Bankruptcy Spillovers between Close Neighbors

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We examine bankruptcy spillovers between very close neighbors. Our fine grained location data allows us to use the cross-sectional difference methodology (e.g. Grinblatt, Keloharju, Ikaheimo (2008), Campbell, Giglio, Pathak (2011)) to control for non-random neighborhood sorting and unobservable neighborhood shocks. This approach subtracts characteristics of inner-ring neighbors (14 households on average) from outer-ring neighbors (207 households and 0.2 square kilometers on average) to control for neighborhood level unobservables affecting both rings. We show that inner-ring neighborhood bankruptcies, controlling for outer-ring neighborhood bankruptcies, impacts the individual's choice of whether or not to default, as well as of the legal mechanism of default.

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The hypothesis that past bankruptcies in an individual's neighborhood can influence the individual to file for bankruptcy has often been proposed in the personal bankruptcy literature (e.g. Fay, Hurst and White, 2002, Gross and Souleles, 2002, Han and Li, 2007, Dick, Lehnert and Topa, 2008, Cohen-Cole and Duygan-Bump, 2009, White, 2011, Agarwal, Chomsisengphet, Liu, 2011). It is usually argued that these neighborhood effects can operate either through stigma (where an awareness of other individuals in a social network who have previously filed for bankruptcy lowers stigma), or information cascades (where interactions with previous bankruptcy filers leads to learning about the legal process involved in a bankruptcy filing). The justification for this relationship is provided by Fay, Hurst and White (2002) who argue that "if households live in a district with a higher bankruptcy filing rate, then they are more likely to hear firsthand about bankruptcy from friends or relatives because the latter are more likely to have filed...This information will tend to make households more comfortable with the idea of bankruptcy, so the level of bankruptcy stigma falls" (p. 710). Similarly Gross and Souleles (2002) argue that "social stigma and information about bankruptcy might change, with the number of people in one's community, appropriately defined, that have already filed for bankruptcy." (p. 339).

While the hypothesis of bankruptcy spillovers from neighbors has often been discussed in the literature, convincing empirical evidence is rare, both because of data constraints as well as methodological issues. Because of data constraints, for example, the "neighborhoods" defined by Fay, Hurst and White (2002) and Gross and Souleles (2002) include many millions of individuals (US bankruptcy court districts, and US States, respectively). More importantly, the existing literature has not convincingly addressed the issue of endogeneity. As is well known in the neighborhood spillover literature, in any study of the impact of neighbors on individuals, endogeneity can arise because individuals with certain preferences or characteristics can self-select to locate in the same neighborhood (non-random sorting), which in turn influences the choices of individuals in the neighborhood. In addition, an unobservable neighborhood specific shock (e.g. a local plant closure or local advertising of bankruptcy services) can also influence choices by both individual's and their close neighbors, resulting in endogeneity problems.

In order to address these causes of endogeneity, this paper uses an identification strategy recently used by Grinblatt, Keloharju and Ikaheimo (2008) (who examine the effects of neighbor's car consumption on individual car consumption), Linden and Rockoff, (2008) (effects of sex offender location on neighborhood house prices), Bayer, Ross, and Topa (2008) (effects of neighbor's place of work on individual place of work), and Campbell, Giglio and Pathak (2011) (effects of foreclosure on neighborhood house prices). Linden and Rockoff (2008) label this procedure the "cross-sectional difference estimator" (p. 112).The common element of all these papers is access to very fine grained geographic location data on the choices of individuals and their close neighbors. The basic idea is to identify two groups of neighbors: (1) those very close to the individual (e.g. within the same city block), which Grinblatt, Keloharju and Ikaheimo (2008) label inner-rings; and, (2) neighbors that are slightly further away from the individual, (e.g. within neighboring city blocks), which Grinblatt, Keloharju and Ikaheimo (2008) label outer-rings.

All of these papers argue that it is possible to address issues of non-random neighborhood sorting and unobservable local shocks by examining the impact on individuals of inner-ring neighbors *relative to* outer-ring neighbors. The Grinblatt, Keloharju and Ikaheimo (2008) specification, for example, involves creating a new independent variable defined as the characteristics of the inner-ring neighborhood (in our case the number of past neighborhood bankruptcies in the inner-ring) *minus* the characteristics of the outer-ring neighborhood (in our case the number of past neighborhood bankruptcies in the outer-ring), weighted by the number of households in each ring. This new inner-ring minus outer-ring (cross-sectional difference) variable is regressed on the individual's choices in a logit regression (in our case the individual's choice to file for bankruptcy). The coefficient on this variable captures the neighborhood spillover effect of the inner-ring neighbors on the individual's choice, while controlling for outer-ring neighbors. Using this new approach in this paper, we find strong support for the neighborhood bankruptcy spillover hypothesis.

The econometric intuition behind this cross-sectional difference approach is that the subtraction of outer-ring neighbor effects from inner-ring neighbor effects controls for unobserved common attributes that are shared by residents of *both* the inner- and outer-rings. In all of these papers above, the assumption that inner-ring and outer-ring neighbors share common attributes is based on the argument that it is difficult for individuals to endogenously sort into areas when the size of the area is very small. For example, Bayer, Ross, and Topa (2008) argue that, “firstly…the thinness of the housing market at such small geographic scales… restricts an individual’s ability to choose a specific block versus a wider neighborhood. Secondly, it may be difficult for individuals to identify block-by-block variation in neighbor characteristics at the time of purchase or lease. That is, while an individual may have a reasonable sense of the socio-demographic structure of the neighborhood more generally, that variation across blocks within a neighborhood is less easily observed *a priori*.” (p. 1166). Similarly, Linden and Rockoff (2008) argue that “individuals may choose neighborhoods with specific characteristics, but, within a fraction of a mile, the exact locations available at the time individuals seek to move into a neighborhood are arguably exogenous” (p. 1110).

Similarly, all of these papers also make use of this cross-sectional difference methodology to control for unobservable local shocks (e.g. local plant closures or local advertising of bankruptcy services). The basic argument is that because both inner-rings and outer-rings are fractions of a kilometer in size, they should *both* be impacted by unobserved local shocks. Thus the subtraction of outer-rings from inner-rings controls for the common unobservable shocks. Campbell, Giglio and Pathak (2011), for example, argue that “if there is a common shock in the neighborhood which generates an overall … trend within this microgeography, it will be captured by the *difference* between these two groups.” (p. 2125).

In this paper we exploit the Canadian postal code system to identify inner-ring and outer-ring neighbors of individual bankruptcy filers. Full details of the post code system are provided below, but in brief, we define inner-ring neighbors using Canadian six digit post codes (where there are a median of 14 households in Canada) and define outer-ring neighbors using a postal geography called the dissemination area (DAs) (where there are a median of 207 households in Canada). The median geographic size of these outer-ring DAs in Canada is 0.2 square kilometers. Thus following Grinblatt, Keloharju and Ikaheimo (2008), Linden and Rockoff (2008), Bayer, Ross, and Topa (2008) and Campbell, Giglio and Pathak (2011), we argue that the exact location chosen by individuals to live within this (~207 household, ~ 0.2 sq km) area, is plausibly exogenous, and based on property availability at the time they moved into the area. Subtracting outer-ring from inner-ring effects allows us to control for these neighborhood sorting issues. Furthermore, if we can make the plausible assumption that unobservable local shocks impact both the outer-rings as well as the inner-rings within this very small area, then we can utilize the inner-ring minus outer-ring methodology to control for unobservable local shocks.

The richness of our data also allows us to examine a new hypothesis not previously examined in the neighborhood bankruptcy spillover literature[1]. While the previous bankruptcy spillover literature, (e.g. Gross and Souleles, 2002, and Fay, Hurst and White, 2002), has examined the hypothesis that neighborhood bankruptcies impact the choice of *whether or not to file for bankruptcy*, this paper is the first to examine the hypothesis that neighborhood bankruptcies also impact the choice that *defaulters make between different legal methods of default.* We are the first to show that neighborhoods impact the choice of the legal mechanism of default, in addition to the choice of whether or not to default.

In order to examine the impact of neighborhoods on the choices made by defaulters, we use a large sample of individual credit card accounts provided by an individual Canadian bank. We follow a variety of authors (e.g. Dawsey and Ausubel, 2004, Dawsey, Hynes and Ausubel, 2009 and White, 2011) in comparing two separate legal mechanisms by which an individual can choose to default on credit card debt and which we can observe in our credit card data; (1) default via bankruptcy and (2) default via credit card charge-off (i.e. default without bankruptcy). In describing the trade-off between bankruptcy and charge-off, White (2011, p 2) argues that "the main punishments for bankruptcy are making filers' names public ..which...stigmatize the bankruptcy filers". The central advantage to bankruptcy is that the bankrupt is no longer liable for unsecured debt (e.g. credit card debt), which is discharged in bankruptcy. In terms of charge-off (i.e. default without bankruptcy), the main disadvantage is that the debtor remains liable for all debts. As White , (2011, p. 2) argues, the "punishments for debtors who default but do not file for bankruptcy, include(s) credit collectors calling them, suing them, and garnishing their wages". The main advantage of charge-off is relative privacy, because charge-offs are not publically disclosed through the courts, thus affording more privacy to the defaulter, compared to bankruptcy. In summary; both bankruptcy and charge-off constitute default, but charge-off

[1] This paper forms part of a rapidly growing literature which examines a variety of possible causes of bankruptcy, including (but not limited to) Domowitz and Sartain (1999), Musto (2004), Lefgren and McIntyre (2009), Dick and Lehnhert (2010), Hankins, Hoekstra and Skiba (2011) Gross and Notowidigdo (2011), Gross, Notowidigso and Wang (2013), as well as the papers cited above.

affords the defaulter more privacy, while the advantages of bankruptcy include the discharge of credit card debt and the avoidance of wage garnishment and other forms of creditor pressure[2].

We follow the previous literature, (e.g. Gross and Souleles, 2002, Fay, Hurst and White, 2002, Dick, Lehnert and Topa, 2008) in arguing that the influence of neighborhood bankruptcies on defaulter's choice between bankruptcy and charge-off can occur either because of stigma effects or because of information cascades[3]. As in this literature, we argue that these two stories are observationally equivalent. The stigma story is based on the institutional fact that every bankruptcy filing is made publically available through the courts. Thus an important "punishment" for bankruptcy is publicity (White, 2011), where social stigma is related to (negative) publicity about the default[4]. Specifically, our new hypothesis states that those individuals for whom privacy about their default is important, because they live in neighborhoods with few previous bankruptcies, and thus face higher neighborhood level bankruptcy stigma, are less likely to choose bankruptcy as a mechanism of default, in order to avoid the negative publicity. We hypothesize that such individuals are more likely to choose charge-off, even though it may be more costly than bankruptcy (no discharge of unsecured credit card debt, continuing creditor harassment), because it affords greater privacy.

The information cascades story in the literature (Gross and Souleles, 2002, Fay, Hurst and White, 2002, Dick, Lehnert and Topa, 2008) is that individuals living in high bankruptcy neighborhoods will be more likely to file for bankruptcy because, they will learn about the possible advantages of bankruptcy through information transfer from their neighbors. We extend this argument to hypothesize that defaulters in low bankruptcy neighborhoods may be more inclined to choose charge-off over bankruptcy – even though bankruptcy may be more beneficial – because they do not receive information on the possible advantages of bankruptcy from their neighbors. The stigma/privacy argument and the information cascades argument are thus

[2]. The significant financial advantages of bankruptcy have been emphasized by White, 1998, who argues that a large number of households could benefit financially by filing for bankruptcy. Bankruptcy, however, does usually involve legal and filing costs, while charge-off does not (see Gross, Notowidigdo and Wang, 2013)

[3] Bertrand, Luttmer and Mullainathan (2000) make similar arguments concerning neighborhood spillovers being the result of either stigma or information cascades to explain local variation in welfare assistance.

[4] Sullivan, Warren and Westbrook (2006, p. 242), for example, argue that "most people want to conceal the fact of their bankruptcy filings from at least some of their families, coworkers, friends, and *neighbors*." They cite a 2001 survey showing that 84.3% of bankruptcy filers "would be 'embarrassed' or 'very embarrassed' if their families, friends, or *neighbors* learned of their bankruptcy (italics added)."

observationally equivalent because both predict that high neighborhood bankruptcies will cause defaulters to choose to default via bankruptcy rather than charge-off.

We find that a one standard deviation increase in neighborhood bankruptcies increases the probability of a defaulter choosing to default via bankruptcy rather than via charge-off by approximately 3%. We also compare results across neighborhoods with different characteristics. We find that neighborhood bankruptcy spillover effects are significantly stronger in low income, compared to high income, neighborhoods. These effects are also significantly stronger in neighborhoods where the income distribution is relatively homogenous compared to neighborhoods with heterogeneous income distributions. The implications of these findings are that close neighbors would appear to have a greater impact on each other, at least in the bankruptcy and default context, in low income and low income distribution neighborhoods.

1. POLICY MOTIVATION

An important motivation for this paper is that the issue of stigma and information cascades has played a key role in policy debates over bankruptcy regulation. Regulators attempting to make bankruptcy more difficult for distressed debtors, have often argued that because of lower levels of stigma or greater information cascades, bankruptcy is becoming more prevalent, to the detriment of creditors (e.g. banks and other financial institutions).

The importance of stigma effects and spillovers in these policy debates can be seen by the comments of various US Senators during the 2005 restructuring of US Bankruptcy Law. Comments from regulators who supported making bankruptcy more difficult, because of lower perceived levels of stigma, included: "Bankruptcy should be difficult, and the moral stigma that used to be associated with bankruptcy ought to be resurrected." (Senator Grassley); "The explosion in bankruptcy filings has less to do with causes and more to do with motivations. The stigma of bankruptcy is all but gone." (Senator Hatch); "There has been a decline in the stigma of filing for bankruptcy and appropriate changes are necessary to ensure that bankruptcy is no longer considered a lifestyle choice." (Senator Kerry); "The social stigma of bankruptcy is gone" (Senator Dodd). At the same time, then Federal Reserve Chair Alan Greenspan commented that "Personal bankruptcies are soaring because Americans have lost their sense of shame." (all quotations from Efrat (2006, p. 486)).

The counter argument during these 2005 debates was proposed by Elizabeth Warren, (who was elected a US Senator from Massachusetts in 2012), and her co-authors (e.g. Sullivan, Warren and Westbrook (2006). These authors attempted to make the case that lower stigma was *not* an important determinant of bankruptcy, with the attendant policy implication that bankruptcy should not be made more difficult for distressed debtors. A central element of the counter-argument of Warren and her co-authors during these debates (e.g. Sullivan, Warren and Westbrook, 2006, p. 217) was their critique of the data and methodologies of the then existing literature on stigma and bankruptcy spillovers, particularly Gross and Souleles (2002) and Fay, Hurst and White (2002). It is for this reason that our new test of this hypothesis, using the cross-sectional difference methodology, has important policy implications.

2. INSTITUTIONAL BACKGROUND: BANKRUPTCY VS. CHARGE-OFF

As described by White (2011), Dawsey and Ausubel (2004), Dawsey, Hynes and Ausubel (2009) and Chatterjee (2011), defaulters face a trade-off when choosing between bankruptcy and charge-off (sometimes referred to as "informal bankruptcy"[5]). Bankruptcy entails increased public disclosure through the courts, but under bankruptcy all outstanding unsecured debts (e.g. credit card debt) can be written off, and all recovery actions by creditors are stayed (stopped). Charge-off entails reduced public disclosure, because charge-off does not involve the court system, but under charge-off creditors are able to continue actions to recover debt through wage garnishment and other actions. The logit models in this paper examine how neighborhood level effects impact the individual defaulter's choice in this trade-off.

Credit card default is different from credit card delinquency, which occurs when there are late payments, because under delinquency the card contract is not legally terminated and the individual is still able to use the card. Under default (either bankruptcy or charge-off), the legal contract between card provider and individual is terminated with debt outstanding. In some specifications below, we include delinquents as part of the comparator group.

Public disclosure of every bankruptcy filing in Canada is provided through the court system, and in addition it is provided on a single Government of Canada web page. A simple

[5] We use the term "charge-off" rather than the term "informal bankruptcy" in this paper because this specific legal term refers precisely to the kind of default captured in our data.

web search can thus reveal the name of every Canadian bankruptcy filer. This is not true for credit card charge-offs, where there is no legal requirement that information on this kind of default be publicly disclosed, either through the courts or on a government web page. While information about both bankruptcy and credit card charge-off appear on the defaulter's credit rating (e.g. FICO score), the distinction we exploit here concerns the public disclosure of the default to those without access to credit ratings, i.e. the defaulter's broader social network (e.g. neighbors).

An important element of the argument in this paper is that an individual defaulter has the choice as to whether to default via bankruptcy or via credit card charge-off. Legally, the individual debtor always has the choice as to whether and when to file for bankruptcy. In addition, we use specific institutional details about credit card charge-off procedures used by the bank that provided us with the data to argue that credit card charge-off at this specific bank is also in effect a choice made by the individual debtor. The procedure used by this bank is that every credit card account that reaches 120 days delinquent is sent a formal letter informing the debtor that the account will be charged-off and declared in default at 180 days delinquency. The key institutional detail is that these actions by the bank are automatic and not discretionary. In other words, because the individual is made aware at 120 days that the account will be charged-off at 180 days, we argue that by not taking alternative action before 180 days (either paying off the outstanding amount or alternatively filing for bankruptcy) the individual is in effect choosing to default via credit card charge-off.

3. DATA AND METHODOLOGY

This paper uses two Canadian database which match individual level data taken from individual credit card accounts, with neighbourhood level data on the geographic location and date of every Canadian bankruptcy filing, provided by the Canadian bankruptcy regulator, the Office of the Superintendent of Bankruptcy (OSB). We can thus observe bank account and geographic location data of credit card holders choosing between bankruptcy and charge-off (from the individual bank account data), as well as all past bankruptcies in each individual’s neighborhood (from the bankruptcy regulator data). Summary statistics of the different databases we use are provided in Table 1.

3.1.The Cross-Sectional Difference Estimator

The specification we use to implement the cross-sectional difference approach follows closely to that of Grinblatt, Keloharju and Ikheimo (2008). We follow Grinblat et al (2008) in using a logit specification where the dependent variable is one of the possible choices made by the individual (e.g. the choice between bankruptcy and charge-off). The key independent variable is the cross-sectional difference estimator (i.e. the inner-ring minus the outer-ring). Our inner-ring and outer-ring neighborhood data are described below. Our definition of the cross-sectional is essentially the same as Grinblatt et al (2008, p. 744) which we adapt to our bankruptcy context and define as:

Cross-Sectional Difference = (number of bankruptcies per household in inner-ring in previous periods) minus (number of bankruptcies per household in outer-ring donut in previous periods).

Our logit specification is thus of the following form:

$$(1)\quad Individual's\ Binary\ Decision_i = \beta_1' Cross - Sectional\ Difference_{t,n-N} + \beta_2' Individual\ Controls_i + \beta_3' Neighborhood\ Controls_N + \varepsilon$$

for individual i, in inner-ring neighborhood n, outer-ring neighborhood N and time t.

3.2. Cross-Sectional Differences: Defining Inner-rings and Outer-rings

The key geographic building block in this study is the Canadian six digit postal code, which is an extremely small geographic area, with a median of 14 households. In our study, these six digit postal codes constitute inner-ring neighbors. We can match the two databases in the study because we are able to observe the six digit post code of every individual in the bank account database, as well as the total number of bankruptcy filings, in every year, in every six digit post code in Canada, (from the bankruptcy regulator data). We are also able to match six digit post codes with slightly larger geographic areas called dissemination areas (DAs). These DAs constitute the outer-ring neighborhoods in our study. The median number of households in each DA is approximately 207, and the median geographic size of each DA is 0.2 square kilometers. The median number of six digit post codes in each DA is 15. The actual outer-ring in our study is donut shaped, because the outer-ring does not include the households in the inner-ring (the donut hole).

We use the Post Code Conversion File (PCCF) provided by Statistics Canada to match every six digit post code to the DA it falls in, thus we can aggregate up the total number of bankruptcy filings in each DA, and thus calculate the number in the donut shaped outer-ring. A key advantage in our use of DAs as outer-rings, not previously used in the cross-sectional difference literature, is that the DA is the smallest level of geographic aggregation at which Statistics Canada makes Census data available. We can thus include a large number of Census based variables, measured at the exact outer–ring (DA) level, to control for *observable* outer-ring neighborhood characteristics (e.g. neighborhood income, neighborhood standard deviation of income etc.). The outer-ring census variables are superior to outer-ring fixed effects that are sometimes used in this literature.

Because the number of households differs across individual post codes or DAs, we need to determine the number of households in each ring. Statistics Canada provides a measure of the number of households in each DA in Canada, but such data does not exist for six digit postal codes, largely because of their very small size. Nevertheless, some household counts do exist at a geographic area known as dissemination blocks (DBs), which are a level of aggregation that is smaller than DAs, but larger than six digit postal codes. Where available, we take the total number of households in the DB and divide by the number of postal codes in the DB to get a DB level average number of households per postcode. For the remaining postcodes, we repeat the process using the slightly larger DA level of aggregation. We can thus generate an estimate of the number of households for every six digit postcode in Canada.

3.3. Cross-Sectional Differences: Administrative Bankruptcy Count Data

The main independent variables in our tests below are counts of annual consumer bankruptcies in each Canadian six digit postal code provided to us uniquely by the Office of the Superintendent of Bankruptcy Canada (OSB). Because these data are measured at the very small six digit post code level, we are able to aggregate these counts up to the larger DA geographic areas. Because stigma and information cascades are slow moving process it is important to capture lagged neighborhood bankruptcies over a number of years. Our main specification in (1) examines lagged neighborhood bankruptcies over the previous five years.

A significant advantage of our neighborhood count data (from the OSB) is that it provides an *exact* count of aggregate bankruptcy filings in each postal code in each year. The issue of measurement error in neighborhood bankruptcy counts is of particular importance because we are dealing with very small neighborhood areas, where there are typically very few bankruptcy filings in a given year. Because annual bankruptcy totals in each neighborhood are so small, any inaccuracies in this count can have large implications on subsequent empirical models. Our OSB data on aggregate insolvency filings, per Canadian six digit postal code (neighborhood), is a complete count of every insolvency in Canada[6] and is thus not subject to this measurement error[7].

An important concern with measuring social interactions using aggregate bankruptcy data across US states (as in Gross and Souleles, 2002) or bankruptcy court districts (as in Fay, Hurst and White, 2002) is that it is difficult to disentangle differences in legal and/or administrative processes across these jurisdictions. In our paper all our data are from a single large Canadian province, in which there are many thousands of post codes. There are indeed legal differences in the administration of bankruptcy *across* the Canadian provinces, but there are no legal or administrative differences *within* a province. We can thus argue that all individuals in our study face the same legal and administrative environment.

An important issue in tests of the impacts of neighbors on individuals relates to issues of timing. Grinblatt, Keloharju and Ikaheimo (2008) emphasize the importance of examining the *lagged* actions of neighbors relative to the actions of the individuals. This is because "*lagged* actions (of neighbors) are not plausibly affected" (p. 736) by individual behavior (in our case, bankruptcy filing). Our credit card data provides us with the exact month of each individual's

[6]Our OSB data by design only include primary filers rather than secondary estates (for example joint filings by separated spouses or other related individuals who could live in separate postal codes). In other words, each filing is allocated to the postal code of the primary filer, and each filing in the data is only counted once.
[7] Cohen-Cole and Duygan-Bump (2009), for example, calculate the sum of bankruptcies within a neighborhood by aggregating from the files of a single credit bureau, which holds credit files on approximately one ninth of all individuals with a credit history. This gives an incomplete count of total bankruptcies in the neighborhood.

delinquency[8], and our neighborhood count OSB data provides us with annual data on bankruptcy filings per neighborhood. We are thus able to ensure that all our neighborhood level data (independent variables) are lagged relative to the individual's default date (dependent variable).

3.4. Individual Choices (Dependent Variable(s))

Our individual level data is taken from monthly credit card account data, provided to us confidentially by an individual Canadian bank. The credit card account level data are measured monthly from Dec 2004 to June 2006. There are approximately 93 000 individual credit card accounts in the database. This individual credit card data is similar in structure to previous bankruptcy stigma research conducted by Gross and Souleles (2002), with one important advantage. This is that our data flags two separate kinds of individual default; bankruptcy and credit card-charge-off[9]. These individual bankruptcies and charge-offs are the main binary dependent variables in our logit specifications below. In addition, we can also observe those bank account holders who are three months delinquent on their credit cards. We include these delinquents in some of our specifications for comparison purposes.

In our data we can observe 108 credit card holders who filed for bankruptcy and 552 credit card holders who had their credit cards charged-off during the 19 month period, out of the total sample of approximately 93 000 credit card holders. These amounts are similar in orders of magnitude to US data used by Dawsey and Ausubel (2004, p.30), who observe 716 bankruptcies and 610 charge-offs out of a sample of 51 000 credit cards, during a 21-28 month period[10].

We argue that issues of bankruptcy stigma and information cascades within a neighborhood are low frequency phenomena that are likely to build up over multiple years,

[8] This is different from the credit report data used by Cohen-Cole and Duygan-Bump (2009) which show whether an individual has filed for bankruptcy at some stage in the previous 7 years, rather than showing the exact timing of the bankruptcy filing.

[9] Gross and Souleles (2002) do examine both bankruptcy as well as three month credit card delinquency (which is not a default because the card contract is not terminated) as dependent variables, but, they do not test the neighborhood spillover hypothesis (i.e. include the lagged US State level data bankruptcy rate as an independent variable) in their three month delinquency models.

[10] One possible reason why there are more bankruptcies per credit card in the Dawsey and Ausubel (2004) data compared to our data, is that bankruptcies per capita in Canada are generally less prevalent than in the United States. OSB data shows that there was a total Canadian bankruptcy rate of 2.7 bankruptcies per 1000 population in 2004, compared to a United States measure of 7.7 bankruptcies per 1000 population.

rather than over a few months. It is for this reason that we define an individual as choosing bankruptcy or charge-off if that individual has made that choice at any time during the 19 month period of our credit card account database.

We use three different specifications of different choices made by individuals, i.e. the binary data included in the logit. First, we restrict our data to only defaulters, i.e. bankrupts (abbreviated BK) plus charge-offs (abbreviated CO). The logit specification in equation (1) sets those choosing for bankruptcy equal to 1 and those choosing charge-off equal to 0. This is the test of the new hypothesis proposed in this paper that past neighborhood bankruptcies impacts the choice that defaulters make between bankruptcy and charge-off.

Our second specification still includes bankrupts and charged-off individual's in the sample, but in addition also includes individuals who are three month delinquent (abbreviated as DEL) on their credit cards, but who have not yet defaulted. This specification thus examines whether past neighborhood bankruptcies impacts the choice that financially distressed individuals (defined as being in bankruptcy, charge-off and delinquency) make between bankruptcy and charge-off. Our third specification includes all 93 000 credit card holders (including the defaulters and delinquents discussed above). This examines the choice that all credit card holders make as to whether or not to file for bankruptcy (i.e. where bankruptcy is coded as 1 in the logit). This is essentially the hypothesis examined by Fay, Hurst and White (2002) and Gross and Souleles (2002). We also examine a specification where charge-off is coded as 1 in the logit, i.e. examining the choice that all card holders make as to whether or not to be charged-off.

The structure of this individual credit card account database is similar to the data used by Gross and Souleles (2002) whose monthly data "are followed ...until they *first* default" (italics added p. 326). Similarly, in our data, in the months prior to a bankruptcy/charge-off the data show the individual's monthly credit card activity; in the actual month of the individual's default the data show either a bankruptcy flag or a charge-off flag; and in subsequent months all the credit card data for that individual are empty, because the credit card contract has been terminated. Our dependent variable thus reflects the choice by the defaulter as to which of bankruptcy or charge-off occurred first[11].

We argue that the timing convention of our data (i.e. being able to observe the choice of the defaulter as to whether to *initially* default via bankruptcy or charge-off) is advantageous to us, in that it allows us to control for issues that may impact strategic interactions between defaulters and creditors that occur in subsequent periods *after* the initial default. The period after the initial default often involves the use of various negotiating and legal strategies between debtors and creditors, attempting to maximize their advantage. These strategic interactions are discussed and modeled by authors such as White (1998a), White (1998b), and Chatterjee (2011). We argue, however, that because our credit card account level data all reflect the choice of the defaulter as to whether to *initially* default via bankruptcy or charge-off, issues related to possible strategic interactions between debtors and creditors in the subsequent time periods after default, will not be captured in our data. Our data thus enable us to tests the specific hypothesis that neighborhood spillovers impacts the initial choice of whether to default via bankruptcy or charge-off.

3.5. Individual Level Control variables

Our data includes all of the various individual level bank account data used by Gross and Souleles (2002), e.g. card balance, card limit, FICO score, card APR, etc. In addition, however, we can also observe each individual's mortgage amount outstanding at that bank[12] (in addition to the outstanding credit card balance). These mortgage balance data were not available to Gross and Souleles, (2002). The importance of being able to observe both credit card (unsecured) debt as well as mortgage (secured) debt outstanding follows from the differences in how different

[11] The actions the bank is legally allowed to take following a bankruptcy filing are very different from the actions the bank can take following a charge-off. After charge-off the bank typically sells the outstanding credit card debt to a collection agency. On the other hand, under Canadian bankruptcy law, once bankruptcy is filed any attempts by any creditor (e.g. the bank) to claim on any unsecured (e.g. credit card) debt have to be stayed (stopped). The implication of this sharp distinction is that the bank has a legal obligation to accurately capture in its records, which of bankruptcy or charge-off occurred first. This is what is captured in our data.

[12] While our data only show mortgage amounts outstanding at the same individual bank where the credit card accounts are held, we follow Scholnick (2013, online appendix A5), in arguing that there is a relatively high probability that Canadians hold mortgage and credit card accounts at a single bank. This is largely because of the very concentrated nature of the Canadian banking system, which is dominated by the "big five" banks, who act as "universal banks" (Ratnovski & Huang, 2009). Under a "universal banking" system a single bank will tend to provide an individual consumer with a large number of different financial products (Ratnovski and Huang (2009).

kinds of debt are dealt with under bankruptcy law. As described in detail by Fay, Hurst and White (2002), under bankruptcy, *unsecured* (e.g. credit card) debt is essentially discharged or written off, while the bankrupt will lose *secured* assets (i.e. the house) up to the value of the non-exempt secured debt outstanding (e.g. mortgage debt minus the provincial homestead exemption[13]). Thus the greater the credit card debt the larger the financial benefits of bankruptcy (because unsecured debt is discharged), while the greater the non-exempt mortgage debt the higher the financial costs of bankruptcy (e.g. the greater the mortgage debt outstanding the larger the probability the bankrupt is forced to liquidate the house in order to repay secured creditors). Thus both of these magnitudes (secured and unsecured debt outstanding) have a strong impact on the choice of whether to file for bankruptcy. Because we can observe these magnitudes, we can examine our main hypothesis (neighborhood spillovers), while at the same time controlling for two of the main magnitudes of the net financial benefits hypothesis of Fay, Hurst and White (2002).

A particular concern with the FICO score data (which is also faced by Gross and Souleles (2002)) is that while the FICO data are largely complete for the vast majority of credit card holders not in financial distress, FICO data are missing for a number of the financially distressed card holders in the database. The number of observations for the FICO and other card account variables can be seen in Table 2. It is for this reason that our main tests do not include the FICO variable.

A further institutional issue that arises because of our comparisons of bankrupts relative to charge-offs is that all defaulters (both bankrupts and charge-offs) tend to have a credit card utilization rate of close to 100% in the period just before default (i.e. "maxing out" the credit card). For this reason, there will be a high correlation among defaulters between the credit card limit and the credit card balance. Because of this high correlation, we should only include one rather than both of these variables as independent variables, and we should not include the utilization rate variable, which is the ratio between them (card balance/card limit). Based on the discussion above concerning the importance of including the actual credit card balance in order to measure the net financial benefits of bankruptcy, we include the credit card balance in our

[13] In our data we subtract the provincial homestead exemption from the mortgage debt outstanding. A negative value for this difference is coded as zero, because the non-exempt mortgage debt outstanding is zero.

main specifications. Because we do not include the utilization rate as an independent variable in our main specification, as an additional robustness check we run alternative specifications where *all* individuals included in the sample are defined to be credit constrained, with a card utilization rate > 90%. By restricting all individuals in all these robustness tests to have a utilization rate > 90%, we can examine whether our main results are relevant to all individuals irrespective of utilization rate, or alternatively whether they are driven by credit constrained individuals with high card utilization rates.

In this paper we follow similar procedures to Gross and Souleles (2002) and Dawsey and Ausubel (2004), which is to measure all of these monthly bank account variables only at the first observable month in the data set[14]. The main reason for this is to control for possible endogeneity between default and monthly credit card behavior in the months leading up to the default. For example, forward looking individuals who are planning to declare bankruptcy in the future, have an incentive to max out their credit card prior to bankruptcy, because they are aware that unsecured credit card debt will be discharged. Because we only include data for these credit card control variables from the first observable month, we do not explore the monthly dynamics of these bank account variables. However, the main focus of this paper is on capturing low frequency stigma effects across neighborhoods, using five yearly summations of OSB neighborhood count data. Because our focus is not on monthly dynamics we use logit rather than duration or hazard specifications. This is the exact reasoning and specification choice used by Dawsey and Ausubel (2004).

3.6. DA (Outer-Ring) Level Observables

The DA area is the smallest area for which Statistics Canada provides census data. Because our outer-rings are measured at the DA level, we can thus include a large variety of DA level census data as observable control variables in our regressions, including median family income, family income standard deviation, population without income, and unemployment rate. All these data are derived from the 2006 Canadian census. In addition to including these neighborhood census data as control variables, we also use them to split up the data to run new

[14] While Gross and Souleles (2002) only use the first observed month of this data in their baseline specifications, they allow this to change in subsequent specifications.

specifications that are restricted to neighborhoods with certain characteristics (i.e. lower income compared to higher income neighborhoods; and lower income dispersion compared to higher income dispersion neighborhoods.)

A unique feature of this paper is that we can employ a measure of numerical literacy, measured at the DA level, to control for the possible influence of financial literacy on personal bankruptcy. There is a large literature linking issues such as bankruptcy with levels of financial literacy (see e.g. Lusardi, 2012 and many others). Furthermore, Lusardi, (2012) argues that a central element of financial literacy is numeracy - i.e. the capacity to conduct relatively complex calculations. Our numerical literacy data were developed by Murray (2011)[15]. This variable is computed using the 2003 International Adult Literacy and Skills Survey (IALSS) and the 2006 census. IALSS evaluated numerical skills for a very large sample of the Canadian population as well as collecting various demographic data. The average level of numerical literacy for each DA was estimated, based on the demographic characteristics of that DA.

4. JUSTIFICATION FOR IDENTIFICATION ASSUMPTIONS

Before we describe our main results, we provide a variety of evidence on the identifying assumptions we use when implementing the cross-section difference estimator.

4.1. Random Sorting between Inner-Rings and Outer-Rings

The first key assumption of the cross-sectional difference estimator is that there is no unobservable sorting between inner-rings and outer-rings – i.e. that there are no systematic differences between individual's living in inner- and outer rings based on unobservable individual characteristics. While it is obviously not possible to provide a direct test of *unobservable* sorting between inner- and outer-rings, both Bayer, Ross and Topa (2008) as well as Grinblatt, Keloharju and Ikaheimo (2008) argue that it is at least possible to examine whether there is sorting based on *observable* individual variables. Bayer Ross and Topa (2008) argue that " provided that the researcher can demonstrate that the within–reference group correlation in *observable* neighbor characteristics does not contribute significantly to outcomes, thereby

[15] We are grateful to Scott Murray for providing us with these data.

ensuring that the key identifying assumption on unobserved characteristics is at least plausible. ” (p. 1153, italics added). Similarly, Grinblatt, Keloharju and Ikaheimo (2008) argue that if there are low correlations with *observable* individual characteristics, then it "is quite reasonable to conclude that this lack of correlation extends to those characteristics that we cannot measure" (p. 739).

We follow these authors, in examining if there are low correlations between *observable* individual characteristics (in our case taken from the individual level credit card account database) and the cross-sectional difference variable (in our case inner-ring minus outer-ring measure of neighborhood bankruptcies). In Table 2 we report these correlations for our main samples. In no case is there an economically significant correlation between the inner-ring minus outer-ring variable and the observable individual level credit card variables, thus providing some justification for our main identifying assumption.

4.2 Removing Observable Controls to Assess the Impact of Unobservables

An alternative method for assessing the possible impact of unobservables in the context of neighborhood spillovers is provided by Bertrand, Luttmer and Mullainathan (2000) (who examine whether neighborhood spillovers impact the receipt of welfare). These authors argue that “if unobservable characteristics…drove our results, one would expect that increasing the set of unobservable characteristics by treating observable characteristics as unobservable would have a large impact on the estimate of network effects” (p. 1043). These authors thus drop observable control variables from their estimated equation and examine whether the estimated neighborhood spillover coefficients (in our case the cross-section difference estimator) are similar with and without the inclusion of these observable controls. If the neighborhood spillover coefficients are indeed similar in magnitude and significance then the argument of Bertrand, Luttmer and Mullainathan (2000) implies that it is less likely that unobservables are driving the results.

We follow this approach in this paper. In Table 6 we report results for four versions of our estimated equation: the original version with both individual and neighborhood (DA) observables included as controls, an equation with observable individual controls dropped, an equation with observable neighborhood controls dropped, and finally a version with both individual and neighborhood controls dropped. As can be seen from Table 6, the magnitudes and significance levels of the cross-section difference estimator are essentially the same across all these specifications (i.e. comparing across rows, but within columns, in Table 6). In other words, our observable controls seem to have very little impact on the cross-section difference coefficients. Thus following the reasoning of Bertrand, Luttmer and Mullainathan (2000), we argue that it is relatively unlikely that unobservables are driving our main neighborhood spillover results. (We describe the actual interpretation of these coefficients in much more detail in our results section below).

4.3. Size of Geographic Areas and Interpersonal Interactions

An important element of our identification methodology is the assumption that the sizes of the geographic areas where neighbors are assumed to interact are small. An important advantage of the data we use in this paper is that we can observe the size in square kilometers of every DA (i.e. the outer-rings in our methodology) in Canada. This is particularly important in the Canadian context, because while most Canadians live in densely populated urban areas, large parts of the Canadian landmass consist of sparsely populated rural areas. This is reflected in the distribution of DAs across Canada. While the median DA size in Canada is 0.2 square kilometers, there is a very long right tail to this distribution, with some DAs being hundreds of square kilometers in size. Given that our key identifying assumption involves individuals in close proximity interacting with each other, in our various specifications below we can limit our samples to only include DAs that are smaller than a certain size.

First, we limit our sample to include all DAs above and below 1 sq km. Thus we can examine whether neighborhood spillovers are greater where outer-ring DAs are geographically smaller, compared to when they are geographically larger. Alternatively, we can increase our sample to include all DAs that are smaller than 4 sq km. Approximately 85% of all DAs in Canada are smaller than 4 sq km, thus providing us with a single large sample, but removing the largest 15% of DAs in Canada. Furthermore, we include the actual geographic size of the DA for each observation in all our tests. (Note, that data do not exist on the geographic size of the inner-ring six digit post codes, because these areas are very small, with multiple post codes possible in single city blocks or single apartment buildings).

4.4. Other Published Evidence on our Identifying Assumptions

An important element in the hypothesis of random sorting between rings is based on the argument of thin housing markets in such very small areas. Bayer, Ross and Topa (2008) provide evidence on the thinness of housing markets at the block level by examining US Census data on mobility. They find that only 11% of blocks have an "owner occupied unit that changed owners in the 2 years prior to the census." (p. 1166). Furthermore, Bayer, Ross and Topa (2008) argue that another "key assumption underlying our research design is that a significant portion of interactions with neighbors are very local in nature" (p. 1167). Bayer, Ross and Topa (2008) cite the Sociology literature that has examined interpersonal interactions between very close neighbors. For example Lee and Campbell (1999) examine surveys of neighbors within city blocks and find that 31% of these very close neighbors are evaluated as being "close" or "very close" by the survey respondents.

5. RESULTS

The full results of all our logit tests from equation (1) are presented in the web appendix. For ease of comparison across the models, we summarize all of our results in Tables 3, 4 and 5, where each cell reports only one coefficient from each specification; the coefficient on the cross sectional difference (inner- minus outer-ring) measure of lagged neighborhood bankruptcy. Table 3 examines specification for all neighborhoods, Table 4 provides results where the sample is split based on neighborhood income and Table 5 provides results where the sample is split based on neighborhood standard deviation of income.

The five columns of Tables 3, 4 and 5 reflect the five different specifications we run in terms of the logit choice variable (either bankruptcy or charge-off are set =1) and sample for the regression (i.e. defaulters only, or defaulters plus delinquents, or all credit card holders). Column 1 in these Tables, where the data is restricted to defaulters only (bankruptcy plus charge-offs) thus provides specific evidence on the new hypothesis proposed in this paper, that past neighborhood bankruptcies will impact the choice made by defaulters as to whether to default via bankruptcy or charge-off. Column 3 in these Tables tests the hypothesis proposed by Gross and Souleles (2002) and Fay, Hurst and White (2002), that past neighborhood bankruptcies impacts the choice of all members of the population as to whether or not to file for bankruptcy.

Tables 3, 4 and 5 report the percentage impact of a one standard deviation change in the RHS neighborhood bankruptcy variable (cross-sectional difference) [16] on the choice logit variable (either BK or CO). Clearly, there will be a large difference in the distributions of the neighborhoods across the different samples (column (1) only includes ~600 observations, while columns (3) and (5) include ~93 000 observations). Thus while it is appropriate to compare the magnitudes of these one standard deviation impacts within columns, it is not appropriate to compare them across columns.

The first row of Table 3 provides results for the full sample, without any adjustment for DA size. Our main new result (row, 1, column 1) shows that, as predicted by our new hypothesis, a one standard deviation increase in past neighborhood bankruptcies in the neighborhoods of defaulters, leads to a 2.80 percent increase in the probability that a defaulter will choose bankruptcy rather than charge-off. This estimate is significant at 5%. All the other models in row 1, where BK is the logit choice variable (columns 2 and 3) are significant at 1% with the predicted positive sign. The remaining rows of Table 3 show various alternative specifications, where the sample is restricted base on the geographic size of the outer-ring DA. In row 2, when we restrict our sample to DAs being smaller than 4 sq km[17] is very robust compared to the sample with all DAs, above, as are the results in columns (2) and (3), where BK is the logit choice variable. In rows 3 and 4 of Table 3, we split our sample into DAs being larger or smaller than 1 sq km. Once again, our main new result (column 1) is robust across all these specifications, although the results in other columns are less robust.

Tables 4 and 5 split the sample based on neighborhood characteristics (taken from DA level census data). Table 4 splits the sample into neighborhoods above or below the median Canadian DA level of household income. Table 5 splits the sample into neighborhoods above or below the median Canadian DA level of the Standard deviation on household income in the DA. Tables 4 and 5 report results for both the full sample of all DAs, as well as DAs restricted to being less than 4 sq km.

[16] The measures of the one standard deviation impact are derived using the PRCHANGE routine in Stata.
[17] We do not report the specification for DAs being larger than 4 sq km, because of the very small sample size.

Results in Table 4 show very strongly that neighborhood spillovers are highly significant for low income neighborhoods, and (with two exceptions) are insignificant for high income neighborhoods. All significant coefficients have the expected signs (positive for BK logits and negative for CO logits). Indeed, the results in Table 4 for low income neighborhoods are stronger than the results in Table 3 for all neighborhoods, in the sense that the low income neighborhood results are significant with the correct signs for both BK as well as CO regressions, while the results for all neighborhoods (Table 3) where only significant for BK regressions.

These stark results imply that neighbors in lower income areas have a very significant impact on individual choices of the mechanism of default, whereas the impacts of neighbors on these individual choices in high income areas are in most cases insignificant. One possible explanation for this finding is that individuals in higher income neighborhoods are able to afford to maintain a social network that is more widely dispersed geographically, whereas because of the costs of developing and maintaining a social network, individuals in lower income areas may be more likely to maintain a social network that is predominately in their intermediate geographic neighborhood.

Table 5 splits the sample between DAs with high and low levels of income dispersion. In other words, we are comparing the influence of neighbors on individuals in neighborhoods that are relatively homogenous in terms of family income, and other neighborhoods where there is wide dispersion in family income. Once again the comparison between high standard deviation and low standard deviation neighborhoods is stark. Table 5 shows that for the low standard deviation (i.e. homogenous) neighborhood, the neighborhood coefficient in all five columns, across both rows, is strongly significant with the expected signs. On the other, hand, for the high standard deviation neighborhoods, only a few of these coefficients is significant. One possible explanation for this finding is that individuals are more likely to be influenced by the opinions and actions of their neighbors if those neighbors are relatively similar to them in terms of income. On the other hand, these findings imply that near geographic neighbors will have less impact on each other if the geographically close neighbors are dissimilar in terms of income.

As we describe above, because the credit card utilization rate (card balance/card limit) is usually close to 100% for defaulters (both bankrupts as well as charge-offs), it is not appropriate to include the both card balance and card limit variables in specifications that attempts to distinguish between defaulters choosing either bankruptcy or charge-off. However, as an additional robustness check in Table 7, we rerun our main specifications above, but limiting our sample to only include credit constrained individuals, who have a utilization rate of above 90%. The main conclusion from Table 7 is that our results for the sample restricted to credit constrained individuals are very similar to our main results for the unrestricted sample reported above. In other words, credit constrained individuals, (where card balances are highly correlated with card limits) are not driving our main neighborhood spillover results.

6. CONCLUSION

An important element of the 2005 policy debates in the US, on the restructuring of personal bankruptcy law, concerned the role of declining bankruptcy stigma as a motivator for rapidly increasing bankruptcy filings. A variety of US Senators, as well as then Federal Reserve Chair Greenspan, all argued that because declining bankruptcy stigma was an important determinant of bankruptcy, this justified the 2005 regulatory changes making personal bankruptcy more difficult for distressed debtors. The counter argument was proposed by Elizabeth Warren and her co-authors, who attempted to make the case that lower stigma was not driving increased bankruptcy, and thus that the proposed regulatory changes should not make personal bankruptcy more difficult. Warren and her co-authors argued that the then available evidence for bankruptcy stigma, from papers such as Fay, Hurst and White (2002) and Gross and Souleles (2002), was subject to important data and methodological concerns.

The aim of this paper is to address these data and methodological concerns. The most important methodological innovation in this paper is the use of the cross sectional difference estimator to examine neighborhood spillover effects on personal bankruptcy. The cross sectional difference methodology has been used by a number of authors in other contexts, but this is the first paper to use it in the context of personal bankruptcy. The methodology subtracts outer-ring neighborhood characteristics from inner-ring neighborhood characteristics, where the sizes of both these rings are fractions of a square kilometer. This allows us to control for unobserved neighborhood shocks, as well as endogenous non-random sorting into neighborhoods. Using this methodology we find strong evidence in favor of neighborhood bankruptcy spillovers. These neighborhood effects are particularly powerful in low income and low income distribution neighborhoods, where neighbors appear to have significant influence on each other.

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Table 1: Summary Statistics

	Source	Obs	Median	Mean	St. Dev
All Credit Cards					
Neighborhood Bankruptcies (Cross-Sectional Difference, previous 5 years)	OSB	90730	0.04	1.15	4.23
Dissemination Area Size (Sq km)	PCCF	93552	0.66	118.12	714.7
Dissemination Area Size (Sq km) if < 4 sq km	PCCF	69310	0.31	0.77	0.89
Mortgage Amount minus Provincial Bankruptcy Exemption ($)	Bank	93552	0	23168	52910
Credit Card Amount Outstanding ($)	Bank	93552	518	1854	3251
Card APR (%)	Bank	93551	17.9	15.86	4.04
Family Median Income ($ avg in DA)	Census	88163	71649	76180	27723
Family Income Dist ($ avg in DA)	Census	88163	6951	9260	8572
Pop Without Income (% in DA)	Census	88163	15	27	37
Financial Literacy (Score in DA)	IALSS	88163	0.3	0.3	0.03
Unemployment Rate (% in DA)	Census	88163	3.4	3.8	3.3
Bankruptcies					
Neighborhood Bankruptcies (Cross-Sectional Difference, previous 5 years)	OSB	104	0.07	3.16	11.03
Dissemination Area Size (Sq km)	PCCF	108	0.55	18.55	92.55
Dissemination Area Size (Sq km) if < 4 sq km	PCCF	90	0.37	0.79	0.92
Mortgage Amount minus Provincial Bankruptcy Exemption ($)	Bank	108	0	11663	39088
Credit Card Amount Outstanding ($)	Bank	108	2080	3357	3504
Card APR (%)	Bank	108	17.9	15.87	4.02
Family Median Income ($ avg in DA)	Census	106	67227	67994	23224
Family Income Dist ($ avg in DA)	Census	106	587	7915	7220
Pop Without Income (% in DA)	Census	106	15	25.75	34.87
Financial Literacy (Score in DA)	IALSS	106	0.3	0.3	0.03
Unemployment Rate (% in DA)	Census	106	3.95	4.65	3.65
Charge-offs					
Neighborhood Bankruptcies (Cross-Sectional Difference, previous 5 years)	OSB	527	0.09	1.06	5.1
Dissemination Area Size (Sq km)	PCCF	552	0.5	79	287.9
Dissemination Area Size (Sq km) if < 4 sq km	PCCF	418	0.29	0.71	0.88
Mortgage Amount minus Provincial Bankruptcy Exemption ($)	Bank	552	0	8359	30199
Credit Card Amount Outstanding ($)	Bank	552	1729.3	3060	3716
Card APR (%)	Bank	552	17.9	17	2.69
Family Median Income ($ avg in DA)	Census	524	67174	69679	23689
Family Income Dist ($ avg in DA)	Census	524	6503	8587	8035
Pop Without Income (% in DA)	Census	524	15	23.8	28
Financial Literacy (Score in DA)	IALSS	524	0.3	0.29	0.3
Unemployment Rate (% in DA)	Census	524	3.95	4.62	4.67

Sources: (1) OSB: Office of the Superintendent of Bankruptcy, Canada; (2) PCCF: Post Code Conversion File, Statistics Canada and Canada Post; (3) Bank: Individual Level Credit Card Bank Accounts; (4) Census; DA Level Averages of 2006 Census Data; (5) IALSS: 2003 International Adult Literacy and Skills Survey, and Murray 2011.

TABLE 2: CORRELATION BETWEEN OBSEVABLE INDIVIDUAL DATA AND CROSS SECTIONAL DISTANCE ESTIMATOR

We follow Grinblatt, Keloharju and Ikaheimo (2008) and Bayer, Ross and Topa (2008) in examining the correlations between the cross section difference estimator (inner-ring – outer-ring) and various observable individual characteristics in our credit card account level data. These authors argue that if there are low correlations between the cross section difference estimator and observables, then it is possible to argue that these low correlations could also extend to unobservables. While there are some statistically significant correlations in the full sample estimates with 90 thousand observations, in no case is there an economically significant correlation. Note the smaller sample sizes for FICO score correlations, which is indicative of missing FICO scores in our data.

Sample		**BK+CO**	**BK+CO+DEL**	**All**
Mortgage Outstanding - Homestd Exmp ($)	corr	-0.0312	-0.0146	-0.0495
	p value	0.4347	0.4958	0
	obs	631	2189	90730
Credit Card Debt Outstanding ($)	corr	0.014	0.0239	0.0135
	p value	0.7247	0.2629	0
	obs	631	2189	90730
Card APR (%)	corr	-0.0074	-0.0017	0.001
	p value	0.8538	0.9365	0.7547
	obs	631	2189	90729
FICO Score	corr	-0.0279	-0.0257	0.0099
	p value	0.6407	0.3257	0.0068
	obs	282	1468	74282

TABLE 3: RESULTS SUMMARY:
Impact of One Standard Deviation Change in the Cross-Sectional Difference Estimator

This table reports the percentage impact of a one standard deviation change in past neighborhood bankruptcies, as measured by the cross sectional difference estimator (inner-ring minus outer-ring) in the previous five years. Each cell represents one regression (equation (1) in the text), and only reports the cross-sectional difference estimator. Full regression results for each regression are reported in the Web Appendix. Coefficient levels taken from Web Appendix.

Column (1) limits the sample to only defaulters, and examines the choice between defaulting via bankruptcy or charge-off. The remaining columns widen the sample to include delinquents (columns 2 and 4) and all credit card holders (columns 3 and 5). The rows limit the sample based on the geographic size of the DA (outer-ring) in square kilometers.

The main theoretical prediction in the paper is that these neighborhood bankruptcy (cross-section difference) coefficients are positive for models where bankruptcy (BK) is the logit choice variable (models 1, 2 and 3), and negative where charge-off (CO) is the logit choice variable (models 4 and 5).

Model	**1**	**2**	**3**	**4**	**5**
Logit= 1	**BK**	**BK**	**BK**	**CO**	**CO**
Sample:	**BK+CO**	**BK+CO+DEL**	**All**	**BK+CO+DEL**	**All**
Full Sample	2.80**	0.65***	0.01***	-1.61	-0.03
DA Area < 4 sq km	3.05**	0.82**	0.02**	-1.5	-0.04
DA Area > 1 sq km	4.08**	0.49*	0.01	-2.58	-0.04
DA Area < 1 sq km	3.05**	0.84***	0.01***	-0.81	-0.02

TABLE 4: RESULTS SUMMARY:
SAMPLE SPLIT BY MEDIAN DA INCOME
Impact of One Standard Deviation Change in the Cross-Sectional Difference Estimator

This table reports the percentage impact of a one standard deviation change in past neighborhood bankruptcies, as measured by the cross sectional difference estimator (inner-ring minus outer-ring) in the previous five years. Each cell represents one regression (equation (1) in the text), and only reports the cross-sectional difference estimator. Full regression results for each regression are reported in the Web Appendix. Coefficient levels taken from Web Appendix.

These samples are split based on the DA (i.e. outer-ring) measure of neighborhood income taken from Census data. The samples are split into high and low DA income categories, where the cutoff is the median DA income level measure across Canada.

Column (1) limits the sample to only defaulters, and examines the choice between defaulting via bankruptcy or charge-off. The remaining columns widen the sample to include delinquents (columns 2 and 4) and all credit card holders (columns 3 and 5). The rows limit the sample based on the geographic size of the DA (outer-ring) in square kilometers.

The main theoretical prediction in the paper is that these neighborhood bankruptcy (cross-section difference) coefficients are positive for models where bankruptcy (BK) is the logit choice variable (models 1, 2 and 3), and negative where charge-off (CO) is the logit choice variable (models 4 and 5).

Model	**1**	**2**	**3**	**4**	**5**
Logit= 1	**BK**	**BK**	**BK**	**CO**	**CO**
Sample:	**BK+CO**	**BK+CO+DEL**	**All**	**BK+CO+DEL**	**All**
LOW DA INCOME					
Full Sample	6.08***	0.78***	0.01**	-7.29***	-0.25***
DA Area < 4 sq km	8.30**	1.05**	0.02	-7.45***	-0.28***
HIGH DA INCOME					
Full Sample	1.78	0.59*	0.01**	0.62	0.02
DA Area < 4 sq km	2.22	0.75	0.01**	0.83	0.02

TABLE 5: RESULTS SUMMARY:
SAMPLE SPLIT BY STANDARD DEVIATION OF DA INCOME
Impact of One Standard Deviation Change in the Cross-Sectional Difference Estimator

This table reports the percentage impact of a one standard deviation change in past neighborhood bankruptcies, as measured by the cross sectional difference estimator (inner-ring minus outer-ring) in the previous five years. Each cell represents one regression (equation (1) in the text), and only reports the cross-sectional difference estimator. Full regression results for each regression are reported in the Web Appendix. Coefficient levels taken from Web Appendix.

These samples are split based on the DA (i.e. outer-ring) measure of neighborhood standard deviation of income taken from Census data. The samples are split into high and low DA standard deviation of income categories, where the cutoff is the median DA level standard deviation of income measure across Canada.

Column (1) limits the sample to only defaulters, and examines the choice between defaulting via bankruptcy or charge-off. The remaining columns widen the sample to include delinquents (columns 2 and 4) and all credit card holders (columns 3 and 5). The rows limit the sample based on the geographic size of the DA (outer-ring) in square kilometers.

The main theoretical prediction in the paper is that these neighborhood bankruptcy (cross-section difference) coefficients are positive for models where bankruptcy (BK) is the logit choice variable (models 1, 2 and 3), and negative where charge-off (CO) is the logit choice variable (models 4 and 5).

Model	**1**	**2**	**3**	**4**	**5**
Logit= 1	**BK**	**BK**	**BK**	**CO**	**CO**
Sample:	**BK+CO**	**BK+CO+DEL**	**All**	**BK+CO+DEL**	**All**
LOW DA INCOME DISPERSION					
Full Sample	6.78***	0.99**	0.02**	-5.45**	-0.13**
DA Area < 4 sq km	10.4***	1.34**	0.03**	-7.32***	-0.2**
HIGH DA INCOME DISPERSION					
Full Sample	1.75	0.49**	0.001***	0.06	0.01
DA Area < 4 sq km	1.53	0.45	0.01**	0.46	0.02

TABLE 6: RESULTS SUMMARY:
REMOVING OBSERVABLE CONTROLS TO ASSESS THE IMPACT OF UNOBSERVABLES
Following Bertrand, Luttmer and Mullainathan (2000)
Impact of One Standard Deviation Change in the Cross-Sectional Difference Estimator

This table reports the percentage impact of a one standard deviation change in past neighborhood bankruptcies, as measured by the cross sectional difference estimator (inner-ring minus outer-ring) in the previous five years. Each cell represents one regression (equation (1) in the text), and only reports the cross-sectional difference estimator.

All Regressions use specification with DA Area < 4 square kilometers.

Individual observable controls include: mortgage outstanding minus homestead exemption, credit card debt outstanding and card APR. DA level observable controls include: DA area, family median income, standard deviation of family income, population without income, numerical literacy and unemployment rate.

The main conclusion of this Table is that removing observable controls has little, if any, impact on the estimate of the cross section difference estimator (i.e. comparing across rows and within columns). Following the argument of Bertrand, Luttmer and Mullainathan (2000), this implies that it is less likely that unobservables are driving these results.

Model	**1**	**2**	**3**	**4**	**5**
Logit= 1	**BK**	**BK**	**BK**	**CO**	**CO**
Sample:	**BK+CO**	**BK+CO+DEL**	**All**	**BK+CO+DEL**	**All**
Include All Observable Controls	3.05**	0.82**	0.02**	-1.5	-0.04
Drop Individual Level Observable Controls	2.97**	0.86**	0.02***	-1.43	-0.04
Drop DA Level Observable Controls	2.90**	0.78**	0.02***	-2.06	-0.03
Drop Both Indiv and DA Observable Controls	2.81**	0.82**	0.02***	-2.02	-0.02

TABLE 7: RESULTS SUMMARY:
RESTRICTING SAMPLE TO ONLY CREDIT CONSTRAINED INDIVIDUALS
All Individuals Have Credit Card Utilization Rate (Card Balance/Card Limit) > 90%
Impact of One Standard Deviation Change in the Cross-Sectional Difference Estimator

This table reports the percentage impact of a one standard deviation change in past neighborhood bankruptcies, as measured by the cross sectional difference estimator (inner-ring minus outer-ring) in the previous five years. Each cell represents one regression (equation (1) in the text), and only reports the cross-sectional difference estimator.

The aim of these robustness checks is to examine whether our main results are driven by credit constrained individual's with high credit card utilization rates. The main conclusion from this table is that these results are more or less similar to our main results above, indicating that credit constraints are not driving our main results.

Model	**1**	**2**	**3**	**4**	**5**
Logit= 1	**BK**	**BK**	**BK**	**CO**	**CO**
Sample:	**BK+CO**	**BK+CO+DEL**	**All**	**BK+CO+DEL**	**All**
Full Sample	2.44**	1.15***	0.06***	-1.21	-0.06
DA Area < 4	2.41*	1.20**	0.07**	-0.75	-0.06
Low Income	4.20**	1.61***	0.06*	-6.16**	-0.17**
High Income	1.59	0.87	0.05**	0.07	0.03
Low SD Income	3.96**	1.64**	0.07	-4.02	-0.39
High SD Income	1.94	0.94**	0.05***	-0.03	0.09

Web Appendix:

Bankruptcy Spillovers between Close Neighbors

TABLE A 1: FULL SAMPLE
Basis of Results in Table 3, Line 1

MODEL	1	2	3	4	5
Logit Variable	**BK**	**BK**	**BK**	**CO**	**CO**
Sample	**BK/CO**	**BK/CO/DEL**	**All**	**BK/CO/DEL**	**All**
Neighbor Bankrupt (Cross Sec Diff 2000-04)	0.0332**	0.0337***	0.0328***	-0.0188	-0.0172
	(0.0136)	(0.0113)	(0.0100)	(0.0131)	(0.0127)
DA Area (Sq Km)	-0.0026**	-0.00284**	-0.00308**	-0.000123	-0.000277
	(0.00129)	(0.00132)	(0.00124)	(0.000168)	(0.000172)
Mortgage Outstanding - Homestead Exmp ($)	2.26e-06	-3.13e-06	-6.31e-06**	-5.51e-06***	-8.6e-06***
	(3.12e-06)	(2.99e-06)	(3.09e-06)	(1.73e-06)	(1.64e-06)
Credit Card Debt Outstanding ($)	-3.31e-05	1.96e-05	8.9e-05***	6.30e-05***	0.000108***
	(3.40e-05)	(2.91e-05)	(1.62e-05)	(1.60e-05)	(8.18e-06)
Card APR (%)	-0.113***	0.0180	0.0362	0.165***	0.145***
	(0.0356)	(0.0298)	(0.0265)	(0.0196)	(0.0169)
Family Median Income in DA ($)	2.66e-06	1.32e-06	-6.29e-06	-5.62e-07	-7.1e-06***
	(5.85e-06)	(4.95e-06)	(4.69e-06)	(2.47e-06)	(2.05e-06)
Family Income Dist in DA ($)	-8.72e-06	-5.62e-06	-3.53e-06	-4.17e-07	4.71e-07
	(1.75e-05)	(1.49e-05)	(1.61e-05)	(6.76e-06)	(6.13e-06)
Pop Without Income in DA (%)	0.00308	0.00322	0.00247	-0.00146	-0.00137
	(0.00358)	(0.00272)	(0.00245)	(0.00175)	(0.00143)
Numerical Literacy in DA (Avg Score)	7.274**	4.188	4.654	-3.436**	-1.346
	(3.696)	(3.337)	(3.288)	(1.681)	(1.433)
Unemployment Rate in DA (%)	0.0139	0.0306	0.0326*	0.0320**	0.0294***
	(0.0268)	(0.0253)	(0.0168)	(0.0140)	(0.00852)
Constant	-2.058	-4.752***	-8.474***	-2.941***	-6.760***
	(1.467)	(1.257)	(1.193)	(0.659)	(0.555)
Observations	601	2,062	85,463	2,062	85,463
R2	0.0563	0.0306	0.0370	0.0550	0.0414

TABLE A 2: DA AREA < 4 SQ KM
Basis of Results in Table 3, Line 2

MODEL	**1**	**2**	**3**	**4**	**5**
Logit Variable	**BK**	**BK**	**BK**	**CO**	**CO**
Sample	**BK/CO**	**BK/CO/DEL**	**All**	**BK/CO/DEL**	**All**
Neighbor Bankrupt (Cross Sec Diff 2000-04)	0.0288**	0.0289**	0.0289**	-0.0154	-0.0166
	(0.0134)	(0.0118)	(0.0113)	(0.0129)	(0.0131)
DA Area (Sq Km)	0.0958	-0.0288	-0.0491	-0.118	-0.114*
	(0.138)	(0.130)	(0.126)	(0.0750)	(0.0658)
Mortgage Outstanding - Homestead Exmp ($)	7.16e-07	-4.30e-06	-8.13e-06**	-6.03e-06***	-1.02e-05***
	(3.6e-06)	(3.63e-06)	(3.61e-06)	(2.09e-06)	(1.96e-06)
Credit Card Debt Outstanding ($)	-3.18e-05	2.39e-05	9.4e-05***	6.83e-05***	0.000110***
	(3.8e-05)	(3.12e-05)	(1.72e-05)	(1.92e-05)	(9.52e-06)
Card APR (%)	-0.11***	0.0134	0.0344	0.166***	0.141***
	(0.0393)	(0.0320)	(0.0281)	(0.0228)	(0.0192)
Family Median Income in DA ($)	3.71e-06	4.12e-06	-3.23e-06	6.28e-07	-6.87e-06***
	(6.2e-06)	(5.35e-06)	(5.09e-06)	(2.81e-06)	(2.33e-06)
Family Income Dist in DA ($)	-1.33e-05	-1.39e-05	-1.84e-05	9.17e-08	-3.74e-06
	(2.1e-05)	(2.01e-05)	(2.24e-05)	(8.61e-06)	(7.90e-06)
Pop Without Income in DA (%)	0.00743	0.00831**	0.00698**	-0.000340	-0.00124
	(0.00484)	(0.00358)	(0.00322)	(0.00278)	(0.00242)
Numerical Literacy in DA (Avg Score)	5.642	2.877	3.404	-3.308*	-0.993
	(3.981)	(3.622)	(3.551)	(1.926)	(1.655)
Unemployment Rate in DA (%)	0.0319	0.0326	0.0272	0.0196	0.0185
	(0.0402)	(0.0335)	(0.0211)	(0.0185)	(0.0114)
Constant	-1.765	-4.444***	-8.154***	-2.978***	-6.663***
	(1.575)	(1.351)	(1.278)	(0.756)	(0.631)
Observations	474	1,558	64,714	1,558	64,714
R2	0.0455	0.0207	0.0318	0.0545	0.0428

TABLE A 3: DA AREA > 1 SQ KM
Basis of Results in Table 3, Line 3

MODEL	**1**	**2**	**3**	**4**	**5**
Logit Variable	**BK**	**BK**	**BK**	**CO**	**CO**
Sample	**BK/CO**	**BK/CO/DEL**	**All**	**BK/CO/DEL**	**All**
Neighbor Bankrupt (Cross Sec Diff 2000-04)	0.113**	0.0504*	0.0330	-0.0474	-0.0229
	(0.0511)	(0.0287)	(0.0228)	(0.0307)	(0.0233)
DA Area (Sq Km)	-0.0023*	-0.00254*	-0.00273**	-5.60e-05	-0.000138
	(0.00134)	(0.00135)	(0.00128)	(0.000167)	(0.000164)
Mortgage Outstanding - Homestead Exmp ($)	5.15e-06	2.04e-06	1.80e-06	-1.88e-06	-2.73e-06
	(3.4e-06)	(2.39e-06)	(2.20e-06)	(2.09e-06)	(1.94e-06)
Credit Card Debt Outstanding ($)	3.42e-05	7.41e-05*	9.81e-05***	4.59e-05**	9.71e-05***
	(4.5e-05)	(3.86e-05)	(2.07e-05)	(2.29e-05)	(1.20e-05)
Card APR (%)	-0.0535	0.0592	0.0559	0.160***	0.147***
	(0.0577)	(0.0469)	(0.0418)	(0.0295)	(0.0261)
Family Median Income in DA ($)	5.63e-06	-2.44e-06	-6.03e-06	-3.15e-06	-4.74e-06
	(1.1e-05)	(8.60e-06)	(8.20e-06)	(4.07e-06)	(3.51e-06)
Family Income Dist in DA ($)	-1.38e-05	2.20e-08	1.15e-06	3.29e-06	6.69e-06
	(2.7e-05)	(2.15e-05)	(2.22e-05)	(9.20e-06)	(8.03e-06)
Pop Without Income in DA (%)	0.00318	0.00262	0.00199	-0.00227	-0.00167
	(0.00441)	(0.00329)	(0.00300)	(0.00211)	(0.00174)
Numerical Literacy in DA (Avg Score)	4.948	3.292	4.331	-1.986	-1.002
	(5.687)	(5.606)	(5.616)	(2.714)	(2.372)
Unemployment Rate in DA (%)	0.0193	0.0365	0.0619*	0.0302	0.0514***
	(0.0365)	(0.0349)	(0.0375)	(0.0193)	(0.0176)
Constant	-2.965	-5.353**	-9.085***	-3.188***	-7.330***
	(2.342)	(2.107)	(2.069)	(1.070)	(0.938)
Observations	241	946	37,649	946	37,649
R2	0.0944	0.0525	0.0480	0.0503	0.0329

TABLE A 4: DA AREA < 1 SQ KM
Basis of Results in Table 3, Line 4

MODEL	**1**	**2**	**3**	**4**	**5**
Logit Variable	**BK**	**BK**	**BK**	**CO**	**CO**
Sample	**BK/CO**	**BK/CO/DEL**	**All**	**BK/CO/DEL**	**All**
Neighbor Bankrupt (Cross Sec Diff 2000-04)	0.0283**	0.0329***	0.0351***	-0.00745	-0.00951
	(0.0136)	(0.0124)	(0.0111)	(0.0127)	(0.0145)
DA Area (Sq Km)	0.454	-0.105	-0.502	-0.495	-0.595*
	(0.691)	(0.649)	(0.649)	(0.362)	(0.319)
Mortgage Outstanding - Homestead Exmp ($)	-1.43e-05	-2.28e-05**	-2.7e-05***	-9.92e-06***	-1.4e-05***
	(1.0e-05)	(9.93e-06)	(9.29e-06)	(2.79e-06)	(2.55e-06)
Credit Card Debt Outstanding ($)	-9.9e-05*	-3.70e-05	7.72e-05***	8.43e-05***	0.000119***
	(5.1e-05)	(4.47e-05)	(2.58e-05)	(2.28e-05)	(1.12e-05)
Card APR (%)	-0.158***	-0.0274	0.0224	0.177***	0.147***
	(0.0480)	(0.0390)	(0.0343)	(0.0272)	(0.0223)
Family Median Income in DA ($)	3.66e-07	4.40e-06	-2.35e-06	1.69e-06	-6.60e-06**
	(7.3e-06)	(6.07e-06)	(5.76e-06)	(3.18e-06)	(2.58e-06)
Family Income Dist in DA ($)	-2.28e-06	-9.43e-06	-5.83e-06	-6.20e-06	-6.11e-06
	(2.3e-05)	(2.15e-05)	(2.10e-05)	(1.04e-05)	(8.94e-06)
Pop Without Income in DA (%)	0.00339	0.00934	0.00347	0.00717*	0.00110
	(0.00794)	(0.00701)	(0.00569)	(0.00418)	(0.00288)
Numerical Literacy in DA (Avg Score)	8.372*	5.384	6.918*	-3.783*	-0.169
	(5.009)	(4.269)	(4.126)	(2.283)	(1.869)
Unemployment Rate in DA (%)	0.0208	0.0236	0.0247	0.0222	0.0218*
	(0.0467)	(0.0380)	(0.0236)	(0.0208)	(0.0115)
Constant	-1.465	-4.277***	-8.812***	-3.060***	-6.904***
	(1.968)	(1.582)	(1.497)	(0.885)	(0.718)
Observations	360	1,116	47,814	1,116	47,814
R2	0.0643	0.0439	0.0480	0.0667	0.0535

TABLE A 5: LOW DA INCOME; ALL DA AREAS
Basis of Results in Table 4, Line 1

MODEL	**1**	**2**	**3**	**4**	**5**
Logit Variable	**BK**	**BK**	**BK**	**CO**	**CO**
Sample	**BK/CO**	**BK/CO/DEL**	**All**	**BK/CO/DEL**	**All**
Neighbor Bankrupt (Cross Sec Diff 2000-04)	0.116***	0.0505***	0.0351**	-0.0902***	-0.0911***
	(0.0400)	(0.0184)	(0.0161)	(0.0298)	(0.0281)
DA Area (Sq Km)	-0.00231	-0.00281*	-0.00337**	-0.000175	-0.000433*
	(0.00148)	(0.00170)	(0.00165)	(0.000213)	(0.000225)
Mortgage Outstanding - Homestead Exmp ($)	-1.55e-05	-1.81e-05*	-1.77e-05*	-2.30e-06	-2.39e-06
	(1.1e-05)	(1.04e-05)	(1.01e-05)	(2.43e-06)	(2.08e-06)
Credit Card Debt Outstanding ($)	-5.33e-05	1.15e-05	8.5e-05***	8.20e-05***	0.000113***
	(5.2e-05)	(4.26e-05)	(2.39e-05)	(2.32e-05)	(1.20e-05)
Card APR (%)	-0.14***	0.0225	0.0508	0.182***	0.169***
	(0.0546)	(0.0439)	(0.0398)	(0.0285)	(0.0251)
Family Median Income in DA ($)	7.23e-06	7.96e-06	5.27e-06	6.01e-06	4.25e-06
	(1.7e-05)	(1.36e-05)	(1.23e-05)	(6.43e-06)	(5.20e-06)
Family Income Dist in DA ($)	-8.94e-07	-3.80e-06	-5.89e-06	1.98e-07	-3.95e-06
	(2.9e-05)	(3.26e-05)	(3.44e-05)	(1.45e-05)	(1.29e-05)
Pop Without Income in DA (%)	-0.00545	-0.000382	-0.000193	0.000628	0.00105
	(0.00829)	(0.00739)	(0.00663)	(0.00300)	(0.00238)
Numerical Literacy in DA (Avg Score)	1.619	2.170	2.755	0.278	0.866
	(4.688)	(4.383)	(4.430)	(2.293)	(1.985)
Unemployment Rate in DA (%)	0.0142	0.0347	0.0321	0.0439***	0.0334***
	(0.0339)	(0.0315)	(0.0197)	(0.0169)	(0.00912)
Constant	0.0635	-4.489**	-8.623***	-4.839***	-8.464***
	(2.159)	(1.758)	(1.647)	(0.954)	(0.796)
Observations	322	1,095	37,868	1,095	37,868
R2	0.104	0.0527	0.0405	0.0653	0.0407

TABLE A 6: LOW DA INCOME; DA AREAS < 4 SQ KM
Basis of Results in Table 4, Line 2

MODEL	**1**	**2**	**3**	**4**	**5**
Logit Variable	**BK**	**BK**	**BK**	**CO**	**CO**
Sample	**BK/CO**	**BK/CO/DEL**	**All**	**BK/CO/DEL**	**All**
Neighbor Bankrupt (Cross Sec Diff 2000-04)	0.125**	0.0444**	0.0280	-0.0863***	-0.0893***
	(0.0519)	(0.0194)	(0.0178)	(0.0322)	(0.0294)
DA Area (Sq Km)	-0.277	-0.318	-0.396*	-0.0836	-0.177*
	(0.247)	(0.218)	(0.217)	(0.108)	(0.0953)
Mortgage Outstanding - Homestead Exmp ($)	-1.27e-05	-1.73e-05*	-1.66e-05*	-4.33e-06	-3.80e-06
	(1.1e-05)	(1.03e-05)	(1.00e-05)	(3.01e-06)	(2.59e-06)
Credit Card Debt Outstanding ($)	-5.31e-05	1.67e-05	9.1e-05***	0.000101***	0.000122***
	(5.5e-05)	(4.39e-05)	(2.51e-05)	(2.76e-05)	(1.40e-05)
Card APR (%)	-0.145**	0.0190	0.0435	0.199***	0.174***
	(0.0573)	(0.0455)	(0.0409)	(0.0338)	(0.0288)
Family Median Income in DA ($)	7.48e-06	8.81e-06	6.87e-06	7.78e-06	5.98e-06
	(1.7e-05)	(1.42e-05)	(1.31e-05)	(7.20e-06)	(5.93e-06)
Family Income Dist in DA ($)	4.12e-06	1.92e-06	5.26e-06	1.70e-07	-7.90e-07
	(2.8e-05)	(2.98e-05)	(2.86e-05)	(1.65e-05)	(1.45e-05)
Pop Without Income in DA (%)	-0.00745	0.000998	-0.000706	0.00589	0.00140
	(0.0106)	(0.00894)	(0.00753)	(0.00476)	(0.00330)
Numerical Literacy in DA (Avg Score)	2.420	2.474	4.012	-0.318	1.688
	(4.993)	(4.625)	(4.662)	(2.565)	(2.266)
Unemployment Rate in DA (%)	0.00707	0.0107	0.0120	0.0251	0.0168
	(0.0512)	(0.0438)	(0.0329)	(0.0239)	(0.0143)
Constant	0.0643	-4.286**	-8.662***	-5.035***	-8.713***
	(2.284)	(1.840)	(1.730)	(1.090)	(0.910)
Observations	258	864	28,436	864	28,436
R2	0.0821	0.0314	0.0268	0.0742	0.0427

TABLE A 7: HIGH DA INCOME; ALL DA AREAS
Basis of Results in Table 4, Line 3

MODEL	**1**	**2**	**3**	**4**	**5**
Logit Variable	**BK**	**BK**	**BK**	**CO**	**CO**
Sample	**BK/CO**	**BK/CO/DEL**	**All**	**BK/CO/DEL**	**All**
Neighbor Bankrupt (Cross Sec Diff 2000-04)	0.0161	0.0263*	0.0316**	0.00715	0.0155
	(0.0155)	(0.0148)	(0.0131)	(0.0129)	(0.0103)
DA Area (Sq Km)	-0.00215	-0.00244	-0.00242	-0.000144	-0.000228
	(0.00240)	(0.00217)	(0.00196)	(0.000311)	(0.000298)
Mortgage Outstanding - Homestead Exmp ($)	5.09e-06	-2.19e-08	-2.98e-06	-7.86e-06***	-1.21e-05***
	(3.5e-06)	(3.07e-06)	(3.24e-06)	(2.57e-06)	(2.42e-06)
Credit Card Debt Outstanding ($)	-1.91e-05	2.56e-05	9.5e-05***	4.60e-05**	0.000102***
	(4.8e-05)	(3.97e-05)	(2.23e-05)	(2.30e-05)	(1.17e-05)
Card APR (%)	-0.110**	0.0148	0.0235	0.149***	0.122***
	(0.0504)	(0.0410)	(0.0361)	(0.0275)	(0.0229)
Family Median Income in DA ($)	3.85e-06	-4.41e-06	-1.82e-05*	-6.57e-06	-1.23e-05***
	(1.0e-05)	(9.45e-06)	(9.94e-06)	(4.62e-06)	(4.22e-06)
Family Income Dist in DA ($)	-7.48e-06	-3.27e-06	1.57e-06	-2.22e-07	2.66e-06
	(2.2e-05)	(1.71e-05)	(1.84e-05)	(7.82e-06)	(7.17e-06)
Pop Without Income in DA (%)	0.00617	0.00359	0.00337	-0.00323	-0.00304
	(0.00417)	(0.00285)	(0.00255)	(0.00234)	(0.00202)
Numerical Literacy in DA (Avg Score)	12.48**	5.713	5.573	-8.255***	-4.290**
	(6.124)	(5.355)	(5.114)	(2.651)	(2.160)
Unemployment Rate in DA (%)	0.0748	0.0457	0.0533	0.000975	0.0195
	(0.0634)	(0.0506)	(0.0464)	(0.0278)	(0.0230)
Constant	-4.181*	-4.795**	-7.720***	-0.475	-4.970***
	(2.312)	(2.063)	(1.963)	(1.058)	(0.877)
Observations	279	967	47,595	967	47,595
R2	0.0696	0.0245	0.0392	0.0679	0.0497

TABLE A 8: HI DA INCOME; DA AREA < 4 SQ KM
Basis of Results in Table 4, Line 4

MODEL	**1**	**2**	**3**	**4**	**5**
Logit Variable	**BK**	**BK**	**BK**	**CO**	**CO**
Sample	**BK/CO**	**BK/CO/DEL**	**All**	**BK/CO/DEL**	**All**
Neighbor Bankrupt (Cross Sec Diff 2000-04)	0.0166	0.0248	0.0307**	0.00784	0.0159
	(0.0160)	(0.0157)	(0.0147)	(0.0132)	(0.0105)
DA Area (Sq Km)	0.144	0.143	0.186	-0.0641	-0.0448
	(0.200)	(0.174)	(0.166)	(0.109)	(0.0928)
Mortgage Outstanding - Homestead Exmp ($)	3.62e-06	-5.24e-07	-4.83e-06	-7.06e-06**	-1.2e-05***
	(4.3e-06)	(3.86e-06)	(3.87e-06)	(2.98e-06)	(2.79e-06)
Credit Card Debt Outstanding ($)	-2.42e-05	2.70e-05	0.000100***	4.03e-05	9.89e-05***
	(5.8e-05)	(4.38e-05)	(2.38e-05)	(2.81e-05)	(1.38e-05)
Card APR (%)	-0.102*	0.0104	0.0283	0.136***	0.114***
	(0.0584)	(0.0457)	(0.0392)	(0.0316)	(0.0257)
Family Median Income in DA ($)	1.15e-05	4.98e-06	-7.12e-06	-6.57e-06	-1.26e-05**
	(1.2e-05)	(1.02e-05)	(1.09e-05)	(5.45e-06)	(5.03e-06)
Family Income Dist in DA ($)	-2.32e-05	-1.96e-05	-2.36e-05	1.01e-06	-2.75e-06
	(3.5e-05)	(2.72e-05)	(3.11e-05)	(1.06e-05)	(9.75e-06)
Pop Without Income in DA (%)	0.0133**	0.00831**	0.00872**	-0.00426	-0.00500
	(0.00665)	(0.00400)	(0.00352)	(0.00389)	(0.00381)
Numerical Literacy in DA (Avg Score)	8.773	2.383	2.628	-7.835**	-4.429*
	(6.829)	(6.057)	(5.801)	(3.153)	(2.549)
Unemployment Rate in DA (%)	0.102	0.0812	0.0826*	0.00763	0.0286
	(0.0692)	(0.0554)	(0.0481)	(0.0308)	(0.0245)
Constant	-4.064	-4.712**	-8.023***	-0.327	-4.671***
	(2.509)	(2.211)	(2.141)	(1.216)	(0.993)
Observations	216	694	36,278	694	36,278
R2	0.0833	0.0369	0.0509	0.0606	0.0527

TABLE A 9: LOW SD OF INCOME IN DA; ALL DA AREAS
Basis of Results in Table 5, Line 1

MODEL	1	2	3	4	5
Logit Variable	BK	BK	BK	CO	CO
Sample	BK/CO	BK/CO/DEL	All	BK/CO/DEL	All
Neighbor Bankrupt (Cross Sec Diff 2000-04)	0.113***	0.0480**	0.0349**	-0.0708**	-0.0551**
	(0.0434)	(0.0190)	(0.0164)	(0.0288)	(0.0242)
DA Area (Sq Km)	-0.00186	-0.00249	-0.00295*	-0.000222	-0.000555*
	(0.00157)	(0.00173)	(0.00163)	(0.000258)	(0.000299)
Mortgage Outstanding - Homestead Exmp ($)	2.44e-06	-2.02e-06	-2.82e-06	-4.00e-06*	-4.16e-06**
	(3.60e-06)	(3.35e-06)	(3.42e-06)	(2.18e-06)	(1.99e-06)
Credit Card Debt Outstanding ($)	-2.24e-05	3.38e-05	0.000104***	6.44e-05***	0.000121***
	(4.49e-05)	(3.70e-05)	(2.29e-05)	(2.31e-05)	(1.27e-05)
Card APR (%)	-0.117**	0.0310	0.0646*	0.164***	0.166***
	(0.0475)	(0.0394)	(0.0360)	(0.0275)	(0.0241)
Family Median Income in DA ($)	1.82e-05*	1.37e-05*	7.30e-06	-7.14e-07	-5.74e-06
	(9.84e-06)	(8.23e-06)	(7.53e-06)	(4.44e-06)	(3.60e-06)
Family Income Dist in DA ($)	-0.000131	-7.47e-05	-0.000116	5.94e-05	3.05e-05
	(0.000129)	(0.000115)	(0.000111)	(6.00e-05)	(5.11e-05)
Pop Without Income in DA (%)	-0.00153	-0.000261	-0.000701	-0.000163	-0.000435
	(0.00470)	(0.00424)	(0.00418)	(0.00237)	(0.00205)
Numerical Literacy in DA (Avg Score)	4.914	1.139	3.110	-3.308	0.0180
	(4.872)	(4.425)	(4.452)	(2.412)	(2.099)
Unemployment Rate in DA (%)	0.0157	0.0339	0.0342*	0.0364**	0.0319***
	(0.0344)	(0.0318)	(0.0181)	(0.0179)	(0.00912)
Constant	-1.633	-4.369**	-8.605***	-3.218***	-7.745***
	(2.055)	(1.716)	(1.593)	(0.956)	(0.800)
Observations	334	1,076	39,086	1,076	39,086
R2	0.0729	0.0308	0.0319	0.0543	0.0384

TABLE A 10: LOW SD OF INCOME IN DA; DA < 4 SQ KM
Basis of Results in Table 5, Line 2

MODEL	**1**	**2**	**3**	**4**	**5**
Logit Variable	**BK**	**BK**	**BK**	**CO**	**CO**
Sample	**BK/CO**	**BK/CO/DEL**	**All**	**BK/CO/DEL**	**All**
Neighbor Bankrupt (Cross Sec Diff 2000-04)	0.147***	0.0479**	0.0329**	-0.0869**	-0.0681**
	(0.0565)	(0.0191)	(0.0166)	(0.0339)	(0.0275)
DA Area (Sq Km)	-0.104	-0.0719	-0.0782	-0.0338	-0.0729
	(0.175)	(0.153)	(0.146)	(0.0937)	(0.0785)
Mortgage Outstanding - Homestead Exmp ($)	5.27e-06	-4.10e-07	-1.45e-06	-6.27e-06**	-6.17e-06**
	(3.99e-06)	(3.27e-06)	(3.35e-06)	(2.88e-06)	(2.57e-06)
Credit Card Debt Outstanding ($)	-4.57e-05	3.44e-05	0.000105***	8.62e-05***	0.000131***
	(5.00e-05)	(3.85e-05)	(2.38e-05)	(2.67e-05)	(1.45e-05)
Card APR (%)	-0.129**	0.0161	0.0537	0.163***	0.161***
	(0.0508)	(0.0404)	(0.0363)	(0.0311)	(0.0262)
Family Median Income in DA ($)	2.3e-05**	1.72e-05*	9.88e-06	7.19e-07	-4.28e-06
	(1.07e-05)	(8.91e-06)	(7.93e-06)	(5.13e-06)	(4.10e-06)
Family Income Dist in DA ($)	-0.000200	-3.62e-05	-7.18e-05	0.000138*	8.77e-05
	(0.000164)	(0.000140)	(0.000129)	(7.72e-05)	(6.34e-05)
Pop Without Income in DA (%)	0.00339	0.00344	0.00237	-0.00105	-0.00255
	(0.00634)	(0.00466)	(0.00450)	(0.00347)	(0.00303)
Numerical Literacy in DA (Avg Score)	7.494	2.508	4.309	-4.642*	-0.906
	(5.208)	(4.656)	(4.679)	(2.641)	(2.303)
Unemployment Rate in DA (%)	0.0484	0.0277	0.0225	0.00893	0.0130
	(0.0552)	(0.0458)	(0.0282)	(0.0259)	(0.0155)
Constant	-2.290	-4.916***	-9.083***	-3.143***	-7.543***
	(2.222)	(1.841)	(1.680)	(1.072)	(0.882)
Observations	275	856	29,442	856	29,442
R2	0.0854	0.0240	0.0224	0.0601	0.0396

TABLE A 11: HIGH SD OF INCOME IN DA; ALL DA AREAS
Basis of Results in Table 5, Line 3

MODEL	**1**	**2**	**3**	**4**	**5**
Logit Variable	**BK**	**BK**	**BK**	**CO**	**CO**
Sample	**BK/CO**	**BK/CO/DEL**	**All**	**BK/CO/DEL**	**All**
Neighbor Bankrupt (Cross Sec Diff 2000-04)	0.0193	0.0299**	0.0367***	0.000660	0.00569
	(0.0148)	(0.0143)	(0.0129)	(0.0129)	(0.0132)
DA Area (Sq Km)	-0.00337	-0.00303	-0.00313	-1.14e-05	-7.15e-05
	(0.00206)	(0.00201)	(0.00191)	(0.000233)	(0.000189)
Mortgage Outstanding - Homestead Exmp ($)	5.34e-07	-7.02e-06	-1.18e-05*	-7.64e-06***	-1.32e-05***
	(6.7e-06)	(5.98e-06)	(6.03e-06)	(2.85e-06)	(2.70e-06)
Credit Card Debt Outstanding ($)	-4.96e-05	6.03e-06	7.9e-05***	6.56e-05***	9.83e-05***
	(5.7e-05)	(4.71e-05)	(2.56e-05)	(2.28e-05)	(1.08e-05)
Card APR (%)	-0.129**	0.00151	0.00849	0.168***	0.128***
	(0.0570)	(0.0462)	(0.0404)	(0.0283)	(0.0239)
Family Median Income in DA ($)	-2.80e-06	-3.18e-06	-1.04e-05	-6.61e-07	-6.57e-06**
	(7.9e-06)	(7.25e-06)	(7.37e-06)	(3.27e-06)	(2.92e-06)
Family Income Dist in DA ($)	4.38e-06	9.10e-06	1.64e-05	2.51e-06	5.20e-06
	(1.8e-05)	(1.44e-05)	(1.33e-05)	(7.31e-06)	(6.17e-06)
Pop Without Income in DA (%)	0.00898	0.00394	0.00210	-0.00419	-0.00377
	(0.00783)	(0.00424)	(0.00386)	(0.00317)	(0.00249)
Numerical Literacy in DA (Avg Score)	11.78*	8.054	7.828	-3.906	-2.878
	(6.150)	(5.426)	(5.323)	(2.415)	(2.027)
Unemployment Rate in DA (%)	0.0358	0.0339	0.0330	0.0273	0.0192
	(0.0563)	(0.0471)	(0.0447)	(0.0236)	(0.0197)
Constant	-3.092	-5.579***	-9.030***	-2.877***	-6.092***
	(2.382)	(2.001)	(1.943)	(0.935)	(0.793)
Observations	267	986	46,377	986	46,377
R2	0.0760	0.0426	0.0491	0.0646	0.0485

TABLE A 12: HIGH SD OF INCOME IN DA; DA < 4 SQ KM
Basis of Results in Table 5, Line 4

MODEL	1	2	3	4	5
Logit Variable	**BK**	**BK**	**BK**	**CO**	**CO**
Sample	**BK/CO**	**BK/CO/DEL**	**All**	**BK/CO/DEL**	**All**
Neighbor Bankrupt (Cross Sec Diff 2000-04)	0.0131	0.0223	0.0322**	0.00433	0.0119
	(0.0161)	(0.0160)	(0.0156)	(0.0129)	(0.0123)
DA Area (Sq Km)	0.242	-0.116	-0.217	-0.240*	-0.255**
	(0.296)	(0.272)	(0.261)	(0.138)	(0.125)
Mortgage Outstanding - Homestead Exmp ($)	-2.56e-05	-2.74e-05*	-3.00e-05**	-5.84e-06*	-1.30e-05***
	(1.7e-05)	(1.59e-05)	(1.44e-05)	(3.10e-06)	(2.96e-06)
Credit Card Debt Outstanding ($)	-5.12e-05	5.96e-06	8.2e-05***	5.64e-05**	9.48e-05***
	(6.9e-05)	(5.14e-05)	(2.73e-05)	(2.81e-05)	(1.32e-05)
Card APR (%)	-0.146**	-0.00835	0.0180	0.175***	0.129***
	(0.0679)	(0.0531)	(0.0454)	(0.0342)	(0.0285)
Family Median Income in DA ($)	-4.12e-06	-2.68e-06	-7.69e-06	-9.80e-07	-8.26e-06**
	(8.6e-06)	(7.73e-06)	(7.81e-06)	(3.77e-06)	(3.42e-06)
Family Income Dist in DA ($)	6.52e-08	4.51e-07	6.15e-06	5.40e-06	5.10e-06
	(2.1e-05)	(1.95e-05)	(1.76e-05)	(9.38e-06)	(7.66e-06)
Pop Without Income in DA (%)	0.0173*	0.0214***	0.0143**	0.000864	-0.00101
	(0.00886)	(0.00807)	(0.00658)	(0.00542)	(0.00454)
Numerical Literacy in DA (Avg Score)	3.125	1.673	2.976	-2.696	-2.178
	(6.740)	(6.099)	(5.866)	(2.922)	(2.456)
Unemployment Rate in DA (%)	0.0404	0.0419	0.0465	0.0252	0.0280
	(0.0649)	(0.0528)	(0.0473)	(0.0270)	(0.0217)
Constant	-0.269	-3.619*	-7.897***	-3.275***	-6.161***
	(2.597)	(2.181)	(2.106)	(1.128)	(0.937)
Observations	199	702	35,272	702	35,272
R2	0.0717	0.0588	0.0612	0.0670	0.0514