and furthermore, our interest is in credit supply and credit limit is the best available proxy for it as has been justified by previous research (e.g. Gross and Souleles, 2002). We also consider availability of secured lending as a robustness check. Unfortunately, we do not observe and therefore are not able to comment on the "price" or cost of available credit to these individuals, which is likely to be an important indicator of credit availability. Nonetheless, we believe our results are

¹⁶Most revolving credit lines are unsecured. However, a small fraction corresponds to secured cards. A secured card requires a cash collateral deposit that becomes the credit line for that account. Our data does not allow us to distinguish between the two.

still informative and provide the first direct evidence on credit access of bankrupt individuals.

For the analysis we drop individuals that have a total credit limit smaller than \$1,000 in year 2003. We define two sub samples. The first one is the sample of individuals that have never filed for bankruptcy, comprising 122,159 individuals with complete information. Second, we construct the sub sample of individuals that go bankrupt between the two observation periods by selecting the individuals that have filed for bankruptcy in 2004 but had not declared bankruptcy before 2003 and, as a data cleaning exercise, drop individuals that in 2004 report more than 18 months since last derogatory public record. Indeed, the number of months permits us to analyze the evolution of credit after bankruptcy across individuals.

Finally, we also use a larger and more recent panel dataset we have from the same credit bureau. This panel, drawn in June 2006 and December 2007, helps us to analyze whether there might have been changes in credit markets, especially as we entered the slow-down in this 2007/2008 crisis. In other words, we use this latter dataset to see whether the associated credit cost for bankruptcy—the ease at which bankrupt individuals can get credit—has changed between the credit boom period of 2003/2004 and the slow-down in 2007.

Table 2 provides the summary statistics for the variables used in our analysis. Appendix Tables A and B provide more detailed descriptive statistics on the average credit limit by credit score brackets for the whole sample (Panel A), for the sub-sample of individuals that never filed for bankruptcy (Panel B), and for the sub-sample that file for bankruptcy (Panel C). In Panel C of Appendix Table B we can see that individuals with the lowest credit score (<300) have the lowest credit limit both before and after filing for bankruptcy, as expected: \$5,105 and \$1,980 in 2003 and 2004 respectively. Access to credit, measured by the percentage of individuals with positive credit limit in 2004, is increasing with pre-bankruptcy credit score: in the complete sample, 66% of individuals in the lowest credit score bracket have access to credit compared to an overall average of 96%. Also note that a significant fraction of the lowest credit score, bankrupt individuals (13%) experience an absolute increase in their credit limit.

5 Empirical Methodology and Results

5.1 Estimation of the credit access cost of bankruptcy

We define the credit availability cost of bankruptcy (Credit Cost) as the difference in credit limit available to individuals that have filed for bankruptcy with respect to the credit limit that would have been available to them had they not filed for bankruptcy. This requires the estimation of a counterfactual credit limit for individuals that file for bankruptcy. Estimation of counterfactuals can be particularly difficult in practice as we cannot observe individuals that have gone bankrupt in the non-bankrupt state (or the non-bankrupts in the bankrupt state). We work around this difficulty in two ways. First, we use both the information available to issuers to approximate their credit issuance methodology. Issuers provide credit based in great part on the information provided by consumer credit agencies. Using credit information, including the bankruptcy status, issuers make credit availability decisions. Second, the very large size of the dataset allow us to observe individuals of nearly identical circumstances and credit histories in two states of the world (bankrupt and non-bankrupt). The combination of these two methods provide us the ability to construct appropriate counterfactuals. That is, we can observe individual *i*, with credit history *x*, and bankruptcy status b = bankrupt as well as an individual *j*, with identical history *x*, and bankruptcy status b = notbankrupt.¹⁷

We proceed in three steps. First, using the sample of individuals that have never filed for bankruptcy in 2003 or 2004, we estimate the following model for the availability of credit in 2004 using observables in 2003 the results of which are provided in Table 3:

$$L_2004_i = \beta_1 L_2003_i + \beta_2 X \ 2003_i + u_i \tag{3}$$

where *i* is defined for all individuals that have never filed for bankruptcy and where $X_2003 = \{creditscore_i, age_i, numbercards_i, income_i, race_i, etc.\}$ is a vector of borrower characteristics in year 2003, and L_2004 and L_2003 are the limits in 2003 and 2004 respectively. We emphasize here that this estimation is based on our understanding of the process used by issuers to determine limits. Credit card issuers typically employ credit bureau information to decide the amount of credit and terms offered, with the credit score itself often acting as the most relevant variable in this decision. Therefore we can assume that, as econometricians, our use of credit bureau information approximates the information set of credit card issuers.

Using model 3, we predict the credit limit in 2004 for the sample of i individuals that have filed for bankruptcy in 2004 but did not in 2003. This is the counterfactual: estimated credit limit that would have been available in 2004 if they had not filed for bankruptcy, conditional on their observable characteristics in 2003.¹⁸

$$\hat{L}_2004_j = \widehat{\beta}_1 L_2003_j + \widehat{\beta}_2 X_2003_j$$

¹⁷It is worth noting here that a bankruptcy impacts an individual credit score; however, the credit score alone is not a sufficient statistic for credit availability. In other words, bankruptcy status provides additional information to explain total credit limit over the information contained in the credit score.

¹⁸Our data does not allow us to control for unobservables in the econometric model by including individual fixed effects given the short time dimension (two periods). We attempt to control for heterogeneity between bankrupt and non-bankrupt individuals by including as many borrowers' characteristics as possible and by complementing the data with census variables that control for unobserved individual characteristics that are shared with the surrounding neighbors. We also run a wide variety of alternative specifications as robustness checks by including interactions and splines with some of the explanatory variables (available upon request). The results are largely unchanged.

 \hat{L}_{2004_j} is the predicted limit in 2004 for individuals that have declared bankruptcy between 2003 and 2004.

Next, we estimate the credit cost of bankruptcy for individuals that filed for bankruptcy between 2003 and 2004 by subtracting the estimated credit limit in (2) from the actual observed credit limit in 2004.

$$CreditCost_j = L_{2004_j} - \hat{L}_{2004_j}$$

The credit cost of bankruptcy is negative when individuals obtain less credit after bankruptcy with respect to the credit limit they would have had if they did not file.

5.2 **Baseline Results**

Figure 4 plots the average credit cost of bankruptcy against months since most recent derogatory public record, which includes bankruptcy filings. As explained above, the credit cost is estimated as of December 2004 for the cross-section of individuals that file for bankruptcy between the two observation periods. By examining the credit cost of bankruptcy of individuals in December 2004 with respect to the number of months since they filed for bankruptcy we can make inferences about how credit availability changes over time after bankruptcy. We observe a U-shaped pattern, with a decrease in available revolving credit during the first six months after filing for bankruptcy, as would be expected. The credit limit loss reaches its maximum five months after bankruptcy and is on average \$24,000 at that point. After that, the credit cost gets smaller and approaches \$15,000, on average, at 18 months after bankruptcy.¹⁹²⁰

5.3 Heterogeneity: Credit Score

While on average a bankrupt individual faces a significant (albeit temporary) drop in available credit there is quite a bit of heterogeneity behind the average plotted in Figure 4. In what follows, we attempt to identify and discuss the factors that explain the different patterns of access to credit post bankruptcy by examining the relationship between credit cost of bankruptcy and various borrower characteristics. In Figure 5 we show the probabilities of receiving an increase in counterfactual credit (a positive credit cost) by credit score. For a significant fraction of individuals (18.3%) the credit cost of bankruptcy is indeed positive, meaning that they actually get more credit than predicted by model 3.²¹ This figure illustrates the phenomenon that we

¹⁹The distribution of the number of bankrupt individuals with respect the months since bankruptcy is fairly homogeneous. Furthermore, there is no relationship between the ex-ante credit score and number of months since bankruptcy filing. For the rest of the analysis, we aggregate all individuals that file for bankrutcy within this 18-month period.

²⁰Notice also that the observed decline in the first months may just reflect the reporting lag to the credit bureau. Due to data limitations we cannot produce this figure using the 2006-2007 data (variable months since bankruptcy is not available).

²¹In appendix Figure A, we plot the average drop in available credit for bankrupt individuals by credit score. It shows that on average there is a loss in available credit and for the highest credit score it is substantial—approaching \$40,000 lost in revolving credit.

highlight; those with very low credit quality are much more likely to receive increases in credit.

In Table 4 one can observe that individuals with the lowest credit scores have, on average, a positive bankruptcy credit cost. We measure this 'benefit' to bankruptcy at \$300 of increased revolving credit. While this increase is only 5.9% of the average credit limit prior to bankruptcy for the group of individuals, it is notable for the fact that it is positive. Importantly, this \$300 reflect an average consumer experience, rather than a few outliers. Indeed, 65% of individuals in the lowest credit score group have a positive bankruptcy credit cost.

We interpret these results as supporting a credit supply story that tracks the Black and Strahan (2002) logic applied to bankruptcy in Dick and Lehnert (2009). Increased lending to low credit quality borrowers post bankruptcy provides a potential reduction in the deterrent to file for these individuals. In spite of the widely believed exclusion from credit markets, a default by a low credit quality borrower had a relatively small impact.

5.4 Heterogeneity: Credit Cycle

We next explore the degree to which our results are a function of the credit cycle. The 2003-04 period is one that has been characterized as a credit boom; indeed one that likely had particularly lax credit standards. Potentially then, credit was easy to obtain both before and after bankruptcy. This section will evaluate how well our results hold up in a more restrictive credit environment.

As a preliminary test of whether these trends in credit access may be dependent on the credit cycle, we compare the mean bankruptcy credit cost in terms of revolving credit limit in 2003–04 against 2006–07. We present our results in Figures 6 and 7 and some additional descriptive statistics in Appendix Table C. As should be apparent, the figures show that in both time periods, the fraction of individuals that faced a positive credit cost of bankruptcy was declining in credit score; high quality borrowers suffered a larger relative decline in credit access.

The second notable feature of the figures is that during the credit boom of 2003–04 the bankruptcy credit cost was substantially lower for those of low credit quality. A much higher fraction of low credit quality individuals received counter-factually higher credit after bankruptcy during the credit boom (2003-04) than during the bust (2006-07). For individuals with high credit scores, the bankruptcy credit cost is similar in both time periods. These same results are shown again in Appendix Table C.

Again, this story is consistent with the supply-driven cause of bankruptcy, in the sense that credit supply has an impact on the consequences of filing, and therefore, determines the propensity to file. Consistent with their results we also find that different credit quality individuals are impacted differently by the credit cycle.

We can use the bank lending framework we presented in Section 3 to interpret these empirical results. We can see that our findings are consistent with (1) a small change in the PDs and LGDs of prime borrowers, which makes them as profitable as before, and (2) a significant increase in the PDs and/or increase in LGDs of subprime borrowers after bankruptcy in a downturn, which makes them a less profitable option than similar subprime non-bankrupt borrowers. Unfortunately, the time period of our sample only captures the beginning of the current downturn period in December 2007. Further research is needed as more recent data becomes available.

5.5 Heterogeneity: Other Factors

Combining data from the US Census on characteristics of the neighborhoods of these individuals, our appendix tables shows that individuals with positive credit cost tend to live in areas with lower educational attainment, higher divorce rates, more blacks, and lower incomes. To further investigate these trends, we dividing the sample by percentage of minorities (Panel A), income brackets (Panel B) and education level (Panel C) of the neighborhoods of these individuals. We find that individuals with the lowest credit score and a lower propensity to repay as proxied by income, race and education are the ones that are offered more credit after bankruptcy, especially in the 2003-04 period. These findings are consistent with the observation that lenders profit from a risky subset of the population. In credit card industry parlance these individuals are referred as "cash cows" because they generate high income and profit margins, usually from high interest rates and fee income, as illustrated in NY Times article referenced in the introduction. Unfortunately, our data does not contain information on the interest rates or fees charged on the accounts, and therefore, we are cautious to derive further conclusions from those observed patterns.²²

5.6 Other Types of Credit

An alternative interpretation of the observed differential change in access to credit between prime and subprime borrowers may be that these individuals use different forms of credit after bankruptcy and looking at revolving credit alone may be misleading. This could manifest in two ways. We may observe relatively high access to revolving, unsecured credit because issuers have maintained these lines at the expense of other types of credit. Alternatively, one may observe differential changes in access if the composition of demand by type of credit changes as a function of credit quality. For example, if low-risk individuals are more likely to apply for credit cards and high-risk individuals for auto-loans.

Accordingly, we repeat our analysis on the bankruptcy credit cost for other types of credit-mortgages,

²²We present an illustration of these results in Appendix Figure B.

installments loans (including auto-loans), and total credit. Figure 6 presents the results from this exercise. The figure shows no evidence of the composition effects mentioned above and that total credit and mortgages follow a similar pattern to those observed using revolving credit alone. Having said so, interpreting the changes in secured lines, such as mortgages, is difficult especially because only unsecured debt is discharged in bankruptcy and not secured loans. Nonetheless, it is interesting that installment credit shows a different picture: a smaller fraction of low credit score individuals have a positive credit cost, as compared to other credit types, while the percentage of individuals with a positive installment credit cost is quite stable across the credit score dimension. This is again consistent with the patterns reported in Porter (2008) for secured lending and is likely driven by other supply factors, such as differences in underwriting standards between secured vs. unsecured loans.

6 Potential caveats

6.1 Endogeneity

As is standard, there are potentially a few factors that confound our interpretation of these observed facts. Among these is the identification of supply vs. demand effects. Recall that one of our central findings is that individuals with higher ex-ante credit scores face a larger credit cost on average. One potential explanation for this might be that individuals who historically had good credit records but ended up in bankruptcy have suffered a permanent income shock or that they have defaulted strategically. Both of these possibilities would explain a decrease in a lender's willingness to lend to such individuals *and* a decrease in the demand for credit by these individuals. After all, individuals would be more likely to reduce their consumption and reliance on borrowing in the face of permanent income shocks.

We emphasize that this on its own cannot explain the differential issuance of credit observed, unless there is reason to believe that the ex-ante low credit-score individuals are more likely to face frequent but temporary shocks. In short, there is currently no evidence that bankruptcy provides a signal about the nature of realized idiosyncratic shocks that differs systematically by ex-ante credit quality. Without such a differential, the results provided in this paper are reflective of lender supply decisions.

Similarly, it may well be that, well-educated individuals and/or those with ex-ante good credit histories are better at reading the fine print on solicitations they receive compared to others, and less likely to accept credit limits at any cost. Accordingly, lenders might well be targeting all bankrupt individuals but only those with low-credit scores accept the offers, explaining the observed patterns in our data.

However, both of these explanations are difficult to justify in an equilibrium framework. In such an

environment, one would expect lenders to respond to react; however, the legal literature provides ample evidence that all types receive continued solicitations for credit after bankruptcy. This suggests that our results emerge from differences in the provided limits rather than systematic demand differences amongst the borrowers.

6.2 Unobservables

Finally, one may imagine that unobservable differences in the reasons for filing could impact our conclusions. That is a particular combination of ex-ante differences, unobservable to the researcher, could bias our results and interpretation. For example, if low credit-quality individuals file for bankruptcy knowing ex-ante that they will demand relatively more credit after the filing and high credit quality individuals file due to unexpected financial hardship and know they will request relatively little credit, our estimates may reflect this differences rather than differences in supply.

Since our evaluation is based on the information set available to the lenders prior to and after the bankruptcy filing, our results are consistent with the lenders' decision process for the issuance of credit. Decisions unobservable to the researcher are also unobservable to lenders. Thus, our estimates of credit issuance post bankruptcy cannot be biased by unobservables in the determination of issuer credit provision.

We similarly cannot systematically rule out the possibility that low credit quality individuals are precisely those that strategically file; however, we find this implausible. In particular, it is implausible because, similarly to above, a pattern of strategic filing by some individuals and not others that would undermine our results is not consistent with equilibrium provision of credit. If low credit quality individuals systematically gamed the system, lenders would react to this phenomenon by refusing credit provision post-bankruptcy to all individuals with low credit quality. Credit is provided post bankruptcy based on expectation of repayment; we see no reason why the unobserved (to the lender) reasons for filing would impact a lender's credit decision.

6.3 Bankruptcy Reform

In October of 2005, bankruptcy laws in the United States changed. The Bankruptcy Abuse Prevention and Consumer Protection Act of 2005 (BACPCA) made two primary changes to the bankruptcy code. One made the cost of filing significantly higher. The other placed a means test on Chapter 7 filers. Any individual with income above the median for his or her local area would not qualify for a Chapter 7 discharge of unsecured debt. Instead, the individual would need to file for a Chapter 13 reorganization. The purpose of this test was to ensure that individuals with good future prospects did not take advantage of the court system to avoid debt

payments. These individuals do not suffer from a debt overhang problem in the sense that debt obligations will not prevent other forms of consumption as they might for individuals at the lower end of the income spectrum.

The debt overhang explanation of post-bankruptcy credit would suggest that individuals with good future prospects (high income) and low credit quality should be those most likely to receive credit after bankruptcy. Those with particularly low income are unlikely to be able to pay future debt even with the removal of other obligations.

As a result, one should see an empirical difference between the relatively wealthy and the relatively poor in terms of access to credit. Figure 7 below show the fraction of individuals with a counter-factual increase in credit across income categories. Two features emerge. One, as Figure 5 above showed, those with low credit qualiity in both income categories disproportionately benefit from a bankruptcy filing as one would expect. Two, even though there are some minor differences in access as a function of income levels prior to the bankruptcy law change, in 2006, the figures are nearly identical.

Thus while the legal change has substantial impacts on the bankruptcy process, it does not appear to impact our primary conclusions.

7 Conclusion

This paper presents an empirical evaluation of credit access of individuals immediately post-bankruptcy, a topic that has generated much discussion and speculation. We first show that while individuals do see significant drops in their credit lines immediately after they file for bankruptcy (probably as their debt gets discharged), they seem to be able to regain access to credit very soon thereafter. Second, we show that those individuals who are effectively the least punished and can get the easiest access to credit afterwards tend to be the ones who have shown the least ability and propensity to repay their debt prior to declaring bankruptcy. In fact, a significant fraction of individuals at the bottom of the credit quality spectrum seem to receive more credit after filing than before.

We interpret this increase in credit access and the difference in credit provision across borrowers as a logical response to the incentives manifest in the bankruptcy code for borrowers and lenders. These incentives lead to lending to low credit quality individuals even after a bankruptcy filing in part because these borrowers are slightly less risky than they were prior to bankruptcy.

Nevertheless we need more analysis to resolve some of the confounding issues to have a clearer, stronger picture. In particular, we need a better understanding of the nature of income shocks or other factors that

derive an individual's bankruptcy decision. After all, such an understanding is the key to whether bankruptcy reveals a change in an individual's future repayment behavior. Similarly, using longer time-series data it will be interesting to see how the exclusion credit cost might have changed over the last couple decades and whether credit availability for recently bankrupt individuals will change as part of the ever changing landscape associated with the current financial turmoil.

References

- [1] Aguiar, M. & G. Gopinath., 2006, "Defaultable Debt, Interest Rates, and the Current Account," Journal of International Economics, 69(1): 64–83.
- [2] Arslanalp, S. & P. Henry., 2005, "Is Debt Relief Efficient?" The Journal of Finance, 60(2):1017-1051.
- [3] Athreya, K., 2002., "Welfare Implications of the Bankruptcy Reform Act of 1999," Journal of Monetary Economics, 49(8): 1567–95.
- [4] Athreya, K., 2006., "Credit Exclusion in Quantitative Models of Bankruptcy: Does it Matter?" Federal Reserve Bank of Richmond Economic Quarterly, 92(Winter), 17–49.
- [5] Berkowitz, J. & M. White., 2004, "Bankruptcy and Small Firms' Access to Credit" The RAND Journal of Economics, 35(1): 69-84.
- [6] Black, S. & P. Strahan., 2002, "Entrepreneurship and Bank Credit Availability" Journal of Finance 57(6), 2807-33.
- [7] Block-Lieb, S. & E. Janger., 2006, "The Myth of the Rational Borrower: Rationality, Behavorialism and the Misguided 'Reform' of Bankruptcy Law," Texas Law Review, 84.
- [8] Braucher, J., 2004, "Consumer Bankruptcy as Part of the Social Safety Net: Fresh Start or Treadmill?"
 44 Santa Clara Law Review, 1065: 1088–1089.
- [9] Bulow, J., 1991, "Sovereign Debt Repurchases: No Cure for Overhang" The Quarterly Journal of Economics, 106(4):1219-1235.
- [10] Campbell, J., 2006, "Household Finance," Journal of Finance, 61:1553-1604.
- [11] Chatterjee, S., D. Corbae, M. Nakajima, & J.V. Rios-Rull., 2007, "A Quantitative Theory of Unsecured Consumer Credit with Risk of Default," Econometrica, 75(6):1525–1589.

- [12] Chatterjee, S., D. Corbae, & J.V. Rios-Rull., 2009, "Credit Scoring and the Competitive Pricing of Default Risk" Working Paper
- [13] Cohen-Cole, E., 2009, "The Option Value of Consumer Bankruptcy, Can Uninsured Idiosyncratic Risk Explain Bankruptcy Patterns?" University of Maryland, mimeo
- [14] Dick, A., & A. Lehnert., 2009, "Personal Bankruptcy and Credit Market Competition" Journal of Finance, forthcoming
- [15] Domowitz, I. & R. Sartain., 1999, "Determinants of the Consumer Bankruptcy Decision," Journal of Finance, 54: 403-420.
- [16] Fernandez-Ruiz, J., 2000, "Debt Buybacks, Debt Reduction, and Debt Rescheduling under Asymmetric Information" Journal of Money, Credit and Banking, 32 (1): 13-27
- [17] Fisher, J., L. Filer, & A. Lyons., 2004, "Is the Bankruptcy Flag Binding? Access to Credit Markets for Post-Bankruptcy Households," American Law & Economics Association 14th Annual Meeting, April, Working Paper 28.
- [18] Gropp, R., J. Scholz, & M. White., 1997, "Personal Bankruptcy and Credit Supply and Demand," Quarterly Journal of Economics, 112: 217-251.
- [19] Jacoby, M., 2005, "Ripple or Revolution? The Indeterminacy of Statutory Bankruptcy Reform," American Bankruptcy Law Journal, 75, 169–190.
- [20] Han, S., & G. Li., 2009, "Household Borrowing after Personal Bankruptcy," Finance and Economics Discussion Series 2009-17, Board of Governors of the Federal Reserve System.
- [21] Livshits, I., J. MacGee, & M. Tertilt, 2007, "Consumer Bankruptcy: A Fresh Start," American Economic Review, 97(1), 402–418.
- [22] Mann, R., 2007 "Bankruptcy Reform and the "Sweatbox" of Credit Card Debt," Illinois Law Review, 375.
- [23] Musto, D., 2004, "What Happens When Information Leaves a Market? Evidence from Postbankruptcy Consumers," Journal of Business, 77(4), 725–748.
- [24] Myers, S., 1977, "Determinants of Corporate Borrowing", Journal of Financial Economics, 5, 147-75

- [25] Porter, K., 2008, "Bankrupt Profits: The Credit Industry's Business Model for Postbankruptcy Lending," Iowa Law Review, Vol. 94.
- [26] Porter, K. & D. Thorne, 2006, "The Failure of Bankruptcy's Fresh Start" Cornell Law Review, Vol. 92.
- [27] Sapriza, H. & G. Cuadra, 2006, "Sovereign Default, Terms of Trade and Interest Rates in Emerging Markets" Working Papers 2006-01, Banco de México.
- [28] Sommer, H., 2005, "Trying to Make Sense Out of Nonsense: Representing Consumers Under the 'Bankruptcy Abuse Prevention and Consumer Protection Act of 2005," American Bankruptcy Law Journal 79.
- [29] Stanley, D., & M. Girth, 1971, Bankruptcy: Problem, Process, Reform, Brookings Institution.
- [30] Staten, M., 1993, "The Impact of Post-Bankruptcy Credit on the Number of Personal Bankruptcies," Credit Research Center, Purdue University, Krannert Graduate School of Management, Working Paper 58.
- [31] Stavins, J., 2000. ""Credit Card Borrowing, Deliquency, and Personal Bankruptcy." New England Economic Review. July/August.
- [32] Sullivan, T., E. Warren, & J. Westbrook, 2006, "Less Stigma or More Financial Distress: An Empirical Analysis of the Extraordinary Increase in Bankruptcy Filings," Stanford Law Review 59 (213).
- [33] Weiner, R., C. Baron-Donova, S. Block-Lieb, & K. Gross, 2005 "Unwrapping Assumptions: Applying Social Analytic Jurisprudence to Consumer Bankruptcy Education Requirements and Policy." American Bankruptcy Law Journal 79 (2).

TABLE 2: SUMMARY STATISTICS

| | COMPLE | ETE SAMPLE | NON-BANKRUPT INDIVIDUALS | | BANKRUP | Γ INDIVIDUALS |
|---|-----------|------------|--------------------------|-----------|-----------|---------------|
| VARIABLES | 2003/2004 | 2006/2007 | 2003/2004 | 2006/2007 | 2003/2004 | 2006/2007 |
| Age | 49.12 | 38.47 | 49.18 | 38.48 | 44.05 | 36.70 |
| Bank Cards: number (t-1) | 1.77 | 1.78 | 1.76 | 1.77 | 2.78 | 2.83 |
| Black (% in 1 mile radius) | 0.092 | 0.096 | 0.092 | 0.096 | 0.138 | 0.131 |
| Credit Score (t) | 664.1 | 703.9 | 667.8 | 705.1 | 347.3 | 500.4 |
| Credit Score (t-1) | 668.6 | 707.5 | 670.9 | 708.7 | 468.0 | 497.9 |
| Divorced (% females in 1 mile radius) | 0.106 | 0.096 | 0.106 | 0.096 | 0.117 | 0.105 |
| Divorced (% males in 1 mile radius) | 0.083 | | 0.083 | | 0.095 | |
| Greater Than High School Equivalency (% in 1 mile radius) | 0.829 | 0.828 | 0.830 | 0.828 | 0.801 | 0.807 |
| Hispanic (% in 1 mile radius) | 0.104 | 0.119 | 0.104 | 0.119 | 0.108 | 0.103 |
| Income Growth | 0.475 | 1.120 | 0.477 | 1.122 | 0.282 | 0.693 |
| Median Household Income | 45,011 | 50,505 | 45,038 | 50,517 | 42,791 | 48,340 |
| No Earnings (% in 1 mile radius) | 0.184 | 0.185 | 0.184 | 0.185 | 0.191 | 0.190 |
| Population Density | 2,195 | 2,484 | 2,207 | 2,487 | 1,128 | 1,806 |
| Public Assistance (% in 1 mile radius) | 0.029 | 0.030 | 0.029 | 0.030 | 0.036 | 0.034 |
| Revolving Credit Limit (t) | 39.14 | 45.09 | 39.53 | 45.30 | 5.51 | 8.60 |
| Revolving Credit Limit (t-1) | 33.93 | 40.11 | 34.05 | 40.18 | 23.65 | 28.79 |
| Revolving Credit Utilization (t) | 24.15 | 23.44 | 24.07 | 23.37 | 33.55 | 44.02 |
| Revolving Credit Utilization (t-1) | 24.63 | 24.20 | 24.17 | 23.99 | 63.54 | 61.11 |
| Total Credit Limit (t) | 117.3 | 140.6 | 118.2 | 141.0 | 47.19 | 67.91 |
| Total Credit Limit (t-1) | 97.75 | 122.8 | 97.83 | 122.8 | 91.22 | 129.1 |
| Unemployment Rate | 5.751 | 5.041 | 5.749 | 5.040 | 5.884 | 5.223 |
| Uninsured (health) | 16.93 | 15.72 | 16.93 | 15.72 | 17.25 | 15.31 |
| Number of observations | 122,159 | 949,976 | 120,726 | 944,567 | 1,433 | 5,409 |

Notes: Based on authors' calculations using credit bureau data, Census, and the Bureau of Labor Statistics. The coefficient reported for Divorced (Female) in 2006/2007 represents the combined male/female divorce rate. All data are the means of the variable indicated.

| | 200 | 3/2004 | 200 | /2007 | |
|---|--------------|--------------|--------------|--------------|--|
| Dependent Variable | Total Credit | Revolving | Total Credit | Revolving | |
| Dependent variable | Limit | Credit Limit | I imit | Credit Limit | |
| | | | Limit | | |
| | (2004) | (2004) | (2006) | (2006) | |
| Total Credit Limit | 0.904*** | 0.0503*** | 0.984*** | 0.0367*** | |
| | (0.00621) | (0.00209) | (0.00162) | (0.000552) | |
| Installment Credit Limit | 0.102*** | -0.0268*** | 0.0950*** | -0.0181*** | |
| | (0.0187) | (0.00629) | (0.00728) | (0.00248) | |
| Revolving Credit Limit | 0.167*** | 0.895*** | 0.0204*** | 0.874*** | |
| | (0.0143) | (0.00482) | (0.00401) | (0.00136) | |
| Revolving Credit Utilization | -0.120*** | -0.0322*** | -0.0795*** | -0.0226*** | |
| | (0.0153) | (0.00515) | (0.00528) | (0.00180) | |
| Revolving Credit Balance | 0.871*** | 0.0595*** | 0.577*** | 0.0115* | |
| <u> </u> | (0.0636) | (0.0214) | (0.0187) | (0.00635) | |
| Revolving Credit Balance - Squared | -0.00887*** | -0.00274*** | -0.00407*** | -0.00160*** | |
| Revolving creat Batalee Bquared | (0.000730) | (0.000246) | (0.000152) | (5.17e.05) | |
| Cradit Sacra | 0.0285*** | 0.0207*** | 0.0201*** | 0.0129*** | |
| Clean Scole | (0.00402) | (0.0207 | (0.00142) | (0.000482) | |
| | (0.00403) | (0.00136) | (0.00142) | (0.000483) | |
| Bank Cards (number) | 0.787*** | -0.526** | 1.244*** | 1.759*** | |
| | (0.0702) | (0.208) | (0.0768) | (0.0261) | |
| Ratio of Revolving to Total Credit Limit | 16.84*** | 1.700*** | 10.10*** | -0.333* | |
| | (1.472) | (0.496) | (0.510) | (0.173) | |
| Ratio of Installment to Total Credit Limit | 18.60*** | 3.791*** | 20.93*** | 2.862*** | |
| | (1.835) | (0.618) | (0.661) | (0.225) | |
| 90-Days Delinquent (Current) | -11.62*** | -0.877 | -14.02*** | -2.303*** | |
| | (2.284) | (0.769) | (0.842) | (0.286) | |
| 90-Days Delinquent (Ever) | -0.464 | -0.300 | -0.810** | -1.244*** | |
| | (1.024) | (0.345) | (0.400) | (0.136) | |
| Age-Squared | -0.0108*** | -0.00345*** | -0.0110*** | -0.00320*** | |
| rige oqualed | (0.000800) | (0.000272) | (0.000693) | (0.000236) | |
| A 90 | (0.000309) | (0.000272) | 0.242*** | (0.000230) | |
| Age | (0.0972) | (0.0203) | (0.0592) | (0.0108) | |
| | (0.0873) | (0.0294) | (0.0582) | (0.0198) | |
| Divorced (Female) | 19.69** | -1.549 | -/.606** | -13.21*** | |
| | (9.090) | (3.062) | (3.445) | (1.172) | |
| Divorced (Male) | -5.259 | -9.824*** | - | - | |
| | (10.51) | (3.540) | | | |
| Greater Than High School Equivalency (Female) | 47.98*** | 5.886*** | 34.71*** | 7.872*** | |
| | (3.973) | (1.338) | (1.633) | (0.556) | |
| Income Growth | 0.648*** | 0.148*** | 0.406*** | -0.00734 | |
| | (0.103) | (0.0348) | (0.0384) | (0.0131) | |
| Median Household Income | 0.00103*** | 0.000143*** | 0.000396*** | 8.87e-05*** | |
| | (4.49e-05) | (1.51e-05) | (1.56e-05) | (5.32e-06) | |
| Percentage with No Earnings | 0.420 | 2.253* | -5.676*** | 1.360*** | |
| | (3.534) | (1.190) | (1.385) | (0.471) | |
| Percentage Black | -2 407 | -0.637 | 2 712*** | -0 599** | |
| Tereonage Black | (1.946) | (0.655) | (0.773) | (0.263) | |
| Persontage Hispania | 0.656*** | (0.055) | (0.775) | 2 220*** | |
| recentage mispanic | (2.750) | (0.020) | (1.084) | (0.260) | |
| | (2.759) | (0.929) | (1.084) | (0.369) | |
| Population Density | 1.84e-05 | 5.18e-06 | 0.000202*** | 5.38e-05*** | |
| | (4.49e-05) | (1.51e-05) | (1.63e-05) | (5.55e-06) | |
| Povery Rate | 1.155*** | 0.137*** | 0.206*** | 0.0509*** | |
| | (0.106) | (0.0357) | (0.0419) | (0.0142) | |
| Percentage on Public Assistance | 12.28 | 4.716 | 38.17*** | 8.422*** | |
| | (12.89) | (4.343) | (5.237) | (1.782) | |
| Unemployment | 0.680*** | 0.0800 | -0.459*** | -0.0544 | |
| | (0.231) | (0.0777) | (0.101) | (0.0342) | |
| Uninsured | 0.106 | -0.0177 | 0.380*** | 0.159*** | |
| | (0.0684) | (0.0230) | (0.0310) | (0.0106) | |
| Constant | -27 92*** | -112 3*** | -61 50*** | -24 47*** | |
| Constant | (1.978) | (5.871) | (2.479) | (0.843) | |
| | (1.770) | (3.071) | (2.77) | (0.0-0) | |
| Observations | 120720 | 120720 | 944567 | 944567 | |
| R-squared | 0.556 | 0.539 | 0.651 | 0.626 | |
| | 0.000 | 0.001 | 0.001 | 0.020 | |

TABLE 3: REGRESSION RESULTS (NON-BANKRUPT INDIVIDUALS)

 $\frac{0.350}{\text{vsquareu}} = \frac{0.350}{0.359} = \frac{0.551}{0.051} = \frac{0.020}{0.000}$ Notes: The numbers reported are the coefficients estimated using a standard OLS model. The coefficient reported for Divorced (Female) in 2006/2007 represents the combined male/female divorce rate. Robust standard errors are reported in parentheses, and we adopt the usual convention: *** p<0.01, ** p<0.05, * p<0.1

TABLE 4: CREDIT COST (REVOLVING CREDIT)

| | 200 | 3/2004 | 200 | 6/2007 | |
|-------------|-------------------------------|--|-------------------------------|--|--|
| | Credit Cost (\$ thousands) | Positive Credit Cost (% of cohort) | Credit Cost (\$ thousands) | Positive Credit Cost (% of cohort) | |
| <300 | 0.302 | 65.2 | (5.880) | 34.6 | |
| 300-400 | (7.393) | 24.7 | (8.164) | 28.4 | |
| 400-500 | (12.72) | 12.6 | (15.99) | 15.6 | |
| 500-600 | (30.47) | 2.0 | (30.60) | 6.1 | |
| 600-700 | (37.32) | 3.1 | (40.59) | 5.0 | |
| 700+ | (39.72) | 4.5 | (34.25) | 11.9 | |
| Full Sample | (19.1) | 18.3 | (23.4) | 15.1 | |

Notes: The values reported pertain to individuals who declared bankruptcy in the time periods 2003-2004 and 2006-2007. The first and third columns report the average difference between forecast revolving credit, as described in the text, and actual revolving credit in thousands of dollars (the bankruptcy credit cost) while the second and fourth columns report the the percentage of individuals who had an increase in counter-factual credit (positive credit cost). Each statistic is reported for the credit score group denoted in the row heading.

FIGURE 1: VANTAGESCORE SEGMENTATION AND SCORE COMPOSITION

Panel A:



Source: Vantage corporation marketing materials. Panel A shows available categories for custom scores including a primary division of the population into bankrupt and non-bankrupt individuals.

FIGURE 2: PERCENTAGE OF INDIVIDUALS 90-DAY DELINQUENT BY CREDIT SCORE AND BANKRUPTCY STATUS



Note: Each observation indicates the percentage of individuals who were 90-days delinquent in December 2004. The lines divide the sample into agents who declared bankruptcy at some point *before* the 90-day delinquency and those who did not declare bankruptcy. The x-axis indicates credit score and the y-axis the percentage of individuals in each group.

FIGURE 3: VALUE OF BANKRUPT VS. NON-BANKRUPT SUBPRIME AND PRIME BORROWERS



Note: Panel A shows the values of Loss Given Default that permit an increase in value for prime borrowers. Panel B shows the values of Loss Given Default that permit an increase in value for sub-prime borrowers. The black shaded regions denote that the value of bankrupt individuals, to the lender, is greater than the value of non-bankrupt individuals.

FIGURE 4: AVERAGE CREDIT COST BY MONTHS SINCE FILING (in thousands of dollars)



Note: Solid line indicates 3-month moving average, dots indicate the average bankruptcy credit cost if filed by bankruptcy X months ago. Methodology for calculating the credit cost is discussed in Section 4. X-axis indicates time since bankruptcy. Y-axis indicates change in credit available versus counterfactual of similar individuals who did not declare bankruptcy in thousands of dollars.

FIGURE 5: INDIVIDUALS (%) WITH AN *INCREASE* IN COUNTERFACTUAL CREDIT FOLLOWING BANKRUPCY (POSITIVE CREDIT COST)



Note: The figure shows the number of individuals who had more credit than would have otherwise have been available divided by the total number declaring bankruptcy, for a particular credit score. The line indicates the moving average across 100 of these credit score groups. Methodology for calculating the credit cost is discussed in Section 4. X-axis indicates continuous credit scores.

FIGURE 6: INDIVIDUALS (%) WITH AN *INCREASE* IN COUNTERFACTUAL CREDIT FOLLOWING BANKRUPCY (POSITIVE CREDIT COST) PANEL A: TOTAL CREDIT LIMIT





Note: The figure shows the number of individuals who had more credit than would have otherwise have been available divided by the total number declaring bankruptcy, for a particular credit score. Solid line indicates the moving average across 100 of these credit score groups. Methodology for calculating the credit cost is discussed in Section 4. X-axis indicates continuous credit scores.

FIGURE 7: INDIVIDUALS (%) WITH AN *INCREASE* IN COUNTERFACTUAL CREDIT FOLLOWING BANKRUPCY (POSITIVE CREDIT COST), BY INCOME



PANEL A: INCOME LESS THAN OR EQUAL TO THE 50th PERCENTILE

PANEL B: INCOME GREATER THAN THE 50th PERCENTILE



Note: The figure shows the number of individuals who had more credit than would have otherwise have been available divided by the total number declaring bankruptcy, for a particular credit score. Solid line indicates the moving average across 100 of these credit score groups. Methodology for calculating the credit cost is discussed in Section 4. X-axis indicates continuous credit scores.



APPENDIX FIGURE A: CREDIT COST BY CREDIT SCORE (in thousands of dollars)

Note: Methodology for calculating credit cost is discussed in Section 4 of the paper. X-axis indicates credit score in year preceding bankruptcy. Y-axis indicates change in credit available versus counterfactual of similar individuals who did not declare bankruptcy in thousands of dollars.

APPENDIX FIGURE B: INDIVIDUALS (%) WITH AN *INCREASE* IN COUNTERFACTUAL CREDIT FOLLOWING BANKRUPCY (POSITIVE CREDIT COST)





Note: The figure shows the number of individuals who had more credit than would have otherwise have been available divided by the total number declaring bankruptcy, for a particular credit score. Solid line indicates the moving average across 100 of these credit score groups (Panel B is the exception where the moving average was calculated across 75 credit scores). Methodology for calculating the credit cost is discussed in Section 4. X-axis indicates continuous credit scores.

APPENDIX

APPENDIX TABLE A: 2003/2004 CREDIT STATISTICS BY CREDIT SCORE (REVOLVING CREDIT)

PANEL A: COMPLETE SAMPLE (N = 122,159)

| CREDIT LIMIT | <300 | 300-400 | 400-500 | 500-600 | 600-700 | 700+ | Full Sample |
|---|----------|----------|----------|-----------|-----------|-----------|-------------|
| Credit Limit in 2003 (\$ thousands) | 3.565 | 7.820 | 11.604 | 25.00 | 37.14 | 39.96 | 33.93 |
| Credit Limit in 2004 (\$ thousands) | 1.991 | 5.168 | 10.555 | 26.63 | 44.77 | 46.55 | 39.14 |
| Credit Change 2004-03 (\$ thousands) | -1.574 | -2.652 | -1.049 | 1.628 | 7.631 | 6.586 | 5.209 |
| Increase in Credit Limit 2003-04 (% cohort) | 18.12 | 24.87 | 39.7 | 54.12 | 64.75 | 55.29 | 54.33 |
| Positive Credit Limit 2004 (% cohort) | 66.47 | 81.08 | 90.45 | 95.67 | 98.05 | 98.15 | 96.09 |
| | n = 2329 | n = 5179 | n = 5791 | n = 16795 | n = 24990 | n = 67075 | n = 122159 |
| PANEL B: NON-BANKRUPT INDIVIDUALS (N = 120,726) | | | | | | | |
| Credit Limit in 2003 (\$ thousands) | 3.420 | 7.559 | 11.502 | 24.75 | 37.08 | 39.95 | 34.05 |
| Credit Limit in 2004 (\$ thousands) | 1.992 | 5.334 | 10.794 | 27.17 | 45.04 | 46.57 | 39.53 |
| Credit Change 2004-03 (\$ thousands) | -1.428 | -2.224 | -0.708 | 2.420 | 7.955 | 6.612 | 5.486 |
| Increase in Credit Limit 2003-04 (% cohort) | 18.56 | 26.23 | 40.8 | 55.49 | 65.22 | 55.32 | 54.89 |
| Positive Credit Limit 2004 (% cohort) | 66.73 | 82.08 | 91.18 | 96.03 | 98.13 | 98.16 | 96.34 |
| | n = 2128 | n = 4815 | n = 5601 | n = 16355 | n = 24796 | n = 67031 | n = 120726 |
| PANEL C: BANKRUPT INDIVIDUALS (N = 1,433) | | | | | | | |
| Credit Limit in 2003 (\$ thousands) | 5.105 | 11.274 | 14.61 | 34.35 | 44.30 | 51.65 | 23.65 |
| Credit Limit in 2004 (\$ thousands) | 1.980 | 2.964 | 3.510 | 6.536 | 10.448 | 19.235 | 5.508 |
| Credit Change 2004-03 (\$ thousands) | -3.124 | -8.310 | -11.10 | -27.81 | -33.85 | -32.42 | -18.14 |
| Increase in Credit Limit 2003-04 (% cohort) | 13.43 | 6.868 | 6.842 | 2.955 | 4.124 | 11.36 | 6.350 |
| Positive Credit Limit 2004 (% cohort) | 63.68 | 67.86 | 68.95 | 82.27 | 87.11 | 86.36 | 75.02 |
| | n = 201 | n = 364 | n = 190 | n = 440 | n = 194 | n = 44 | n = 1433 |

Notes: The numbers reported are the mean of the credit variable indicated in the row header for a particular to the credit score in 2003. Panel A reports the statistics for the complete sample, Panel B reports the statistics for individuals who have never declared bankruptcy, and Panel C reports the statistics for individuals who did declare bankruptcy between 2003 and 2004.

APPENDIX

APPENDIX TABLE B: 2006/2007 CREDIT STATISTICS BY CREDIT SCORE (REVOLVING CREDIT)

PANEL A: COMPLETE SAMPLE (N = 949,976)

| CREDIT LIMIT | <300 | 300-400 | 400-500 | 500-600 | 600-700 | 700 + | Full Sample |
|---|-----------|-----------|-----------|------------|------------|--------------|-------------|
| Credit Limit in 2006 (\$ thousands) | 6.040 | 7.631 | 12.306 | 22.75 | 41.70 | 47.58 | 40.11 |
| Credit Limit in 2007 (\$ thousands) | 4.241 | 6.246 | 12.271 | 25.33 | 48.31 | 53.37 | 45.09 |
| Credit Change 2007-06 (\$ thousands) | -1.799 | -1.385 | -0.035 | 2.59 | 6.60 | 5.80 | 4.98 |
| Increase in Credit Limit 2006-07 (% cohort) | 25.06 | 30.85 | 44.7 | 58.24 | 64.82 | 55.86 | 56.15 |
| Positive Credit Limit 2007 (% cohort) | 73.89 | 78.57 | 87.61 | 94.45 | 98.11 | 99.34 | 97.00 |
| | n = 11396 | n = 28934 | n = 50766 | n = 103938 | n = 186095 | n = 568847 | n = 949976 |
| PANEL B: NON-BANKRUPT INDIVIDUALS (N = 944,567) | | | | | | | |
| Credit Limit in 2006 (\$ thousands) | 5.854 | 7.495 | 12.199 | 22.57 | 41.66 | 47.58 | 40.18 |
| Credit Limit in 2007 (\$ thousands) | 4.308 | 6.345 | 12.420 | 25.55 | 48.51 | 53.39 | 45.30 |
| Credit Change 2007-06 (\$ thousands) | -1.546 | -1.150 | 0.221 | 2.98 | 6.85 | 5.82 | 5.12 |
| Increase in Credit Limit 2006-07 (% cohort) | 25.91 | 31.55 | 45.4 | 58.93 | 65.15 | 55.88 | 56.41 |
| Positive Credit Limit 2007 (% cohort) | 74.55 | 79.10 | 88.01 | 94.69 | 98.20 | 99.35 | 97.14 |
| | n = 10835 | n = 27938 | n = 49752 | n = 102525 | n = 185007 | n = 568510 | n = 944567 |
| PANEL C: BANKRUPT INDIVIDUALS (N = 5,409) | | | | | | | |
| Credit Limit in 2006 (\$ thousands) | 9.634 | 11.460 | 17.558 | 35.16 | 49.87 | 50.90 | 28.79 |
| Credit Limit in 2007 (\$ thousands) | 2.941 | 3.487 | 4.958 | 9.11 | 14.68 | 22.41 | 8.60 |
| Credit Change 2007-06 (\$ thousands) | -6.694 | -7.973 | -12.600 | -26.04 | -35.19 | -28.50 | -20.18 |
| Increase in Credit Limit 2006-07 (% cohort) | 8.73 | 11.35 | 11.0 | 8.21 | 9.01 | 16.91 | 10.08 |
| Positive Credit Limit 2007 (% cohort) | 61.14 | 63.55 | 67.95 | 77.07 | 83.00 | 83.68 | 72.82 |
| | n = 561 | n = 996 | n = 1014 | n = 1413 | n = 1088 | n = 337 | n = 5409 |

Notes: The numbers reported are the mean of the credit variable indicated in the row header for a particular to the credit score in 2006. Panel A reports the statistics for the complete sample, Panel B reports the statistics for individuals who have never declared bankruptcy, and Panel C reports the statistics for individuals who did declare bankruptcy between 2006 and 2007.

APPENDIX TABLE C: DISTRIBUTION OF INDIVIDUAL CHARACTERISTICS -POSITIVE VS NEGATIVE CREDIT COSTS

| | MEAN | | | MEDIAN | | | |
|---|-------------|-----------------|----------------|-------------|-----------------|----------------|--|
| | Negative | Positive Credit | Difference | Negative | Positive Credit | t Difference | |
| | Credit Cost | Cost | | Credit Cost | Cost | | |
| PANEL A: 2003/2004 | | | | | | | |
| Black (% in 1 mile radius) | 0.1193 | 0.2196 | (0.1003122)*** | 0.0333 | 0.0601 | (0.0267724) | |
| Greater Than High School Equivalency (% in 1 mile | | | | | | | |
| radius) | 0.8088 | 0.7651 | 0.0436923*** | 0.8277 | 0.7830 | 0.0447033*** | |
| Divorced (% females in 1 mile radius) | 0.1153 | 0.1235 | (0.0081883)*** | 0.1154 | 0.1242 | (0.0087478)*** | |
| Divorced (% males in 1 mile radius) | 0.0936 | 0.0993 | (0.0056993)*** | 0.0912 | 0.0986 | (0.0073737)*** | |
| Public Assistance (% in 1 mile radius) | 0.0338 | 0.0463 | (0.0124632)*** | 0.0249 | 0.0329 | (0.0080182)*** | |
| No Earnings (% in 1 mile radius) | 0.1878 | 0.2069 | (0.0191085)*** | 0.1813 | 0.2051 | (0.023841)*** | |
| Income Growth (in 1 mile radius) | 0.3351 | 0.0460 | 0.2890982*** | 0.0733 | -0.1634 | 0.2367139*** | |
| Hispanic (% in 1 mile radius) | 0.1075 | 0.1101 | (0.0026069) | 0.0414 | 0.0312 | 0.0102375*** | |
| Median Household Income | 43,269 | 40,700 | 2569.149*** | 42,143 | 40,736 | 1407.5*** | |
| Bank Cards (number) | 3 | 1 | 2.3791083*** | 3 | 1 | 2*** | |
| | n = 1170 | n = 262 | | n = 1170 | n = 262 | | |
| PANEL B: 2006/2007 | | | | | | | |
| Black (% in 1 mile radius) | 0.1216 | 0.1874 | (0.0658803)*** | 0.0373 | 0.0623 | (0.025056) | |
| Greater Than High School Equivalency (% in 1 mile | | | | | | | |
| radius) | 0.8119 | 0.7824 | 0.0295308*** | 0.8347 | 0.8010 | 0.0337*** | |
| Divorced (% in 1 mile radius) | 0.1042 | 0.1114 | (0.0071866)*** | 0.1030 | 0.1107 | (0.0077)*** | |
| Public Assistance (% in 1 mile radius) | 0.0329 | 0.0402 | (0.0072722)*** | 0.0233 | 0.0292 | (0.0059115)*** | |
| No Earnings (% in 1 mile radius) | 0.1872 | 0.2069 | (0.0197069)*** | 0.1822 | 0.2044 | (0.022205)*** | |
| Income Growth (in 1 mile radius) | 0.7270 | 0.5021 | 0.2249104*** | 0.2976 | 0.1112 | 0.1864375*** | |
| Hispanic (% in 1 mile radius) | 0.1047 | 0.0961 | 0.0086499*** | 0.0362 | 0.0309 | 0.0052895*** | |
| Median Household Income | 48,828 | 45,588 | 3240.82*** | 46,456 | 43,993 | 2463*** | |
| Bank Cards (number) | 3 | 1 | 2.3150063*** | 3 | 1 | 2*** | |
| | n = 4594 | n = 815 | | n = 4594 | n = 815 | | |

Notes: Based on authors' calculations using credit bureau data, Census, and the American Community Survey. The values reported pertain to individuals who declared bankruptcy between 2003 and 2004 (Panel A) and between 2006 and 2007 (Panel B). Each sample is partitioned into two groups: positive credit cost and negative credit cost. The statistics reported are the mean and median values for each of the demographic measures in the row heading. We adopt the usual convention: *** p<0.01, ** p<0.05, * p<0.1 to indicate if the difference between the positive credit cost statistic and the negative credit cost statistic is meaningful.