Household Bankruptcy Decision: the role of social stigma vs. information sharing*

Ethan Cohen-Cole
Federal Reserve Bank of Boston

Burcu Duygan-Bump
Federal Reserve Bank of Boston

10 July 2008

PRELIMINARY DRAFT — PLEASE DO NOT QUOTE OR CITE

Abstract

Using a large sample of individual credit information provided by a US credit bureau, this paper investigates the empirical relevance of stigma and information sharing on household bankruptcy and its trend. Many observers of bankruptcy patterns have conjectured that there exists an increased willingness to default that reflects a diminution of social stigma. In this paper, we use a new methodology to disentangle stigma and social learning—two acknowledgedly important social factors affecting default. While our results indicate a large and important role for stigma, changes in information costs seem to be the more relevant factor in explaining the observed bankruptcy trends. Furthermore, we show that this aggregate trend disguises enormous heterogeneity. While social factors appear quite important among the very poor and less educated, stigma seems to have increased and information costs to have decreased among these very groups. On the contrary, we show that it is primarily among the relatively rich and well educated that stigma has declined. These compositional findings further suggest that the overall increase in the bankruptcy rates cannot be explained by a decrease in social stigma. We argue that the secular increase in bankruptcy is more likely attributable to decreased information costs rather than to changes in social stigma.

JEL Classification Codes: D14, I30, K45, Z13.
Keywords: personal bankruptcy, social interactions, social stigma, information

---

*Federal Reserve Bank of Boston, 600 Atlantic Avenue Boston, MA 02210. Email: Ethan.Cohen-Cole@bos.frb.org, Burcu.Duygan-Bump@bos.frb.org.

We are grateful to Nicholas Kraninger, Jonathan Larson and Jonathan Morse for excellent research assistance. We are also grateful for helpful comments and suggestions from Hans Degryse, Luc Renneboog, as well as seminar participants at University of Cambridge, University of Bonn, University of Humboldt, and Tilburg University. We are looking forward to the comments at the NBER Summer Institute. The views expressed in this paper are those of the authors and do not necessarily reflect those of the Federal Reserve Bank of Boston or the Federal Reserve System.

1 Introduction

Accompanying a secular increase in the bankruptcy rate (see Figure 1), the past decade has seen a resurgence of research on the determinants of personal bankruptcy. Spurred by the policy debate and talks of bankruptcy reform, researchers have attempted to disentangle the roles of strategic behavior and economic shocks. Commonly discussed explanations for rising bankruptcies have centered around: i) adverse events, such as unemployment, health shocks, and divorce and ii) changes in the credit market environment, such as decreased transaction costs, expansion of credit to riskier households, and decreased costs of filing for bankruptcy, which includes information costs as well as social stigma associated with bankruptcy. The present paper focuses on this last explanation—the social phenomena—which is inextricably linked with bankruptcy even if it is much harder to measure empirically than some of the other factors. We believe that the recent turmoil in the household credit market (especially among the US sub-prime borrowers) further underscores the need to better understand the micro-dynamics of household bankruptcy decisions. For example, one might imagine that decreases in social stigma from bankruptcy could, even under constant economic conditions, lead to increases in bankruptcies and, as a consequence, higher borrowing costs as banks pass on the losses from these individuals to the rest of its borrowers. Accordingly, the policy response to increasing bankruptcies would be quite different if this increase is driven by a decrease in stigma as opposed to an increase in risk or information.

The primary motivation for focusing on social factors, especially stigma, in explaining personal bankruptcy follows naturally from the public debate and the current literature in economics and sociology. From congressional hearings to newspaper stories, it is not hard to find anecdotes about social stigma associated with bankruptcy. A recent Wall Street Journal article, "Now, Even Borrowers With Good Credit Pose Risks" by George Anders, quotes Bank of America CEO Kenneth Lewis, "There's been a change in social attitudes toward default."[1] Similarly, though on a seemingly contradictory note, sociologists continue to provide evidence that the stigma associated with filing is alive and well, as they quote survey respondents, such as this one: "I thought of [bankruptcy] as a mark against my name…It was too embarrassing…I feel like I failed. You know, to go bankrupt, that's a sign of failure."[2] Moreover, we observe that there is a high degree of clustering in bankruptcy decisions, even in relatively affluent areas (Figure 2), which suggests that social factors might be just as important as the usual socioeconomic criteria.

In the economics literature, which we review in detail below, stigma has also been at the heart of a lively debate both among those who use quantitative macroeconomic models and those few who have done empirical analyses. For example, Gross and Souleles (2002) conclude that bankruptcy has become more common over their sample period, and attribute this to declining social stigma felt by defaulters. Similarly, Fay et al. (2002) conclude that the key explanatory variables for explaining household default are financial benefits from filing for bankruptcy as well as "local trends" in bankruptcy filings. Both studies show that the individual probability of bankruptcy cannot be fully explained by individual covariates intended to proxy for idiosyncratic shocks or community level covariates used as systematic shocks. Instead, they show that a significant portion of the residual variation can be absorbed using the average bankruptcy rate of their state, an acknowledgedly inaccurate proxy of the social effect. Still, even at this diffuse level, both find an economically and statistically significant role for social context.

Given these results, many have come to believe that the bankruptcy decision depends on both idiosyncratic economic shocks and on social context. Broadly, the idea is that interacting with others who have gone bankrupt or are in the process may increase the likelihood of an individual going bankrupt himself.

[1] Wall Street Journal, December 19, 2007, page A2.

[2] Thorne and Anderson (2006).

One reason why such an effect may exist is that being surrounded by many people who have gone through bankruptcy decreases the associated embarrassment: the perception that "everybody does it" reduces the psychological pressure to fully pay incurred debts regardless of the circumstances. Essentially, this weakens the social norm associated with taking responsibility for one's debts. This is generally known as the stigma channel, a phenomenon that has been recognized in other contexts, such as welfare participation (Moffitt, 1983, Bertrand et al., 2000, Cohen-Cole and Zanella, 2008b).

However, it is also possible that the same causal relation between group and individual outcome is caused by information sharing. People may share information on eligibility, application procedures, bureaucratic details, etc. with acquaintances, colleagues, friends, or relatives. We refer to this interchangeably as the information or social learning channel.

Using data from one of the largest credit bureaus in the US, collected at four points in time between 2003 and 2007, we adopt a recently developed method (Cohen-Cole and Zanella, 2008a,b) to separate the roles of social stigma and information sharing on the individual bankruptcy decision. As we already mentioned, this distinction is especially important for policy purposes, as the strength of the two effects imply different policy responses. The methodology we use to disentangle these two channels is based on sociological evidence that different types of social interactions are related with particular associations that a person might have. For instance, one might imagine that an individual shares information with his/her neighbors, but suffers social stigma from colleagues as well as neighbors and family. For example, in the welfare context, Luttmer (2001) and Alesina and Glaeser (2004) find that preferences for redistribution are impacted by the number of welfare recipients in one's community.

Psychologists have highlighted the distinction between various types of social effects for years. In a recent example, Zitek and Hebl (2007) describe differences between *normative* and *informational* social influence. The former describes conforming to norms based on doing what others expect, and the latter relates to the use and exchange of accurate information. We argue that normative social influence is a broad proxy for the phenomenon that economists label social stigma. This stigma derives from opinions and perceptions of individuals in a given society about certain behaviors and are determined by current interactions as well as anticipation of future interactions with neighbors or strangers. Conversely, we use informational social influence to describe the local exchange of information. Accordingly, we make assumptions on the source of each social effect. In particular, we assume that information is a 'local' phenomenon, while stigma is defined more broadly and is derived from multiple sources. By exploiting this assumption, we are able to identify the relative roles of different social factors.

We start our analysis by estimating the total effect of social factors on individual bankruptcy decisions. We then move to disentangle the stigma component from informational (social learning) factors. Our results show that social factors matter more than other controls including the conventional risk factors, as have also been argued in Gross and Souleles(2002): the magnitude of the estimated social effects ranges between 3% and 11% relative to the baseline filing rate, while the effect of the risk controls are much less than 0.1%. These results also show that on average societal stigma dominates the role of information, especially after 2005.

As for the trends, we find that both information costs and stigma have indeed decreased between 2003 and 2007: in 2006 and 2007, the magnitudes of both the stigma and the information effects were as much as three times larger than those estimated using the 2003 and 2004 samples. In other words, in the last few years community perceptions have become increasingly more important in household bankruptcy decisions. However, we also show that changes in social stigma cannot explain the changes in personal bankruptcy rates. Our estimated stigma coefficients move in the opposite ('wrong') direction with the bankruptcy filings, while changes in the information costs seem to move in the right direction (Figure 3).

Given the failure of stigma and individual risk factors at explaining the bankruptcy trends, and the overall importance of social factors and especially information sharing, we extend our analysis by studying social effects in different parts of the population, and assess the role of economic and demographic factors by exploiting our enormously rich data set. This is the first study to our knowledge that has shown such variation in social phenomena across population groups at this level of detail.[3] We find that the relative importance of each social factor (stigma and information) and their trends are highly heterogeneous across income groups and educational levels.[4] While social factors appear quite important among the poor and less educated, stigma seems to have increased among these very groups—particularly the very poorest. On the contrary, we show that it is among the richer and well educated that stigma has declined. However, social learning appears to be changing in a more secular and consistent fashion across most socioeconomic groups. These findings suggest that the effects of social stigma maybe more temporary compared to social learning. In fact, a very recent study by Dick et al. (2008) also finds that the effects of social spillovers in the context of bankruptcy tend to be temporary. The key implication of these findings is that policy discussions centering around the ease or difficulty of bankruptcy access may be more effective than those intended to increase the social stigma associated with the process.

The compositional differences in our results across socioeconomic groups further highlight our main conclusion: the overall increase in the bankruptcy rates cannot be explained by a decrease in social stigma, because it has fallen only for the portion of the population that has not been greatly impacted by bankruptcy. This suggests that the key driver of the recent increases in bankruptcy is primarily changes in information costs.

The paper proceeds as follows. We provide an overview of the US bankruptcy law and the related literature in Sections 2 and 3, respectively. The methodology used in estimation of social interactions is presented in section 4, followed by a discussion of our data in Section 5. Section 6 presents our preliminary results and Section 7 concludes the paper.

2 Personal Bankruptcy in the US: some background on the historical and current rules and the stigma discussion

Prior to the turn of the 20th century, bankruptcy was a legal condition rather than an individual choice. Creditors would be forced to file petitions proving that the debtor had committed an 'act' of bankruptcy—typically something akin to fraud (Coleman 1974). The prevailing notion was that bankruptcy was rooted in fraud (Efran 2006) or in a fundamental disregard for the morals of society (McIntyre 1989, Channing 1921). For example, Efrat (2006) presents a range of evidence showing how bankruptcy stigma has historically been particularly strong. He finds quotations that refer to bankrupts as deserving lower social respect than criminals (Jones 1979). Similarly, Adam Smith, in his famous "Wealth of Nations", argues that bankruptcy is the 'most humiliating calamity' that can occur to an individual.

Over the past couple of hundred years, legal standards have reflected social efforts to penalize and shame those in bankruptcy. The laws themselves emphasize the near criminal nature of bankruptcy (see Tabb 1991

[3]With 27 million observations in our original data-set (which does get reduced to about 12 million observations due to missing information), we are able to precisely estimate social interactions coefficients across the country even at very low levels of spacial aggregation, such as neighborhoods. This facilitates analyzing the variation of these effects across subgroups and populations.

[4]We find similar, but less intuitively described, heterogeneity across states. Figure 4 shows the distribution of the changes in the stigma and information coefficients across states based on state-by-state regressions. Detailed version of these results are available from the authors upon request.

for an overview) and imposed penalties that would now be regarded as draconian.[5]

In the 1960s and 1970s, bankruptcy policy began to reflect changes in American perceptions of bankruptcy stigma. In 1978, congress passed a new bankruptcy law, in part aimed at reducing stigma (Efrat 2006). Nonetheless, public views of bankruptcy remained strong. And, in spite of evidence of the remaining strong stigma and the almost complete absence of empirical studies that measure its fall, the run-up to the 2005 bankruptcy reform found many arguing that rising bankruptcies were due to a decline in stigma.[6]

Currently, the United States has two different personal bankruptcy procedures—Chapter 7 and Chapter 13—and prior to the 2005 bankruptcy reform, debtors had great flexibility in choosing between them. Under both procedures, once the debtor has filed for bankruptcy, legal actions to collect any debt by creditors must be ceased. All unsecured debt is discharged in bankruptcy with some exceptions, such as student loans, debts incurred by fraud, and credit card debt incurred shortly before filing. On the other hand, secured loans, such as mortgages and car loans, are not discharged, but bankruptcy generally allows debtors to delay creditors from foreclosing or repossessing related assets.

Under both procedures, bankrupt individuals must pay various additional costs, including court and lawyers' fees, associated with gathering information about the bankruptcy process and legal advice. Flynn and Bermant (2002) report that these costs ranged between $600 for Chapter 7 and $1600 for Chapter 13 as of 2001. Moreover, debtors who file under Chapter 7 are not permitted to re-file under Chapter 7 for six years, although they may file under Chapter 13 as often as every six months.

As bankruptcy rates rose five fold to about 1.5 million per year (see Figure 1), lenders grew increasingly aggressive at lobbying. In congressional testimony that predated the law by almost a decade, Visa USA submitted testimony claiming a decline in social stigma associated with bankruptcy (see discussion in Efran 2006). This line of discussion became a principle motivating factor behind the new legislation that came into effect in 2005. The name of the new act reflected the intent to restore the stigma associated with bankruptcy. The Bankruptcy Abuse Prevention and Consumer Protection Act (BAPCPA) took effect in late 2005. Filings reached about 2 million in 2005 as debtors rushed to file under the old law, and then dropped to 600,000 in 2006, before beginning to rise once again.

The new legislation made bankruptcy much less financially attractive by increasing the time and financial costs associated with filing and forcing some Chapter 7 debtors to repay from post-bankruptcy earnings. The new law also imposed other requirements on filers. Filers can no longer choose between the codes. Instead, one submits to a means test, where a debtor qualifies to file under Chapter 7 if their average monthly family income over the past six months (prior to filing) is less than the median monthly family income in their state, adjusted for family size. As well, the law abolished an individual's ability to propose repayment plans under Chapter 13 and imposed a standardized procedure to determine payment plans. Finally, the new law greatly raised filing costs, mandates detailed information, and requires debtors to take a credit counseling course. Elias (2006) estimates that these new requirements raised debtors' filing costs to around $2500 for Chapter 7 and $3500 for Chapter 13.

Without question, the law raised the financial and temporal costs of filing, and, at least over the short run, has decreased the number of filings. It is an open question whether the law has impacted the social stigma of bankruptcy, the cited prominent reason for its passage.

---

[5] For example, debtors in colonial America would have their hair shaved, be branded with a T for "thief," and be required to have an ear cut off (Pomykala 2000).

[6] See Efrat (2006) for an exhaustive listing of studies that show a decline in stigma using indirect methods. Efrat argues that none of these estimate the effect directly.

3 Bankruptcy in Economics: A review of related studies

Following the dramatic rise in bankruptcies over the last couple of decades and the surrounding policy discussions, many researchers have attempted to study household bankruptcy decisions. The literature to date can be grouped into two broad categories, based on the approaches adopted: i) quantitative macroeconomic models that use a modeling/calibration approach to match related stylized facts, such as the increase in household debt as well as bankruptcies and ii) applied analyses that exploit different sources of micro data to understand the empirical factors that drive households' bankruptcy decisions. Unfortunately, due to lack of data, the number of studies in this second group are quite small.

The quantitative macroeconomic models are part of a recent literature on equilibrium models of consumer bankruptcy. Examples include Livshits et al. (2007a) and Chatterjee et al. (2005), which outline dynamic equilibrium models where interest rates vary with borrowers' characteristics. The models, for reasonable parameter values, can match the level of U.S. bankruptcy filings and debt-income ratios. Athreya (2002) analyzes the welfare implications of different bankruptcy laws while Li and Sarte (2006) analyze consumers' choice of Chapter 7 versus Chapter 13 using dynamic equilibrium models of bankruptcy.

More recently, Livshits et al. (2007b) use these models to evaluate the potential alternative explanations of the rise in bankruptcies. They broadly categorize these explanations into two categories. The first set they consider is that there has been an increase in idiosyncratic uncertainty at household level due to increased labor earnings volatility or an increase in the number of households without medical insurance coverage (Barron et al., 2000 and Warren and Warren Tyagi, 2003). This category also captures the demographic scenario that argues that the passing of the baby-boomers through the prime bankruptcy ages and changing family structure have increased the number of risky households (Sullivan et al. 2000).

The second category they analyze is the role of the changes in the credit market environment that have made bankruptcy more attractive or expanded credit to a broader set of households, including higher-risk ones. This second set of explanations includes the story that credit market innovations (such as the development and spread of credit scoring) facilitated the increase in credit granted to households by reducing the transaction costs of lending (Athreya 2004). But it also includes the possibility that the personal costs incurred by defaulters have fallen substantially, either as a result of improved bankruptcy filing procedures, the learning by households from each other as to how to navigate the bankruptcy process, or a decrease in social stigma associated with default.

The results from their quantitative exercise show that the rise in filings mainly reflects the changes in the credit market environment. They find that credit market innovations, as opposed to increased uncertainty, which caused a decrease in the transactions cost of lending and a decline in the cost of bankruptcy can largely account for the rise in consumer bankruptcy. Athreya (2004), on the other hand, argues that the increases in bankruptcy due to a decrease in stigma should generate a supply-side response whereby borrowing on the unsecured credit market grows more expensive. In other words, lenders should respond by increasing interest rates if borrowers become more willing to default, which would in turn lead to smaller debt holdings across households: an observation that contradicts the stylized facts for the period under study. In particular, he uses an equilibrium model of personal bankruptcy (similar to Athreya 2002) to show that decreasing the non-pecuniary cost of bankruptcy, as a fall in stigma implicitly does, indeed increases bankruptcy rates but yields counterfactual implications for the time path of debt held by households. Consequently, he concludes that the facts can be better explained by changes in the credit market environment and associated decrease in transaction costs, but that social stigma is still relevant to a small degree. Although these results do not speak directly to the stigmatization question or to our question on the decomposition of the social effect, they do lend support to a declining cost story, a phenomenon correlated with increased information exchanges.

These findings are in general consistent with those reported in the two seminal papers in the applied analysis category based on micro data. Fay et al. (2002) estimates a model of the household bankruptcy decision, using the PSID and show that households are more likely to file for bankruptcy when their financial benefit from filing—the value of debt discharged in bankruptcy minus the value of nonexempt assets—rises. Similar to the findings of Livshits et al. (2007b), they find little support for the alternate hypothesis that households file for bankruptcy when adverse events occur. They also find that, even after controlling for state and time fixed effects, households are more likely to file for bankruptcy if they live in districts which have higher aggregate bankruptcy filing rates. Their interpretation of this finding is that local trends in bankruptcy filings are an important determinant of whether households file. They conjecture that this result "could reflect local differences in the level of bankruptcy stigma or local differences in the administration of bankruptcy law that make the district differ from the state, or could reflect the influence of information cascades."[7]

Gross and Souleles (2002) use administrative credit-card account data to analyze credit card delinquency and personal bankruptcy. They estimate duration models for default to disentangle the two explanations of default: a deterioration of the risk-composition of borrowers and declining default costs that lead to an increase in borrowers' willingness to default. To capture the changes in associated costs of default, they use time dummies to capture the changes in the hazard function over time, as well as the lagged bankruptcy filing rate in the state as in Fay et al. (2002). Their results rule out the risk effect, and conclude that households did appear to be more willing to default in the late 1990's than in earlier periods, all else equal. The authors do acknowledge that these results do not directly identify what underlies the estimated demand effect, even though the finding that default rises with the bankruptcy filing rate in the state is "suggestive" of a decline in stigma or information costs.

Similarly, to understand the relative importance of the role of adverse shocks and the costs of default, Duygan-Bump & Grant (2008) use the European Community Household Panel and exploit the institutional differences in punishment for and legal costs of default across the EU countries. Their results show that adverse shocks, such as unemployment and health shocks, are important, but the extent to which they matter depends crucially on the punishment associated with default.

In this paper, we focus on the social cost of default, usually termed as stigma, and try to disentangle the role of stigma from information costs. So far, the literature has used the coefficient on the lagged bankruptcy filing rates in the state to capture social influences. This coefficient, while useful, is a compound measure; that is, it says nothing about the source of these social influences. In other words, we do not know whether the social effect is due to information sharing (people communicate and pass along information about bankruptcy procedures, for example), social learning (people observe others' behavior and infer the distribution of outcomes from taking certain actions), or stigmatization (the prevalence of a certain behavior makes its adoption less embarrassing), and so on. The separate identification of these different social effects is especially important for policy discussions because different channels will generally require different policies, and the appropriate measures will depend on the relative magnitudes of stigma and information effects. The goal of this paper is to shed stronger light on the empirical importance of these social factors.

While this paper is the first attempt at more rigorously recovering the effect of stigma and other social factors on bankruptcy, we follow a large literature that analyzes social interactions effects in general. Examples include the seminal work by Moffitt (1983) on the role of stigma in explaining low participation rates in welfare programs, as well as the more recent work again on welfare cultures by Bertrand et al. (2000). Our motivation of disentangling the different channels of social interactions follow from the discussion in Manski (2000), while our methodology draws from the existing sociology literature, which shows that cer-

[7] Fay et al. (2002), p. 710.

tain types of social interactions can be related to particular associations that a person might have. The next section provides the details of the methodology we use to bring in this additional information, and discusses how we disentangle and understand the varying effects of social interactions.

4 Methodology

Understanding Information and Stigma

Bankruptcy in the United States, as discussed above, allows for some discharge of debt, and even allows for households to keep a portion of their homes (if not all) and other assets. Accordingly, even though most researchers study why bankruptcies have been rising, some also wonder why more people do not file for bankruptcy given the potential financial benefits (White 1998). One potential explanation could be the social stigma associated with bankruptcy, as evidenced by sociologists' surveys of bankrupts, discussed in the introduction. Another explanation is that an individual that could benefit from filing for bankruptcy may not be sufficiently aware of the possibility or able to navigate the system. To disentangle and identify the relative empirical importance of these effects, we will exploit the sociological literature that shows that certain social influences are related to certain associations within a population. In particular, we assume that individuals draw information and learn from people who are geographically closer to them (e.g. neighbors), while stigmatization occurs among a broader group (family, friends, what "others" in general are doing, as well as neighbors). We argue that the local community forms a type of social network from which individuals can obtain information about the bankruptcy process. They may observe nearby neighbors going through the process and inquire about procedures and institutional details. Similarly, households also face social stigmatization from these same neighbors but in fact they face social stigma from a potentially wider sample of people. This explanation forms the core of our key separation assumption.[8]

Basic social effect modeling

More formally, we start by modeling the bankruptcy decision of an individual i, which we'll denote π_i. Next, we denote the relatively large social community an individual lives in by a superscript s. We assume that the behaviors of others in this community generate the social environment that contributes to the utility of an individual's own decision. We further specify two subsets of the community, a 'local' group, subscript g, and a 'non-local' one, subscript o. We use these subsets to help distinguish the two key channels of social effects as we assume that information effects are derived from a 'close' social group "g," while stigma can come from local as well as more diffuse sources "o."

Of course, bankruptcy has many potential causes in addition to the social ones. To capture these we specify the bankruptcy decision problem in the absence of social effects as follows.

$$B_{ig} = b + cX_i + dY_g + \varepsilon_{ig} \tag{1}$$

where B_{ig} is an indicator set equal to 1 if individual i in community g has declared bankruptcy. To control for individual differences in credit quality, one can include a vector of individual specific variables X_i. Since individuals are also impacted as a group by the environment in which they live, for example by changes in employment conditions, we can include a vector of variables Y_g that are common for all individuals in community g. In Y_g we also include community level demographic characteristics as proxies for individual demographics. For example, we include average marriage and divorce rates, educational achievement averages and income levels.

[8] This justification follows Cohen-Cole and Zanella (2008b) closely. The phenomena driving welfare decision making and bankruptcy are similar in the distinction between information and stigma effects and the social construction of these social influences.

If individuals respond to aggregate behavior in addition to price factors, the estimates of c in 1 will be biased due to correlation with the error term. The bankruptcy literature to date has augmented equation 1 to include a measure of average bankruptcy rates in a large, non-local area (state of residence), m^s such that we can write:

$$B_{ig} = b + cX_i + dY_g + J_s m^s + \varepsilon_{ig} \tag{2}$$

where $m^s = \frac{1}{n-1}\sum_{j\neq i\in s} B_{js}$, and n is the number of individuals in the state. Thus m measures the average bankruptcy rate in s excluding the individual i. Note that this is similar to the specification used in Fay et al (2002) and Gross and Souleles (2002).

Composite Social Effects

Our principal two modifications to this specification follow from the discussion above. First, using very specific information on geographic locations of individuals (see data description in the next section), we are able to include community-level information (e.g. income, income growth), which helps us get closer to individual level data—an improvement over state averages. Second, we measure the impact of aggregate behavior on individual behavior at two levels of aggregation, looking at local and non-local networks.

Mechanically, we augment this specification in a number of ways to allow both for interactions at a level below the state, and to separate the stigma and information effects. First, we define a vector Y to capture all community level controls, where $Y \equiv (Y_g\, Y_o\, Y^s)'$, Y_g is these same community controls but one where community is defined at some small local level, such as a 1 mile radius from an individual's home, and Y_o captures these controls over a larger community (exclusive of the local area), such as a 1-4 mile radius. Where we specify Y^s, this refers to averages taken over the full 0-4 mile radius. We also allow for heterogeneous social interactions among different local communities within a county. In order to do this, we define m_o as a vector of average bankruptcy rates of other local communities, γ, with the 1-4 mile radius with respect to own locality g: $m_o = \frac{1}{m}\sum_{\gamma}\{m_\gamma\}_{\gamma\neq g}$.[9]

A simple choice for estimating equation 1, above, with the addition of our specified social effects, is a linear function allowing for local (0-1 mile) and non-local (1-4 miles) social coefficients:

$$B_{igs} = b_g + c_g X_i + d_g Y + J_g^{SI} m_g^s + \widetilde{J}_o^S m_o^s + \varepsilon_{igs}. \tag{3}$$

Note that this specification brings in additional notation, which we believe clarifies our methodology and assumptions. More specifically, note that m_g is the average of local bankruptcies. Because we assume this is associated with both stigma, S, and information, I; we use the coefficient notation J_g^{SI}. Similarly, the coefficient $\widetilde{J}_o^S$ incorporates only stigmatization effects at a non-local level.

By construction, the two sets of coefficients J_g^{SI}, a scalar, and $\widetilde{J}_o^S$, a $1\times N$ vector, capture the joint effect of stigma (S) and information (I) from own locality (g) and of stigma from other localities (o) both within the county or state, s. In Manski's (1993) terminology, c_g expresses individual effects, d_g contextual effects, and J_g^{SI} and $\widetilde{J}_o^S$ endogenous social effects. We focus in this study on the latter, the endogenous portion. It is well known that a model like this poses several problems. Perhaps the most discussed in the peer-effects literature is how to define reference groups, including the geographic level. As we discuss, we define them as localities within 0–1 and 1–4 mile radii.

Three other econometric problems require treatment. We begin with the *reflection problem* (Manski, 1993), which potentially affects any linear model with social interactions. Self-consistency requires that the expected participation rate of an individual of locality g in county s be equal to the mathematical expectation of the individual participation indicator in the reference group, that is given Y_g^s:

[9]Mechanically, we take the average bankruptcy rate of all census blocks that fall into the 1-4 mile 'donut' around the individual.

$$m_g^s = \mathbb{E}\left(\pi_{igs} | Y_g^s\right). \tag{4}$$

This condition, coupled with equation (3), forms a simultaneous equation system. Notice that we are treating m_o^s as another contextual, exogenous, effect. Suppose, as is typically the case, that the group-level controls, Y_g^s, are the group-level mean of the individual level ones, X_i. That is, $\mathbb{E}\left(X_i | Y_g^s\right) = Y_g^s$ too. Then, in absence of valid instruments, one cannot identify the endogenous social effects, in our case J_g^{SI} and $\widetilde{J}_o^S$, without an exclusion restriction.[10] This problem appears in both Fay et al. (2002) and Gross and Souleles (2002). They handle the problem with a common procedure—using the lagged bankruptcy rate instead of the current period rate. This means that the expectation of the other contextual effects, in the current period, will be distinguishable from the lagged endogenous effect. We address the problem by drawing on the fact that probit models are nonlinear in form. This nonlinearity, as discussed in Brock and Durlauf (2001), permits identification.

The second problem is the *selection problem*: individuals in the sample chose to live in a particular area. If residential choices depend on unobservables that also affect the probability of entering bankruptcy, then group-level variables are endogenous, and the estimated social effects will be affected by selection biases. How to get around this selection problem in models of social interactions based on individual-level data is a current research topic—though one without a clear solution. A number of methods have been suggested, including a strict characterization of error distributions that allows for closed-form identification of social multipliers (see Zanella 2007). In our case, the selection problem is the degree to which neighborhood choice is correlated with bankruptcy, an issue minimized by the growing consensus (evidence) that, on average, households do not move across state lines to "shop" for asset exclusions.

The third problem is labeled the *conflation problem*. As we already discussed, the decision to enter bankruptcy may be influenced by the members of some reference groups in a variety of ways, a fact we take into account when defining J_g^{SI}: this coefficient is the composite of stigma and information effects. Clearly, even if identification of equation (3) were not a problem, we could not identify them separately. In dealing with this problem, we draw on prior work from sociology to establish our separation strategy. The details of the methodology come from Cohen-Cole and Zanella (2008a), which has been used to address low welfare program participation rates (Cohen-Cole and Zanella, 2008b). As we discussed earlier, the strategy rests on an assumption that individuals obtain information on procedures, timing, and the bankruptcy process from others that live and work near them. However, the stigmatization that results from going bankrupt can be felt on a number of levels, both at the local level and at a wider one.

First, define α_γ^k as the percentage of individuals of group γ, $\gamma \neq g$, in region s and consider equation (3) again, the *primary model*:

$$B_{igs} = 1 = b_g + c_g X_i + d_g Y_g^s + J_g^{SI} m_g^s + J_o^S \sum_{\gamma \neq g} \alpha_\gamma^s m_\gamma^s. \tag{5}$$

That is, we define the stigma effect from other groups as composed of common and group-specific factors, $\widetilde{J}_o^S = \left\{J_o^S \alpha_\gamma^s\right\}_{\gamma \neq g}$, where the specific factor is the local population share in the 0–1 vs. 1–4 mile radii. If proximity generates the feeling of being observed and such feeling generates stigma, its intensity is

[10] There are now a number of methods available for the identification of endogenous effects, though with limited applicability here. For example, Bramoulle et al. (2007) identify peer effects in networks by utilizing the fact that networks have so-called intransitive links (X talks to Y and Y to Z, but X does not talk to Z). This is effectively an instrument and allows identification. Similarly, Cohen-Cole (2006) finds that allowing an individual to be associated with multiple reference groups allows identification (of a single effect) in a linear model.

plausibly proportional to the relative number of individuals in a given outer group that can observe somebody who has gone bankrupt. Second, we must define a parameter α_g in order to specify a functional form for the total stigma function:

$$S\left(m_g^s, m_o^s\right) = \alpha_g m_g^s + (1-\alpha_g)\sum_{\gamma\neq g}\alpha_\gamma^s m_\gamma^s. \tag{6}$$

Following Cohen-Cole and Zanella (2008a,b), we assume that stigma from the local area and stigma from surrounding areas are perfect substitutes, with marginal rate of substitution equal to α_g. Our basis for choosing the parameter comes from an approximation of the frequency of contact with individuals in the two radii. Though the outer area composes a space 15 times as large, we assume that the frequency of contact within the local area is somewhat larger. As such, our analysis uses 0.25 to start with, which places a 3:1 weight on non-local stigma. That is, we make the tentative assumption that stigma derives more from the nearby communities than from immediate neighbors. Cohen-Cole and Zanella (2008b) provide evidence on the sociological foundations for the construction of stigma and argue that individuals use wider communities than the immediate area to form the basis of their social expectations. Function (6) is used to construct a new specification, the *auxiliary model*:

$$\begin{aligned} B_{igs} &= b_g + c_g X_i + d_g Y_g^s + J_g^I m_g^s + \\ &\quad + J_{go}^S\left(\alpha_g m_g^s + (1-\alpha_g)\sum_{\gamma\neq g}\alpha_\gamma^s m_\gamma^s\right). \end{aligned} \tag{7}$$

The total stigma function captures, by construction, all social effects that work within and across localities, but excludes social effects that work exclusively within a locality. This leaves out information sharing, which is captured by the function $J_g^I m_g^s$. In equations (5) and (7) there are four distinct endogenous social interactions coefficients: J_g^{SI} is the stigma and information effects (in the superscript) from one's own group (in subscript), J_o^S is the stigma effect from all other localities, J_g^I the information effect from own-group, and J_{go}^S is the compound stigma effect from both one's own group and other groups. We will use the collected information below to estimate J_g^S, the stigma effect from one's own locality. This is possible because conditional on locality, the auxiliary model does not involve new information. Therefore, the corresponding regression models have the same errors, which is also why the coefficients on individual and contextual effects are denoted with the same symbol in both models:

$$B_{igs} = b_g + c_g X_i + d_g Y + J_g^{SI} m_g^s + J_o^S \sum_{\gamma\neq g}\alpha_\gamma^s m_\gamma^s + \varepsilon_{igs}, \tag{8}$$

$$\begin{aligned} B_{igs} &= b_g + c_g X_i + d_g Y + J_g^I m_g^s + \\ &\quad + J_{go}^S\left(\alpha_g m_g^s + (1-\alpha_g)\sum_{\gamma\neq g}\alpha_\gamma^s m_\gamma^s\right) + \varepsilon_{igs}. \end{aligned} \tag{9}$$

In other words, by construction, these two models are both "true models". Consequently, we can compare the coefficients of different social effects across them. Our estimator for the stigma effect from group g only, J_g^S, is the following:

$$J_g^S \equiv J_{go}^S - J_o^S. \tag{10}$$

That is, under our assumptions we can compare coefficients across models, and to obtain the effect of stigma from group g only, we subtract from total stigma the portion that does not come from group g. For the same reason, the following estimator is also appropriate:

$$J_g^S \equiv J_g^{SI} - J_g^I. \tag{11}$$

Social Multipliers

To understand the aggregate impact of an individual shock, we follow Cohen-Cole and Zanella (2008a) to calculate the implied social multiplier[11] from these results. Suppose that because of an exogenous shock, the individual probability of going bankrupt for a certain locality decreases by 1 percentage point. In the absence of any cross-group effect, and assuming $J_g^{SI} < 1$, i.e. stability, the equilibrium cumulative effect, the so-called social multiplier, would simply be:

$$1 + J_g^{SI} + \left(J_g^{SI}\right)^2 + ... = \left(1 - J_g^{SI}\right)^{-1}. \tag{12}$$

However, in the presence of cross-group stigma, the other localities are also affected by the shock, which generates further feedback effects. The unit increase is therefore given by:

$$J_g^{SI} + J_o^S \sum_{\gamma \neq g} \alpha_\gamma^s \frac{\partial m_\gamma^s}{\partial m_g^s}. \tag{13}$$

Accordingly, the social multiplier implied by our model is the reciprocal of one minus such a quantity, or

$$\left(1 - J_g^{SI} - J_o^S \alpha_g^s m_g^s \sum_{\gamma \neq g} \alpha_\gamma^s J_{o(\gamma)}^S\right)^{-1} \tag{14}$$

which of course, under the model assumptions, is larger than $1/\left(1 - J_g^{SI}\right)$. The $1 - J_g^{SI}$ component should be easily recognizable as the own-group effect. The final term is the portion of the shock that passes through to other groups. The equality follows from the fact that the response of group s's participation rate to group g's, $\partial m_\gamma^s / \partial m_g^s$, is simply $J_{o(\gamma)}^S \alpha_g^s m_g^s$, where $J_{o(\gamma)}^S$ is the cross-group coefficient for group γ. Therefore, the social multiplier generated by our model is special in two respects: (1) it is group-specific, so that in general a given policy will impact localities differently; (2) it depends on the initial bankruptcy rate, so that the effect of a certain policy depends on initial conditions.

5 Data

5.1 Credit Bureau Data

The principal data set used in our analysis is a unique, very large proprietary data set from 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

[11] A social multiplier is the cumulative response to an individual shock. Notice that in any model in which individuals respond to the behavior of others, a shock to one individual will lead to changes in the aggregate as well. These can be calculated from the structural coefficients of a model such as equation 2 by calculating $SM = \frac{1}{1-J}$. In this model, as in Cohen-Cole and Zanella (2008b), the multiplier is more complicated and is discussed below.

open accounts, defaulted accounts, current and past delinquencies, size of missed payments, credit lines, credit balances, etc. The information spans all credit lines, from mortgages, bank cards, installment loans to department store accounts. The credit bureau also provides a summary measure of default risk (an internal credit score). As is customary, account files have been purged of names, social security numbers, and addresses to ensure individual confidentiality. However, they do provide geo-coding information that allows us to match these personal credit history files with information from the US Census, and to infer social networks.

The data were drawn from four periods in time in 18 month intervals—June 2003, December 2004, June 2006, and December 2007. The first two portions of the data provide a balanced, short panel of 285,780 individuals, while the second two comprise a very large repeated cross-section with about 27 million individuals, as well as a smaller short panel of about 2.2 million individuals. The huge size of the repeated cross section is especially important for our analysis of social interactions, because it allows us to be more confident that the sample average of community-level effects are very close approximations of the true population means. Twenty seven million individuals amount to an approximate 1 in 9 draw of all individuals with a credit history.

One of the benefits of the credit database used here is that it includes a measure of credit risk. For each individual, the data provider includes information on a 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. As in Gross and Souleles (2002), we use this internal credit score as a control for changes in the risk composition of borrowers, together with account information on credit lines, balances, and utilization rates.

The data set includes information on individual public bankruptcy filings. The credit bureau keeps the bankruptcy on file for at least 7 years after the filing, so our data encompass bankruptcies as early as 1996. Given the availability of geo-coding information for the individuals, we are able to compute *local* bankruptcy rates.[12] This is an advantage over public measures of bankruptcy, particularly when one wants to understand the role of social networks. Fay et al. (2002) and Gross and Souleles (2002) use publicly available information on bankruptcy rates by district and state, respectively. However, using our own credit bureau data, we are able to construct bankruptcy rates at much lower levels of aggregation, which allow more precise interpretations of local or network effects than the state-level average. After all, it is difficult to argue that people in San Francisco and Los Angeles share the same networks that may influence bankruptcy decision making. We use constant geographic radii of 1 mile and 4 miles as measures of relevant reference rates for social information. The credit bureau data do not distinguish between types of bankruptcy (Chapter 7 vs. Chapter 13), as such, our measure is a total personal bankruptcy rate.

These data have a number of advantages that mirror other studies using individual level credit card data (e.g. Gross and Souleles 2002). First, these data allow us to look at various features of borrowing behavior without concern for measurement error, which is quite common in survey data. Second, we have many individuals who have filed for bankruptcy—a low probability event that is hard to capture in samples like the PSID. And finally, unlike the Gross & Souleles (2002) credit-card data, this data set provides individual location information, which helps us investigate social and economic effects at a more micro-level, beyond state-level information, while also providing information in risk-characteristics of borrowers. The key dis-

[12] The bankruptcy variable used is an indicator of whether an individual has filed bankruptcy in the past 7 years. This has the advantage of capturing lingering stigma and information effects of individuals that filed over the past few years. It has the disadvantage that measure of changes will be muted due to the fact that they will only pick up the incremental changes to the stock of bankruptcies.

advantage, however, is that unlike in survey data we do not have information on variables like household income and employment status. We try to circumvent this shortcoming using community-level information from the Census as explained in the next subsection.

5.2 Census Data and Other Information

As already mentioned, we use an individual's geo-coded census block address from the credit bureau data, and link a wide variety of information on location characteristics. In particular, because we do not have individual-level data on variables, such as income and education, we use the following variables to control for local economic and demographic conditions. For demographic controls (education, race, and marital status), we use data from the US 2000 Census national summary files and merge information at the neighborhood level (defined as a 1 mile radius) averages. We use data on median household incomes and poverty rates from the US 2000 Census and the 2005 and 2006 American Community Surveys at the county level. We also match information from the Current Population Survey and Local Area Unemployment Statistics of the BLS on health insurance coverage (at the state level) and unemployment rates (at the county level), respectively, for the corresponding years. The key advantage here is that we are able to link information at a more granular level in most cases than state-level information as used in the Gross and Souleles (2002) framework. By using this granular level of information, we are able to control for the wide heterogeneity in economic shocks faced in the US economy.

When all this information has been merged, of the original sample of observations, a certain number of individuals get dropped due to missing data, for example on credit scores. Once these and other similar missing observations are removed, we have about 150,000 observations available for 2003 and 2004, and about 12 million for 2006 and 2007.[13] Table 1 provides detailed description of all the variables we use in our analyses as well as their respective sources, and Table 2 presents some summary statistics.

6 Results

In this section, we present two sets of results. First, we re-produce results from the reduced form specifications used in the micro literature on bankruptcy. While our data sets are different than those used in other papers (Fay et al., 2002 and Gross and Souleles, 2002), we are able to broadly repeat their exercises. Second, we apply the methodology above to disentangle the information and the stigma effects on bankruptcy.

6.1 Baseline Specification

Our goal here is to re-estimate the basic equations used in the literature in order to highlight the presence of a positive and significant coefficient on the average state bankruptcy rate. To do so, we estimate a reduced form specification:

$$B_{ik} = b + cX_i + dY_g + J_s m^s + \varepsilon_{ik} \tag{15}$$

[13] Missing information on credit file information comes from gaps in the original data. Missing information from the demographic files is due to discrepancies between the geo-codes from the credit bureau and the census. When a geo-code from the credit bureau lay more than a mile from the closest census block group centroid from the census, the data point is excluded. One can also match these remaining points by associating the individual with the closest centroid and run the risk of connecting the individual with an incorrect neighborhood. Nonetheless, the key coefficients on a regression using this methodology are substantively unchanged from the baselines below.

where X_i are individual-specific credit characteristics taken from our credit file. These include age of the account holder, and amount of outstanding debt, total credit line and utilization rates for revolving credit, mortgage line, as well as an aggregate measure of credit quality (the internal credit score). These variables correspond to the risk-controls used in the Gross & Souleles (2002) model, and capture differences in risk compositions of borrowers. We also include community-level controls to proxy for local economic conditions and demographic composition of the neighborhood and the county, labeled Y_g. This vector includes controls for neighborhood race, education, and marital status composition, together with median household income and unemployment rate in the county of residence, average income growth in the neighborhood between 2000 and 2005, the percentage of people without health insurance in the state of residence, and the percentage of people on public assistance in the neighborhood. Finally, we include the bankruptcy rate for the state of residence, computed using our own sample averages from the credit bureau data.

Table 3 presents the results from this exercise in each of our four dated observations (June 2003, December 2004, June 2006, December 2007). In each of the four time periods, almost all of the credit risk controls are significant. For example, the credit bureau score is significant and is in line with expectations: people with higher credit scores are less likely to file for bankruptcy. Similarly, people with higher credit limits but lower balances are less likely to default. The age variables are also in line with expectations, where probability of default increases with age but then flattens out. Interestingly, communities with higher proportions of non-white populations are less likely to default, which we believe must be because credit is already rationed to the very best borrowers within these areas.[14] The effect of income is as expected: bankruptcy rates are lower in neighborhoods with high median income. Similar to previous findings, we also show that the neighborhoods with high poverty and unemployment rates, and high numbers of people without health insurance coverage also seem to have higher proportion of individuals that become bankrupt. A key thing to note in this table how demographic and economic factors seem to dominate in magnitude the effects of risk controls, such as outstanding debt balances. These results also show that social context and aggregate behavior indeed play a significant role in individuals' bankruptcy decisions: the coefficients of the average bankruptcy rate in the state are all highly significant and positive, as in Fay et al. (2002) and Gross and Souleles (2002).[15]

6.2 Disentangling Stigma and Information

While the results from Table 3 show that social factors are very important to an individual's bankruptcy decision, the estimated coefficients reported above are all compound measures. They do not tell us the channels through which an individual's decision is affected by aggregate behavior. Our goal is to separate the role of social stigma and information, and identify their relative empirical relevance. In doing so, we use the methodology discussed above. Recall that the key 'separation' assumption follows from the sociological literature: Stigma originates from a wider social perspective on the acceptability of certain actions (e.g. bankruptcy), both local and non-local. However, information is an inherently more 'local' phenomenon. One can acquire information from a variety of sources, including diffuse ones such as the internet. However,

[14]See Cohen-Cole (2008) for a discussion of redlining in credit cards.

[15]It is worth noting that our baseline results show similar directional social effects as the other two papers. However, we find much larger impacts. We attribute this finding to differences in data and specification. Principally, we noted a great deal of sensitivity in the magnitude of the coefficient in this specification, particularly with respect to the inclusion of nonlinear credit score terms. Inclusion of the squared or cubed credit score leads to a drop in the magnitude of the social coefficient. Since credit scores are ordinal scales, non-linear terms are akin to rescaling of the variable. This may or may not be appropriate, but requires much more information on the nature of the variable than is typically available. This sensitivity is much lower in our detailed specifications below. Once we look at lower levels of aggregation, our coefficient magnitudes are broadly in line with the literature.

if there are 'social' transfers of information, they will necessarily come from personal contact. Since we don't have detailed network structures, we use local geography as a proxy for social proximity.

Table 4 shows the results from the auxiliary model discussed in Section 4, assuming that the marginal rate of substitution between stigma from non-local to local groups is 0.25 (i.e. 3:1 weight on non-local stigma). The numbers reported are the marginal effects based on coefficients estimated using a probit model. This regression includes all the independent variables from the baseline specifications, together with a constant term, but we report only the marginal effects related to the variables of interest—information (J_g^I) and stigma (J_{go}^S).

These results show that the social effects of both stigma and information are statistically significant and highly relevant. In the early portions of the data, the effect of information appears slightly larger than stigma, with the relationship reversed in 2006 and 2007, which suggests a larger increase in the role of stigma in this time frame. These numbers also show that both social stigma and information costs have indeed decreased on a national basis: in 2006 and 2007, the magnitudes of both the stigma and the information effects were as much as three times larger than those estimated using the 2003 and 2004 samples. In other words, in the last few years community perceptions have become increasingly important in household bankruptcy decisions. These twin trends imply that bankruptcy might indeed be losing its stigma, as many have speculated. However we show that the changes in information costs, not stigma, explain the trend in bankruptcy rates. As shown in Figure 3 and discussed earlier, these estimated stigma coefficients actually move in the opposite direction to bankruptcy trends, which suggest that even though stigma is very important, and have decreased in general over the last 5 years, the decreases in it do not match the periods of rising bankruptcy rates.

Finally, notice that the total social effect in the two most recent time periods is particularly large. This implies a much larger social multiplier, as well. Recall from above that an implied multiplier from a coefficient of 0.1 implies a cumulative response to a shock of about $\frac{1}{1-.1} = 1.11$, e.g. a response of 11%. The cumulative response with a coefficient of 0.3 implies $\frac{1}{1-.3} = 1.42$, e.g. a response of 42%. In other words, the aggregate implications of these micro-dynamics have also become very large in this period.

6.3 Stigma and Information By Social Context (Education and Income)

The social context in which individuals live may be important to understanding the nature of the social interactions guiding their decision making. As an example, one might imagine that an individual facing an adverse shock, such as unemployment, may speak to his or her neighbors for advice more often if he knows that they are also experiencing hardship. This is important for the understanding of social interactions as it implies that the estimates of social effects may differ based on macroeconomic circumstances. Notice that there are a couple of ways that individuals may react to an economic shock. First, their individual actions such as a declaration of bankruptcy may change. Second, an individual's economic decisions may be influenced in addition by the collective decisions of his or her social group. This is the basis for now common estimates of social interactions and are the results shown in the prior section. Finally, their social behavior itself may change, which in turn may impact how often or intensely they relate to others, which can then impact their economic decisions over and above the two forces above. That is, the strength of the social interactions coefficient (the Manski endogenous effect) may change over time as a function of economic conditions (the Manski contextual effects), or vary in the cross section in ways that correlate with contextual factors. Broadly, this is an argument that the strength of social interactions may not be universal, and that understanding how these interactions differ across the population may be useful in understanding the economic phenomena in question.

We look at this possibility by parsing our data along two dimensions, income and educational levels.

That is, we subdivide the individuals in our data set into five quintiles of income and education, creating a total of 25 groups.[16] Then we re-estimate the principal models above and report the social interactions coefficients for stigma and information in Table 5, panels A and B. Panel A includes information from 2006 and panel B for 2007. Unfortunately, we are not able to repeat our analysis of the temporal changes using the 2003 and 2004 samples due to limited number of observations in those years. Despite having more than 250,000 observations, the 2003 and 2004 data are not sufficiently dense to allow for a precise estimation of these effects. In other words, the education-income "cells" are very sparsely populated, especially because we are interested in bankruptcy—an already low-probability event.

A few patterns emerge from this table. Social factors, either social learning or social stigma, seem to have a higher impact on individual decisions among the less-educated and poorer communities, compared to areas with higher education levels and incomes. In 2007, the coefficients for stigma in the poorest, least educated cell (.168) are three times larger than in its complement (.057). We see a similar pattern in the case of the information coefficient. In other words the social import of shared information and the role of social pressure (or lack of it) is much higher in poor and less educated areas.

Perhaps more importantly, we can see the changes in these coefficients in Table 6, with stigma in panel A and information in panel B. The first point to notice is that the increases in the stigma coefficient (a decline in social stigma associated with bankruptcy) occur throughout most of the cells, except the upper left corner. In other words, the largest declines in social stigma seem to have occurred among the more-educated and richer individuals, while the very poorest show the opposite effect. Information patterns show a uniformity across socioeconomic groups reflecting an increasing importance of information sharing.

These patterns are illuminating in the context of the recent credit crisis in that they suggest both an increase in the value of financial education, particularly for at-risk segments of the population, and a pattern of stigmatization changes. These patterns imply declines in stigma not amongst the poorest or least well educated individuals, but instead amongst the more educated in society.

These findings also strengthen our main conclusion that the overall increase in bankruptcy rates cannot be explained by a decrease in social stigma, but by decreasing information costs. After all, stigma seems to have fallen only for a small group of the population over the last couple of years, and one that does not comprise a large proportion of bankrupts (See Tables 7 and 8). Table 9 shows the relative contribution of each of the 25 segments to the change in stigma or information between 2006 and 2007, using the results from Tables 6 and 8. That is, for a total change of 100%, a cell with 5% indicates that 1/20 of the change derives from that cell. One can immediately observe that the upper left corner, representing the poorest and least well educated segment of the population accounts from more than 80% of the change. Thus, this group is principally responsible for the increase in social stigma between the two sample time periods.

We suspect that the key driver of the recent bankruptcy trends lies elsewhere: perhaps with the secular rises in information sharing observed in the data and possibly due to heterogeneous exposures to economic shocks. One plausible interpretation is that the economic shocks of recent years, though muted until the recent crisis, have disproportionately impacted some segments of the population. Another potential explanation is the increased availability of credit following bankruptcy. We argue that the most recent credit expansion have significantly reduced one of the most traditional costs of bankruptcy: being excluded from the credit market for a period of time. Preliminary findings from Cohen-Cole, Duygan-Bump, and Montoriol-Garriga (2008) suggest that households face only very temporary restrictions to credit. But these conclusions remain as conjectures to be explored in future research.

[16]Since we don't have individual information on income or education level, we ascribe the median household income and education level in the community to the residents that live in the same community. (Communities are defined either as counties or as a 0–1 mile radius around the residence of the individual.)

7 Conclusions

In this paper, we estimate a model of the household bankruptcy decision, using data from one of the largest US credit bureaus. In particular, we analyze the empirical relevance of stigma and social learning on household bankruptcy decisions. As in the previous literature, we first show that, even after controlling for various economic and individual credit quality factors, households are much more likely to file for bankruptcy if they live in neighborhoods which have higher aggregate bankruptcy rates. In other words, local bankruptcy rates are an important determinant of households' individual bankruptcy decisions.

We then analyze the different channels through which aggregate behavior (social influences) can affect households' individual decisions. We want to know whether it is the changes in the social stigma attached to bankruptcy that makes individuals more likely to default, or whether it is because they learn from friends and neighbors about how to file for bankruptcy (information costs). Importantly, we find that in the last few years, community perceptions have become increasingly more important in household bankruptcy decisions. In other words, households have become more willing to follow what others in their community are doing. More specifically, we find that while stigma has declined in general over the past 5 years, changes in information costs seem to be the more likely candidate in explaining the observed bankruptcy trends. Moreover, we show that the changes in stigma are strongly correlated with social context. The segments of the population that make up the majority of bankruptcies in fact appear to be showing an increase in social stigma over time, while segments that face few bankruptcies show the opposite pattern.

Our findings are illuminating in that they suggest an increasing value to information and a nuanced pattern of social stigma evolution that is new to the literature and the policy debate. If during a crisis time period, the social stigma of bankruptcy increases amongst the least educated and falls amongst the most, it implies that the patterns of foreclosures and bankruptcies often reported in news sources in late 2007 and early 2008 are likely due to economic conditions rather than social phenomena. Put differently, social stigma seems to have fallen among a group of the population that represents few bankruptcies in general, and is therefore not likely to explain the overall increase in bankruptcies. However, changes in information costs seem to have a greater potential in explaining these macro trends. Similarly, we conjecture that these bankruptcy trends may also be driven by increased availability of credit to bankrupt households and the increased exposure to economic risk by some groups vs. others, i.e. heterogeneity in exposure to economic shocks. The former would lead to individuals being more willing to declare bankruptcy as the ex-post penalties have shrunk. The latter is implied by the heterogeneous social interactions results observed in this study. A better understanding of the feedback between socioeconomic conditions and social drivers of bankruptcy (and of course bankruptcy itself) could be important to understanding the rise in bankruptcies.

We encourage continued attempts to understand the source and nature of social effects at a level deeper than what has been done in this literature (or this paper) to date. Since the effects appear to be non-stable over time and their strength conditional on social context, an understanding of the feedback between these effects is essential, especially for understanding the distributional implications of policy changes.

References

[1] Alesina, A., and E. Glaeser. 2004. *Fighting Poverty in the US and Europe*. New York: Oxford University Press.

[2] Athreya, K., 2002, "Welfare Implications of the Bankruptcy Reform Act of 1999," *Journal of Monetary Economics,* 49: 1567–95.

[3] Athreya, K., 2004, ”Shame As It Ever Was: Stigma and Personal Bankruptcy,” *Federal Reserve Bank of Richmond Economic Quarterly,* 90(2): 1–19.

[4] Barron, J. M., G. Elliehausen, and M. E. Staten, 2000, “Monitoring the Household Sector with Aggregate Credit Bureau Data,” *Business Economics*.

[5] Bertrand, M., E. Luttmer, and S. Mullainathan, 2000, “Network Effects and Welfare Cultures,” *Quarterly Journal of Economics*, 115 (3): 1019–55.

[6] Bramoullé, Y., H. Djebbari, and B. Fortin, 2007, “Identification of Peer Effects through Social Networks,” IZA Discussion Paper, No: 2652.

[7] Brock, W. and S. Durlauf, 2001, “Discrete Choice With Social Interactions,” *Review of Economic Studies* 68(2): 235-60.

[8] Channing, Edward, 1921. *A History of the United States.* Macmillan.

[9] Chatterjee, S., D. Corbae, M. Nakajima, and J.-V. Rios-Rull, 2007, “A Quantitative Theory of Unsecured Consumer Credit with Risk of Default,” *Econometrica* 75(6): 1525-89.

[10] Cohen-Cole, E., 2006, “Multiple Groups Identification in the Linear-in-Means Model,” *Economics Letters* 92(2), 753-58.

[11] Cohen-Cole, E., 2008, “Credit Card Redlining,” Federal Reserve Bank of Boston, mimeo.

[12] Cohen-Cole, E, B. Duygan-Bump, and J. Montoriol-Garriga. (2008), “Bankruptcy and Forgiveness: Are bankrupt borrowers excluded from credit markets?” Federal Reserve Bank of Boston, mimeo.

[13] Cohen-Cole, E. and G. Zanella, 2008a, “Unpacking Social Interactions,” *Economic Inquiry* 46(1), 19-24.

[14] Cohen-Cole, E. and G. Zanella, 2008b, “Welfare Cultures or Information Sharing? Decomposing Race-Linked Peer Effects in Social Benefit Use,” Boston Fed mimeo.

[15] Coleman, P., 1974, *Debtors and Creditors in America.* Beard Books.

[16] Dick, A., A. Lehnert, and G. Topa (2008), “Social Spillovers in Personal Bankruptcy,” Federal Reserve Bank of New York, mimeo.

[17] Duygan-Bump, B. and C. Grant, 2008, “Household Debt Repayment Behaviour: what role do institutions play?” Boston Fed mimeo.

[18] Efrat, R., 2006. “The Evolution of Bankruptcy Stigma,” *Theoretical Inquiries in Law* 7(2):365–393.

[19] Elias, S., 2006, *The New Bankruptcy: Will it Work for You?* Nolo Press.

[20] Fay, S., E. Hurst, and M. White, 2002, “The Household Bankruptcy Decision,” *American Economic Review*, 92(3): 706–18.

[21] Flynn, E., and G. Bermant, 2002, “Bankruptcy by the Numbers: A Tale of Two Chapters: Financial Data,” *American Bankruptcy Institute Journal*, 21(8): 20 and 38.

[22] Gross, D. and N. Souleles, 2002, "An Empirical Analysis of Personal Bankruptcy and Delinquency," *The Review of Financial Studies*, 15(1):319–47.

[23] Li, W., and P.-D. Sarte, 2006, "U.S. consumer bankruptcy choice: The Importance of General Equilibrium Effects," *Journal of Monetary Economics*, 53(3): 613–31.

[24] Livshits, I., J. MacGee, and M. Tertilt, 2007a, "Consumer Bankruptcy: A Fresh Start," *American Economic Review*, 97: 402–18.

[25] Livshits, I., J. MacGee, and M. Tertilt, 2007b, "Accounting For The Rise In Consumer Bankruptcies," *NBER Working Paper*, no: 13363.

[26] Luttmer, E. 2001., "Group Loyalty and the Taste for Redistribution." *Journal of Political Economy*, 109 (3): 500-528.

[27] Manski, C., 1993, "Identifications of Endogenous Social Effects: The Refection Problem," *Review of Economic Studies*, 60: 531–42.

[28] Manski, C., 2000, "Economic Analysis of Social Interactions,"*Journal of Economic Perspectives*, 14: 115–36.

[29] MacIntyre, L. 1989, "A Sociological Perspective on Bankruptcy," *Indiana Law Journal* 65: 123–136.

[30] Moffitt, R., 1983, "An Economic Model of Welfare Stigma," *American Economic Review*, 73 (5): 1023–1035.

[31] Pomykala, J. 2000, "Bankruptcy Laws: the Need for Reform," in *Legal Environment of Business,* K. Stanberry, ed.: 178–180.

[32] Sullivan, T. A., E. Warren, and J. L. Westbrook, 2000, *The Fragile Middle Class*, Yale University Press, New Haven and London.

[33] Tabb, C., 1991. "The Historical Evolution of the Bankruptcy Discharge," *American Bankruptcy Law Journal* 65: 325–330.

[34] Thorne, D. and L. Anderson, 2006, "Managing the Stigma of Personal Bankruptcy," *Sociological Focus* 39 (2):77–97.

[35] Wall Street Journal, December 19, 2007, "Now, Even Borrowers With Good Credit Pose Risks," by George Anders, p. A2.

[36] White, M., 1998, "Why Don't More Households File for Bankruptcy?" *Journal of Law, Economics, and Organization*, 14(2): 205–31.

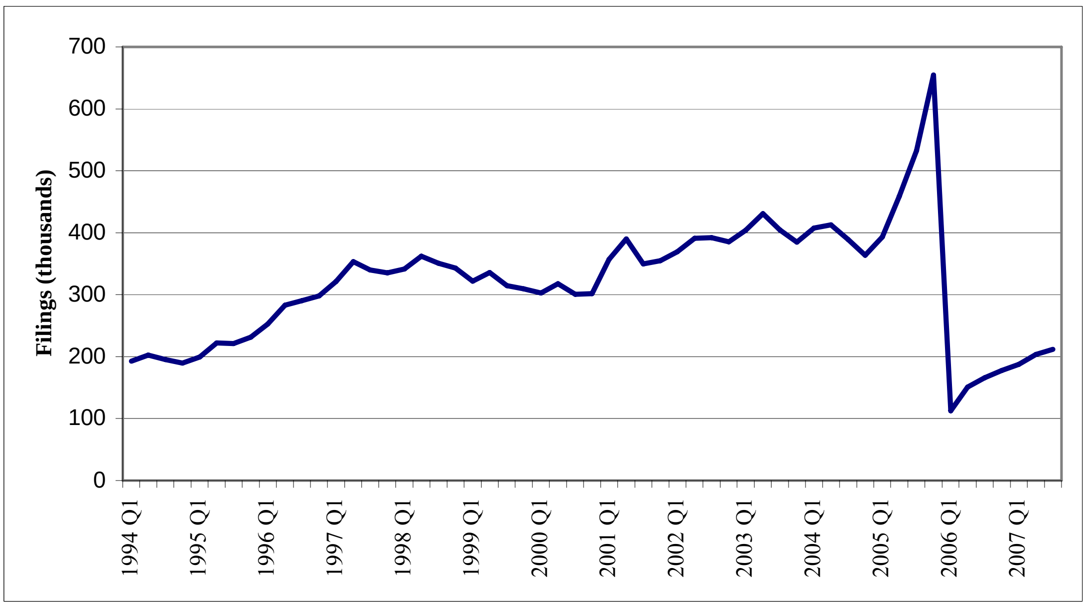
[37] White, M., 2007, "Bankruptcy Reform and Credit Cards," *Journal of Economic Perspectives*, 21(4): 175–199.

[38] Warren, E., and A. Warren Tyagi, 2003, *The Two Income Trap: Why Middle-Class Mothers & Fathers Are Going Broke (With Surprising Solutions That Will Change Our Children's Futures)*, Basic Books, New York.

[39] Zanella, G., 2007, "Discrete Choice with Social Interactions and Endogenous Memberships," *Journal of the European Economic Association*, 5(1): 122–153.

[40] Zitek, E. and Hebl, M., 2007, "The Role of Social Norm Clarity in the Influenced Expression of Prejudice over Time," *Journal of Experimental Social Psychology,* 43: 867–867.

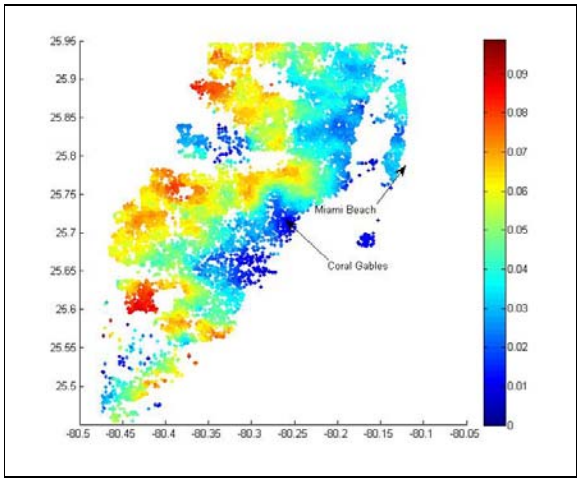
FIGURE 1: QUARTERLY NONBUSINESS BANKRUPTCY FILINGS (IN THOUSANDS)



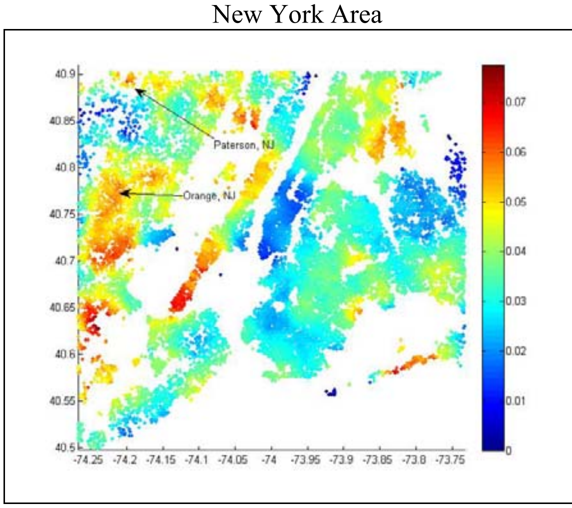
Source: American Bankruptcy Institute.

FIGURE 2: BANKRUPTCY DENSITY PLOTS OF MIAMI, NEW YORK, AND CHICAGO

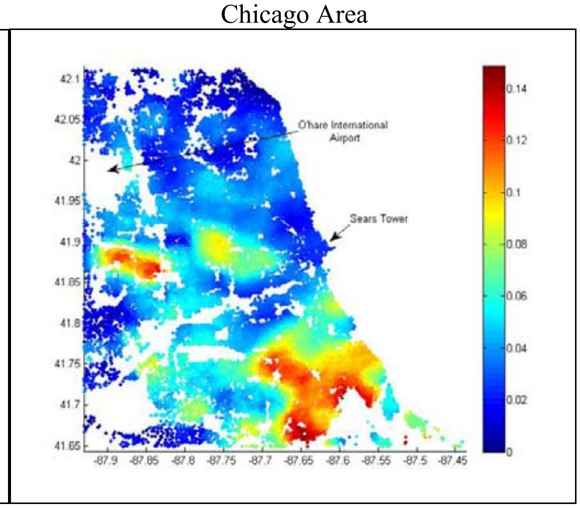
Miami Area



New York Area

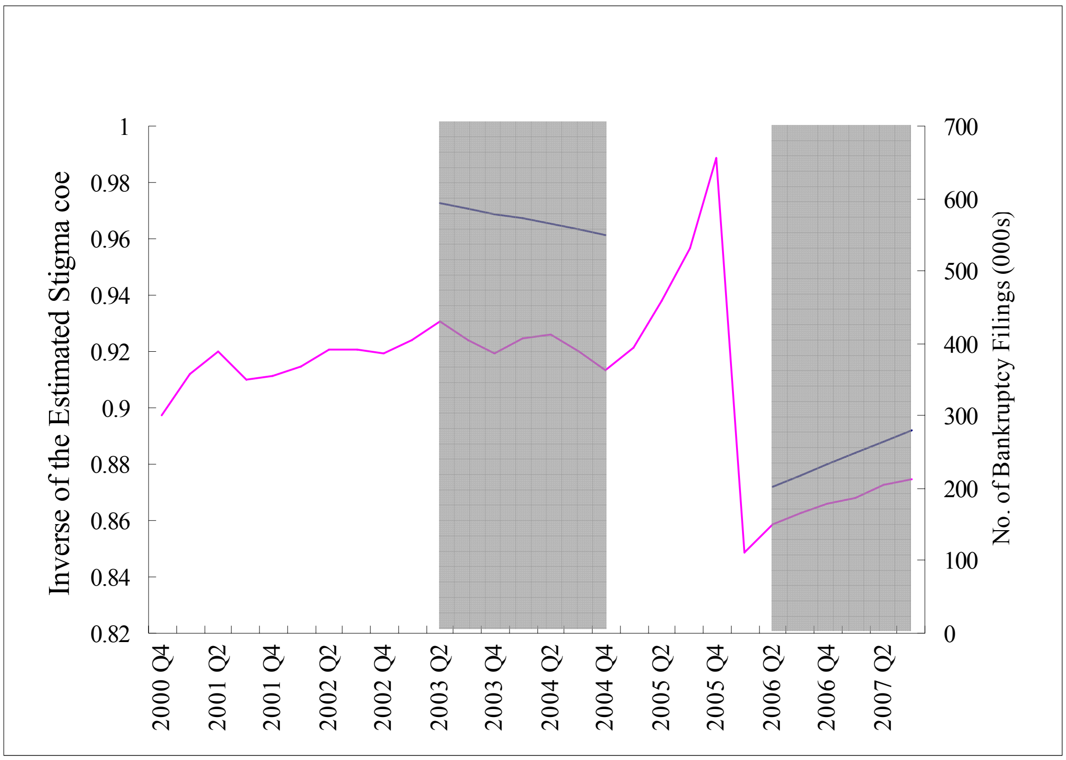


Chicago Area



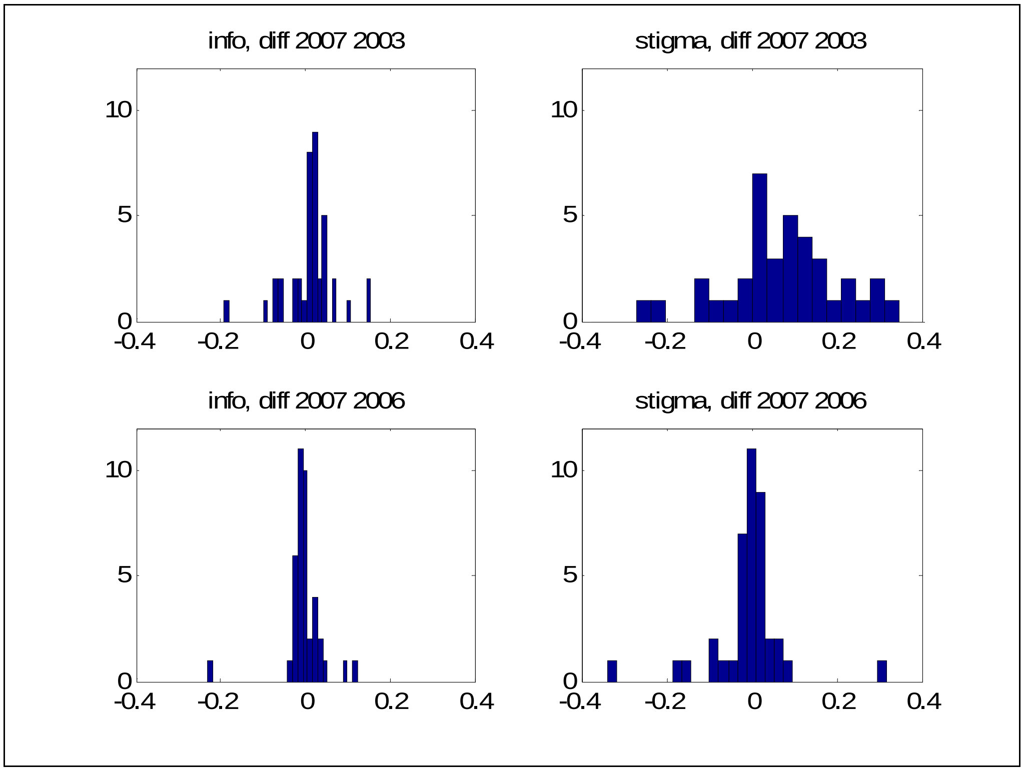
Source: Authors' calculations based on the 2006 Credit Bureau data.

FIGURE 3: STIGMA AND BANKRUPTCY



Source: American Bankruptcy Institute & Author's calculations using Credit Bureau and Census 2000 data.

FIGURE 4: CHANGES IN INFORMATION AND STIGMA, 2003-2007 AND 2006-2007



Notes: Authors' calculation based on the results from auxiliary model with α = 0.25, run separately for each state.

TABLE 1: VARIABLE DEFINITIONS

VARIABLES	DEFINITION	SOURCE
age2	age of individual squared	authors' calculation based on credit bureau data
avgbkrpt_state	average number of bankruptcies filed in the state	authors' calculation based on credit bureau data
BRP_ind	indicator of public record bankruptcies	authors' calculation based on credit bureau data
mortgage_limit	mortgage high credit/credit limit	authors' calculation based on credit bureau data
credit_util	credit utilization, in thousands of dollars	authors' calculation based on credit bureau data
credit_utilsq	credit utilization, in thousands of dollars, squared	authors' calculation based on credit bureau data
age	age of individual	credit bureau data
revolve_cred	total revolving high credit/credit limit, in thousands of dollars	credit bureau data
c.score	internal credit score	credit bureau data
gt_eq_HS_01	percentage of residents in a one mile radius who have achieved high school equivalency or greater	authors' calculation based on data from U.S. Census 2000
married_01	percentage of residents in a one mile radius who are married	authors' calculation based on data from U.S. Census 2000
divorced_01	percentage of residents in a one mile radius who are divorced	authors' calculation based on data from U.S. Census 2000
perc_black_01	percentage of residents in a one mile radius who are black	authors' calculation based on data from U.S. Census 2000
perc_hispanic_01	percentage of residents in a one mile radius who are Hispanic	authors' calculation based on data from U.S. Census 2000
public_assistance_01	percentage residents who receive public assistance in a one mile	authors' calculation based on data from U.S. Census 2000
incgrowth_inflation	average income growth	authors' calculation based on data from ACS 2000 & 2005
median household income	median household income in county of residence	U.S. Census 2000, 2005-2006 American Community Survey
poverty_rate	percentage of people below poverty level in county of residence	U.S. Census 2000, 2005-2006 American Community Survey
unemployment	percentage of unemployed residents in county of residence	Bureau of Labor Statistics: Local Area Unemployment Statistics
uninsured	percentage of residents in the state who are uninsured	U.S. Census Bureau: Current Population Survey

TABLE 2: SUMMARY STATISTICS

	2003		2004		2006		2007	
VARIABLES	**MEAN**	**SD**	**MEAN**	**SD**	**MEAN**	**SD**	**MEAN**	**SD**
BRP_ind	0.054	0.226	0.057	0.232	0.054	0.227	0.049	0.215
mortgage_limit ($ thousands)	56.104	121.326	69.965	140.755	71.648	161.225	82.598	181.627
revolve_cred $ thousands)	35.310	49.141	40.544	59.715	24.741	29.857	25.539	30.465
credit_util ($ thousands)	6.852	14.087	7.968	17.286	7.405	18.536	8.203	20.624
credit_utilsq ($ thousands)	245.40	2,639.08	362.29	4,030.66	398.42	7,989.51	492.65	10,670.38
c. score	648.080	140.447	650.194	139.487	697.180	142.987	696.443	145.356
age	48.798	17.133	49.661	17.032	37.379	11.221	37.405	11.314
age2	2,674.74	1,843.14	2,756.26	1,852.51	1,523.08	898.49	1,527.15	900.33
perc_blac~01	0.094	0.169	0.096	0.172	0.103	0.176	0.099	0.172
perc_hisp~01	0.108	0.167	0.110	0.169	0.124	0.181	0.123	0.181
gt_eq_HS_01	0.828	0.117	0.821	0.119	0.827	0.121	0.829	0.120
married_01	0.577	0.108	0.572	0.106				
divorced_01					0.096	0.034	0.097	0.034
public_as~01	0.030	0.032	0.031	0.032	0.030	0.032	0.031	0.032
incgrowth_inflation	1.004	2.940	0.995	2.917	0.996	2.931	0.959	2.898
median_HH_inc	45,016	10,803	44,827	10,820	50,090	12,309	52,516	12,614
unemployment	5.788	1.433	5.993	1.496	5.038	1.323	4.599	1.283
poverty_rate	11.676	5.131	11.708	5.144	12.481	4.893	12.487	4.642
uninsured	15.020	4.091	15.355	3.879	15.729	4.188	15.619	4.486
avgbkrpt_state	0.048	0.012	0.053	0.013	0.054	0.012	0.049	0.011
Number of observations	145,567	145,567	152,441	152,441	16,801,971	16,801,971	17,051,621	17,051,621

Notes: Based on authors' calculations using credit bureau data, Census and other information as described in the data section, and Table 1.

TABLE 3: BASELINE SPECIFICATION

	2003	2004	2006	2007
	(1) **g094_ind**	**(2)** **g094_ind**	**(3)** **g094_ind**	**(4)** **g094_ind**
mortgage_limit ($ thousands)	0.00000426**	0.00000599***	-0.00000327***	-0.00000762***
	(0.000002)	(0.0000022)	(0.00000023)	(0.00000020)
revolve_cred $ thousands)	-0.000572***	-0.000497***	-0.000467***	-0.000499***
	(0.000014)	(0.000014)	(0.0000014)	(0.0000012)
credit_util ($ thousands)	0.0000508	-0.00000479	-0.0000416***	0.000278***
	(0.000038)	(0.000039)	(0.0000038)	(0.0000028)
credit_utilsq ($ thousands)	0.000000864***	0.000000933***	0.000000374***	0.000000108***
	(0.00000013)	(0.000000088)	(0.0000000032)	(0.0000000025)
c.score	-0.000117***	-0.000150***	-0.000138***	-0.0000967***
	(0.0000042)	(0.0000042)	(0.00000040)	(0.00000033)
age	0.00274***	0.00318***	0.00833***	0.00766***
	(0.00011)	(0.00011)	(0.000026)	(0.000024)
age2	-0.0000243***	-0.0000281***	-0.0000928***	-0.0000858***
	(0.000001)	(0.0000011)	(0.00000031)	(0.00000029)
perc_black_01	-0.00875***	-0.0101***	-0.0107***	-0.00738***
	(0.0014)	(0.0016)	(0.00017)	(0.00016)
perc_hispanic_01	-0.000654	-0.00132	0.00108***	0.000534**
	(0.0019)	(0.0022)	(0.00024)	(0.00023)
gt_eq_HS_01	0.0139***	0.0135***	0.00350***	0.00236***
	(0.0028)	(0.0032)	(0.00037)	(0.00034)
married_01	0.00333	0.00149		
	(0.0024)	(0.0028)		
divorced_01			0.0389***	0.0359***
			(0.00088)	(0.00081)
public_assistance_01	0.0236***	0.0361***	0.0442***	0.0376***
	(0.0086)	(0.01)	(0.0012)	(0.0011)
incgrowth_inflation	0.000148**	0.000159*	0.0000749***	0.0000537***
	(0.000075)	(0.000091)	(0.00001)	(0.00001)
median_HH_inc	0.0000000184	-0.0000000476	-0.0000000657***	-0.000000104***
	(0.000000034)	(0.000000041)	(0.000000004)	(0.000000004)
unemployment	0.0000237	0.0000246	0.00000124	0.000138***
	(0.00017)	(0.00019)	(0.00002)	(0.00002)
poverty_rate	-0.000214***	-0.000348***	-0.000367***	-0.000397***
	(0.000078)	(0.000091)	(0.00001)	(0.00001)
uninsured	-0.000326***	-0.000453***	-0.000248***	-0.000182***
	(0.000063)	(0.000079)	(0.0000079)	(0.0000066)
avgbkrpt_state	0.345***	0.404***	0.289***	0.260***
	(0.019)	(0.021)	(0.0024)	(0.0024)
Number of observations	145,567	152,441	12,300,000	12,400,000

Notes: The numbers reported are the marginal effects based on coefficients estimated using a probit model. See Table 1 for a detailed description of each of the variables. A constant term was also included but is not reported here. Standard errors are reported in parentheses, and we adopt the usual convention: *** p<0.01, ** p<0.05, * p<0.1

TABLE 4: TOTAL STIGMA AND INFORMATION

	2003	2004	2006	2007
Stigma	0.0275**	0.0384**	0.118***	0.106***
	(0.0141)	(0.0157)	(0.0018)	(0.0016)
Information	0.0532***	0.0638***	0.0948***	0.0746***
	(0.00612)	(0.00709)	(0.0014)	(0.0013)
Number of Observations:	131,430	135,046	12,300,000	12,300,000

Notes: The numbers reported are the marginal effects based on coefficients estimated using a probit model. This regression includes all the independent variables from the baseline specifications, together with a constant term, but are not reported here. Instead we report only the marginals effects related to the variables of interest – information and stigma. These results are based on the auxiliary model, where we assume α=0.75, which denotes the marginal rate of substitution between stigma from local and non-local groups, and puts 3:1 weight on the non-local stigma. The stigma variable shown in this table refers to 'total stigma' as defined above. Local and non-local stigma estimates are available from the authors upon request. Standard errors are reported in parentheses, and we adopt the usual convention: *** p<0.01, ** p<0.05, * p<0.1

TABLE 5: STIGMA AND INFORMATION ACROSS EDUCATION AND INCOME QUINTILES

2006

Stigma:

	Income Quintile				
	1	2	3	4	5
Education					
1	0.314***	0.197***	0.176***	0.0830**	0.009
2	0.105***	0.245***	0.197***	0.161***	0.139***
3	0.128***	0.140***	0.154***	0.117***	0.105***
4	0.106***	0.170***	0.178***	0.113***	0.0608***
5	0.0500***	0.132***	0.137***	0.130***	0.0607***

Information:

	Income Quintile				
	1	2	3	4	5
Education					
1	0.135***	0.122***	0.0768***	0.020	0.000
2	0.223***	0.125***	0.0739***	0.0470***	-0.003
3	0.136***	0.131***	0.118***	0.0822***	0.0356***
4	0.015	0.0948***	0.0748***	0.0867***	0.0703***
5	0.0380***	0.0510***	0.0723***	0.0752***	0.0658***

2007

Stigma:

	Income Quintile				
	1	2	3	4	5
Education					
1	0.168***	0.0903***	0.116***	0.129***	0.045
2	0.152***	0.212***	0.166***	0.119***	0.0354*
3	0.154***	0.169***	0.146***	0.130***	0.0697***
4	0.0983***	0.191***	0.193***	0.130***	0.0734***
5	0.0526***	0.170***	0.173***	0.136***	0.0570***

Information:

	Income Quintile				
	1	2	3	4	5
Education					
1	0.144***	0.116***	0.0234*	-0.017	0.023
2	0.151***	0.0963***	0.0691***	0.0400***	0.0235*
3	0.105***	0.0887***	0.0874***	0.0453***	0.0449***
4	0.0353**	0.0722***	0.0509***	0.0540***	0.0511***
5	0.0354**	0.029	0.0243*	0.0424***	0.0519***

Notes: The numbers reported are the marginal effects based on coefficients estimated using a probit model. These regressions includes all the independent variables from the baseline specifications, together with a constant term, but are not reported here. Instead we report only the marginals effects related to the variables of interest – information and stigma. These results are based on the auxiliary model, where we assume α=0.75, which denotes the marginal rate of substitution between stigma from local and non-local groups, and puts 3:1 weight on the non-local stigma. The values are aggregated across two dimensions, lowest to highest income quintiles (based on aggregate household income in a zero to one mile radius) and lowest to highest education quintiles (based on percentage of residents with high school equivalency or greater in a zero to one mile radius). The stigma variable shown in this table refers to 'total stigma' as defined above. Local and non-local stigma estimates are available from the authors upon request. Standard errors are reported in parentheses, and we adopt the usual convention: *** p<0.01, ** p<0.05, * p<0.1

TABLE 6: CHANGES IN STIGMA AND INFORMATION COEFFICIENTS BY EDUCATION AND INCOME QUINTILES

Change in Stigma: 2006 - 2007

Stigma:	**Income Quintile**				
	1	2	3	4	5
Education					
1	(0.146)	(0.107)	(0.060)	0.046	0.036
2	0.047	(0.033)	(0.031)	(0.042)	(0.104)
3	0.026	0.029	(0.008)	0.013	(0.035)
4	(0.008)	0.021	0.015	0.017	0.013
5	0.003	0.038	0.036	0.006	(0.004)

Change in Information: 2006 - 2007

Information:	**Income Quintile**				
	1	2	3	4	5
Education					
1	0.009	(0.006)	(0.053)	(0.037)	0.023
2	(0.072)	(0.029)	(0.005)	(0.007)	0.026
3	(0.031)	(0.042)	(0.031)	(0.037)	0.009
4	0.021	(0.023)	(0.024)	(0.033)	(0.019)
5	(0.003)	(0.023)	(0.048)	(0.033)	(0.014)

Notes: The values reported are the difference in information and stigma coefficients from 2006 to 2007. The values are aggregated across two dimensions, lowest to highest income quintiles (based on aggregate household income in a zero to one mile radius) and lowest to highest education quintiles (based on percentage of residents with high school equivalency or greater in a zero to one mile radius).

TABLE 7: BANKRUPTCY RATES BY EDUCATION AND INCOME QUINTILES

2003

Bankruptcy Rate:			**Income Quintile**		
	1	2	3	4	5
Education					
1	5.23	6.20	5.08	4.76	2.90
2	6.69	7.01	5.99	4.57	4.27
3	6.03	6.38	6.44	5.03	3.39
4	5.62	6.03	6.32	5.44	3.76
5	3.68	5.65	5.36	5.40	3.15

2004

Bankruptcy Rate:			**Income Quintile**		
	1	2	3	4	5
Education					
1	6.36	6.66	6.32	5.06	7.19
2	7.89	7.22	7.10	5.39	4.42
3	6.63	7.00	7.12	5.74	3.86
4	4.65	7.15	7.27	5.64	4.21
5	4.83	5.97	6.01	5.85	3.65

2006

Bankruptcy Rate:			**Income Quintile**		
	1	2	3	4	5
Education					
1	5.45	5.94	5.21	3.95	2.31
2	7.55	7.29	6.34	4.62	3.16
3	6.97	7.83	7.18	5.22	3.48
4	4.84	7.55	7.08	5.52	3.58
5	3.54	5.87	6.34	5.48	3.18

2007

Bankruptcy Rate:			**Income Quintile**		
	1	2	3	4	5
Education					
1	5.08	5.49	4.91	3.63	2.17
2	7.26	6.96	5.93	4.32	2.85
3	6.82	7.53	6.81	4.85	3.16
4	4.98	7.19	6.81	5.21	3.31
5	3.39	5.55	6.07	5.24	2.99

Notes: The values reported are the bankruptcies rates for each income and education quintile in 2003, 2004, 2006 and 2007. The values are aggregated across two dimensions, lowest to highest income quintiles (based on aggregate household income in a zero to one mile radius) and lowest to highest education quintiles (based on percentage of residents with high school equivalency or greater in a zero to one mile radius).

TABLE 8: DISTRIBUTION OF BANKRUPTCIES BY EDUCATION AND INCOME QUINTILES

2003

% of Total Bankruptcies:	Income Quintile				
	1	2	3	4	5
Education					
1	13.74	5.33	0.91	0.21	0.03
2	4.80	10.93	6.31	1.36	0.30
3	1.24	5.65	8.67	4.96	0.90
4	0.47	1.75	5.70	8.17	3.62
5	0.30	0.41	1.28	5.08	7.88

2004

% of Total Bankruptcies:	Income Quintile				
	1	2	3	4	5
Education					
1	14.73	5.20	1.13	0.20	0.07
2	5.23	10.31	6.56	1.45	0.25
3	1.25	5.78	8.70	5.04	0.89
4	0.40	1.92	5.85	7.38	3.52
5	0.35	0.38	1.16	4.57	7.70

2006

% of Total Bankruptcies:	Income Quintile				
	1	2	3	4	5
Education					
1	14.62	4.41	0.75	0.16	0.05
2	3.78	9.04	5.44	1.40	0.35
3	0.93	4.83	7.75	5.14	1.35
4	0.37	1.38	4.94	8.26	5.05
5	0.30	0.34	1.12	5.04	13.21

2007

% of Total Bankruptcies:	Income Quintile				
	1	2	3	4	5
Education					
1	14.62	4.39	0.76	0.17	0.06
2	3.80	9.03	5.39	1.42	0.36
3	0.96	4.85	7.70	5.12	1.36
4	0.35	1.39	5.00	8.23	5.03
5	0.27	0.33	1.15	5.06	13.20

Notes: The values reported are the percentage of total bankruptcies in 2003, 2004, 2006 and 2007 that fall in each income and education quintile. The values are aggregated across two dimensions, lowest to highest income quintiles (based on aggregate household income in a zero to one mile radius) and lowest to highest education quintiles (based on percentage of residents with high school equivalency or greater in a zero to one mile radius).

TABLE 9: Contribution of Each "Group" to Total Changes in Stigma and Information

Change in Stigma: 2006 - 2007

Stigma:	**Income Quintile**				
	1	2	3	4	5
Education					
1	(0.863)	(0.184)	(0.017)	0.002	0.001
2	0.095	(0.126)	(0.055)	(0.018)	(0.008)
3	0.012	0.064	(0.022)	0.017	(0.010)
4	(0.001)	0.013	0.028	0.035	0.011
5	0.000	0.004	0.018	0.008	(0.007)

Change in Information: 2006 - 2007

Information:	**Income Quintile**				
	1	2	3	4	5
Education					
1	0.074	(0.014)	(0.021)	(0.003)	0.001
2	(0.203)	(0.153)	(0.012)	(0.004)	0.003
3	(0.021)	(0.129)	(0.116)	(0.068)	0.004
4	0.004	(0.020)	(0.063)	(0.095)	(0.024)
5	(0.000)	(0.004)	(0.033)	(0.064)	(0.038)

Notes: The values reported are the relative contribution of each of the 25 segments to the change in stigma or information between 2006 and 2007. They are computed using the changes estimated in Table 6 and the distribution of bankruptcies reported in Table 8, normalized to a total change of 100%.