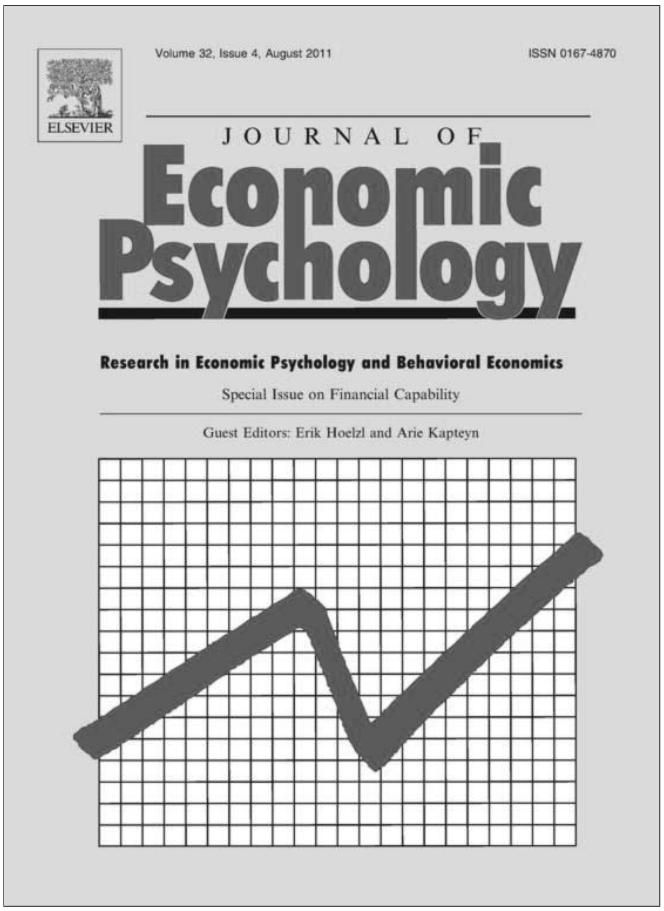

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Consumer bankruptcy and default: The role of individual social capital

Sumit Agarwal [a,*], Souphala Chomsisengphet [b], Chunlin Liu [c]

[a] Research Department, Federal Reserve Bank of Chicago, 230 South LaSalle Street, Chicago, IL 60604, USA
[b] Risk Analysis Division, Office of the Comptroller of the Currency, 250 E Street SW, Washington, DC 20219, USA
[c] College of Business, University of Nevada-Reno, Reno, NV 89557, USA

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ABSTRACT

In this paper, we empirically assess the role of individual social capital on personal bankruptcy and default outcomes in the consumer credit market. After controlling for a borrower's risk score, debt, income, wealth, and legal and economic environments, we find that default/bankruptcy risk rises and then falls over the lifecycle, while a borrower who owns a home or is married has a lower risk of default/bankruptcy. Moreover, a borrower who migrates 190 miles from his "state of birth" is 17% more likely to default and 15% more likely to file for bankruptcy, while a borrower who continues to live in his state of birth is 14% and 10% less likely to default and file for bankruptcy, respectively. A borrower who moves to a rural area is 9% and 7% less likely to default and declare bankruptcy, respectively. We also find that measures of social networks, norms, and cooperation and trust (i.e., aggregate social capital) are inversely related to consumer bankruptcy.

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1. Introduction

Sociologists define social capital as the social networks, norms, and cooperation and trust created by human interactions in a community (see e.g., Putnam, 1995, 2000). Accordingly, community engagement, e.g., voter turnout at referenda or membership in a non-profit organization, generates positive externalities. Conventional economic theory suggests that social interactions play a role in repeated games (Abreu, 1988), contract theory (Arrow, 1972), and solving free rider problems (Greif, 1993). Studies have found that social capital can enhance many desirable socioeconomic outcomes. For example, communities with higher social capital enjoy higher economic growth (Knack & Keefer, 1997) and greater judicial efficiency and lower corruption (LaPorta, Lopez-de-Silanes, Shleifer, & Vishny, 1997.

In this paper, we attempt to empirically assess the role of individual social capital on personal bankruptcy and default outcomes. Specifically, we us a loan-level panel data set of more than 170,000 credit cardholders to investigate the relationship between cardholder's bankruptcy and default behavior and his/her socioeconomic characteristics, which serve

* Corresponding author. Tel.: +1 2402770838.
E-mail addresses: sagarwal@frbchi.org (S. Agarwal), souphala.chomsisengphet@occ.treas.gov (S. Chomsisengphet), liuc@unr.edu (C. Liu).

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as proxies for the individual's social capital formation. In our data, we observe a borrower's default and bankruptcy filing status in each month over the sample period. We also have information that enables us to control for important financial distress factors that are predicted to drive a borrower into default or bankruptcy such as a borrower's "riskiness", spending, debt, income, and wealth, as well as economic conditions and legal environment. In addition, we have information on a borrower's socioeconomic characteristics (e.g., age, marital status, and homeownership status). Moreover, our data set is unique in that there's information about the zip code of an individual's current residence and the state of birth (or state of immigration entry for foreign born individuals), allowing us to identify mobility for each borrower. Thus, in addition to age, marital status, and homeownership status, our individual social capital variables also include: whether a borrower still lives in the "state of birth"; the distance in miles between the state of residence and state of birth; and whether a borrower has migrated to a rural area. With the information of individual social capital variables, we are able to investigate whether the risk of default or bankruptcy to be lower for a borrower who has higher individual social capital.

After controlling for an individual's credit risk score, spending, debt, income and wealth, as well as macroeconomic conditions and legal variations across states, we find that individual social capital variables can significantly explain cardholder bankruptcy and default outcomes. First, we find that defaults and bankruptcies rise and then fall over the lifecycle. Equally important, a borrower who is married is 24% less likely to default on his credit card debt and 32% less likely to file for bankruptcy. Finally, an individual who owns a home is 17% less likely to default and 25% less likely to file for bankruptcy.

Furthermore, we find that the risk of personal bankruptcy and default is higher for an individual who migrates out of his state of birth. For example, an individual who continues to live in his state of birth is 9% less likely to default on his credit card debt and 13% less likely to file for bankruptcy, while an individual who moves 190 miles from his state of birth is 17% more likely to default and 15% more likely to declare bankruptcy. Moreover, compared to individuals who move to an urban area, those who move to a rural area are 9% and 7% less likely to default and declare bankruptcy, respectively.

We also assess the correlation between Putnam's state social capital index (Putnam, 2000) and state bankruptcy filing rates in 2000. We find that states that are ranked higher on Putnam's social capital index (e.g., Vermont and Minnesota) have lower bankruptcy filing rates, while states that are ranked lower on the social capital index (e.g., Georgia and Tennessee) have higher bankruptcy rates. Controlling for variations in unemployment conditions, percentage of state population without health insurance coverage, and state bankruptcy laws, we find that states with a 1 point lower social capital index face a 0.3% points higher state bankruptcy rate per capita.

Our findings have some implications for the ongoing debate surrounding the rise in consumer bankruptcy over the past almost two decades. We show that individual social capital variables, such as mobility, rural residency, homeownership, marital status, and borrower age play a statistically and economically significant role in consumer bankruptcy and default outcomes. These individual social capital variables collectively can affect the strength of a community's social networks and norms and, in turn, shape the community's attitudes toward certain socioeconomic behaviors or outcomes. Therefore, the explanatory significance of an individual's social capital variables on the need to default on debt or to file for bankruptcy provide additional insights into the role of social capital on consumer bankruptcy.

Our paper also contributes to the literature studying the impact of social capital on household financial decision-making. Madrian and Shea (2001) find that an individual's decision to participate in a particular employer-sponsored retirement plan is influenced by the choices of their co-workers. Guiso, Sapienza, and Zingales (2004) find that Italian households in regions with higher social capital are more likely to use formal credit channels, such as writing more checks and investing in stocks. Hong, Kubik, and Stein (2004) show that people who attend church and interact with their neighbors are more likely to invest in the stock market.

A study which is closely related to ours is Buckley and Brinig (1998), which analyzes the impact of state-level social capital characteristics on aggregate consumer bankruptcy. The authors find that the rise in bankruptcy filings in 86 federal judicial districts over the 1980–1991 period can be attributed to higher per capital interstate migration into a state, plus intercounty migration within a state, and a smaller percentage of population living in metropolitan statistical areas. Thus, the explanatory significance of individual social capital variables on household default and bankruptcy outcomes in our study nicely complements that of Buckley and Brinig.

The paper proceeds as follows: Section 2 provides a brief theoretical motivation that articulates the relationship between consumer default behavior and individual social capital. Section 3 describes our data and empirical methodology. Section 4 discusses the empirical results, and section 5 concludes.

2. Individual social capital and consumer bankruptcy and default

Sullivan, Warren, and Westbrook (2000) show evidence of the two major causes of the recent increase in bankruptcy filings in the US: increases in credit card and mortgage debt; and unexpected adverse events (such as unemployment, divorce, health problems, or medical debts) have reduced the ability of households to repay their debt and eventually compel them to file for bankruptcy.[1] Despite such compelling evidence, many contend that increases in debt and adverse income or spending shocks cannot entirely explain the rise in consumer bankruptcy over the past almost two decades.

[1] See also Domovitz and Sartain (1999) and Barron, Elliehausen, and Staten (2000). Hence, Chatterjee, Corbae, Nakajima, and Rios-Rull (2007) incorporate simultaneously the role of household earnings and unsecured debt, as well as shocks to earnings, debt, and preferences (e.g., divorce) in their theoretical household default/bankruptcy dynamic equilibrium model.

Fay, Hurst, and White (2002) show that state bankruptcy exemption creates financial gains for debtors to file for bankruptcy and, in turn, induces households to *strategically* default.[2] Using a panel of individual credit card accounts and controlling for individual risk composition and economic environments, Gross and Souleles (2002) find that credit cardholders in 1997 were 1% point more likely to file for bankruptcy than individuals with similar characteristics in 1995, suggesting that their finding is perhaps due to a decline in the cost of bankruptcy such as a decline in *social stigma* attached to bankruptcy due to changing social norms. Fay et al. (2002) also suggest a decline in social stigma could explain their finding that households living in areas with higher aggregate bankruptcy filing rates face higher risk of bankruptcy filing. Other studies suggesting that the decline in social stigma can partially explain the recent rise in bankruptcy include Buckley and Brinig (1998), who present empirical evidence at the state level, and Livshits and MacGee (2007), who generate predictions using an equilibrium bankruptcy model.[3]

Above evidence provides strong support for argument that social capital can have the potential benefits for consumer bankruptcy and default behavior. According to Putnam (2000), social capital creates positive externalities for education, health, and public service performance through strengthening a community's social networks and norms and, in turn, shaping the community's attitudes toward certain socioeconomic behaviors or outcomes. To file bankruptcy or default is not considered a favorable behavior and also costlier in high social capital communities. Its consequences range from loss in social status and trust in the group to limiting employment prospects. Social punishment costs associated with the bankruptcy and default can be potentially greater than the financial benefit to file for bankruptcy. If this is the case, we expect that social capital should discourage households to *strategically* file bankruptcy or default.

Social capital also correlates strongly with social stigma. Mobility weakens an individual's investment in social capital (DiPasquale & Glaeser, 1999; Glaeser, Laibson, & Sacerdote, 2002) and reduces reputational concerns (Buckley & Brinig, 1998), while rural areas or small town communities have stronger social norms due to homogeneity (Alesina & LaFerrara, 2000) and face a higher cost of social connection due to greater distance (Glaeser & Sacerdote, 2000). These all indicate that asocial stigma is more likely to be higher in high social capital communities.

More recently, Glaeser et al. (2002) contend that decisions to optimally invest in social capital (as in human capital) are determined by individuals, and individual social capital formation is then aggregated up to the community level. In their framework of economic behavior, an individual maximizes the returns to his investment in social capital; such an investment decision is determined by the socioeconomic characteristics of that individual. For instance, homeownership increases neighborhood social capital investment because homeowners face high real estate transaction costs (which reduce mobility) and have a financial incentive to increase their property value (see also DiPasquale & Glaeser, 1999). The return to social capital investment depreciates when one moves out of a community; thus, mobility reduces the individual's investment in the social capital of a community.[4]

Based on the individual social capital formation economic model of Glaeser, Laibson and Sacerdote (2002), we expect the risk of default or bankruptcy to be lower for a borrower who has greater incentive to invest in social capital.

3. Data and methodology

3.1. Data

We use a proprietary 24-month panel data set from a large financial institution that issues credit cards nationally. There are several unique and important features of this data set that enable us to test the impact of individual social capital variables on consumer bankruptcy and default. This data set includes a representative sample of more than 170,000 individual credit card accounts that were issued between January 1997 and June 2000.

For each credit cardholder, we observe the individual's repayment or bankruptcy status each month from June 2000 to June 2002. If an account is 90-days past due in any given month over our 24-month sample period, a delinquency flag was created for that account. If the account was in formal bankruptcy at any time, a bankruptcy flag was created for that account. Since a cardholder can declare bankruptcy before they are 90-days delinquent (approximately 20–30% do so), the model captures individuals that are either delinquent or delinquent and have declared bankruptcy.[5] Hence, for the rest of the paper, whenever we refer to an account being 90-days delinquent (i.e., default), we do include accounts that declared bankruptcy prior to being delinquent. Furthermore, accounts with a flag indicating lost, stolen, never active, closed due to fraud/death status are excluded from the analysis.

We have additional important information that has previously been found in the literature to predict default or bankruptcy outcomes, such as the cardholder's monthly credit limit, spending balance, and credit card debt as well as other debt

[2] Gropp, Scholz, and White (1997) also show that debtors are more likely to file for bankruptcy and repay less in bankruptcy as the bankruptcy exemption level rises. They also argue that the exemption laws provide partial wealth insurance and the insurance coverage rises with the exemption levels. See also Agarwal, Liu, and Mielnicki (2003) and Agarwal, Chomsisengphet, Liu, and Mielnicki (2005) for empirical evidence on the impact of bankruptcy exemptions on consumer and small business bankruptcies, respectively.

[3] However, in the model of Athreya (2004), a decline in social stigma cannot explain the simultaneous increase in both debt and bankruptcy. Athreya (2004) and Livshits et al. (2007) also attribute the recent increase in bankruptcy filings to lower transaction costs of lending.

[4] Frequent mobility also weakens social connections (see e.g., Glaeser & Sacerdote, 2000) and reduces reputational concerns (see e.g., Buckley & Brinig, 1998). Conversely, immobility can also lead to strong social networks through information pooling and risk-sharing.

[5] The results for the default analysis are qualitative the same when we exclude the bankruptcy accounts.

(which includes mortgage, home equity, or auto balance). We also know each cardholder's credit bureau risk score (FICO score), which is updated quarterly over the 2-year period. Furthermore, the data contain other important information at the time of account origination, such as the cardholder's personal income and wealth category (low, medium, and high).

Equally important, our data contain key information given by the borrower at the time of application that enables us to construct the individual social capital variables as outlined by Glaeser et al. (2002). If the credit cardholder has a spouse listed on the application, then we code the applicant as married. Borrower age is determined from the birth date of the applicant. Homeownership is determined if the applicant has a mortgage balance reported at the credit bureau at the time of the credit card application.[6] Based on the first three digits of the applicant's social security number, their state of birth (and state of immigration entry for foreign born) can be identified.[7] Based on the applicant's current zip code, we create an indicator variable denoting that they still live in their "state of birth"; calculate the distance moved between state of birth and the current zip code centroid (Distance Moved)[8]; and create an indicator variable denoting that they moved to a rural area.[9]

To control for macroeconomic shocks and legal environments, we augment our loan-level data with county unemployment rates, as well as state-level demographics such as percentage of the state population without medical coverage.[10] We also augment our data with state legal variables, such as homestead and personal property exemption levels, as well as garnishment rates. Since we do not know the exact date of the move to the current state, one potential reason for the move could be forum shopping for a potential bankruptcy filer – that is, a debtor considering bankruptcy could be moving to a state with more lenient exemption levels (Elul & Subramanian, 2002). Therefore, we include the change in the homestead and property exemptions levels and the change in garnishment rates between a borrower's state of birth and state of current residence. See Table 1 for the summary statistics.

3.2. Methodology

Let $D_{i,t} = 1$ to indicate an account i in bankruptcy or default in month t. Our data set is a monthly discrete-time panel such that if, for example, the account becomes 90-days delinquent or the borrower files for bankruptcy in month 18, then $D_{i,t} = 0$ for the first 17 months and $D_{i,18} = 1$, and the rest of the observations will drop out of the sample thereafter.[11] We estimate the conditional probability that $D_i = 1$ at time t, given that the consumer is current from the start of the performance period up to time $t-1$.

We estimate the following Cox-proportional hazard model with robust standard errors:

$$h(t|X_{i,t}) = h_0(t)\exp(\beta X_{i,t}) \tag{1}$$

where $h(t|X_{i,t})$ represents the conditional probability that an individual will default on his credit debt or file for bankruptcy in month t, given that he has "survived" up to month $t-1$. The baseline hazard function at month t is represented by h_0, which does not take any specific functional form. The vector $X_{i,t}$ comprises time-varying as well as time-constant covariates as follows:

$$X_{i,t} = \beta_1 Time_t + \beta_2 Zip_i + \beta_3 S_{i,t} + \beta_4 L_{i,t} + \beta_5 W_{i,t} + \beta_6 Y_{i,t} + \beta_7 SC_i \tag{2}$$

β is a vector of parameters to be estimated. The vector $Time_t$ represents calendar month dummies to pick up any calendar time effects. We estimate the above specification with zip code fixed effects (Zip_i is a vector of zip code dummies representing the credit cardholder's zip of residence) to account for possible systematic variations within a zip code. By controlling for zip code fixed effects, we pick up the impact of socioeconomic characteristics at the zip code level that are not included in our model, such as characteristics of people within each zip code that may also affect credit card default and personal bankruptcy. The vector $S_{i,t}$ represents state-specific socioeconomic characteristics, such as county unemployment rate and frac-

[6] It is possible that some card holders do not list their spouses on the credit card application or own the house without have a mortgage. Both of these effects should attenuate our results.

[7] To convert the three digits into a state code, we follow the guidelines from the social security administration http://www.socialsecurity.gov/employer/stateweb.htm. We exclude 0.75% of the applicants since they did not match one of the 50 US states. For example, we exclude 534 consumers because the three digits of 580 and 586 represent Virgin Islands, Puerto Rico, Guam, American Samoa and Philippines. We exclude another 81 consumers because the three digits between 700 and 728 were assigned to railroad workers prior to 1964. Finally, we exclude 526 consumers because the first three digits were invalid.

[8] Distance moved between state and zip code centroid is calculated as follows:{

$$\text{Longitude to radians(if in decimal form omit the division by one million)} = (\text{longitude}/1,000,000) * (\pi/180)$$
$$\text{Latitude to radians(if in decimal form omit the division by one million)} = (\text{latitude}/1,000,000) * (\pi/180)$$
$$\text{Distance between two points, with both points' longitudes and latitudes in radians} = \arccos(\sin(\text{lat1}) * \sin(\text{lat2}) + \cos(\text{lat1}) * \cos(\text{lat2}) * \cos(\text{lon2} - \text{lon1})) * 6370 * 0.62$$

[9] We used the metropolitan statistical area (MSA) definition.

[10] We also tried to control for state divorce rates; however, four states (California, Colorado, Indiana, and Louisiana) do not report divorce rate information, while two other states (Nevada and Texas) do not have a complete time series for the period covered in our study (see http://www.cdc.gov/nchs/nvss.htm). As discussed in the robustness section, when we include state divorce rates (without the six states) in our estimation, our results remain qualitatively similar.

[11] This common form of incomplete data is defined as right censored. Accordingly, all customers start at time $t = 0$ and a customer could drop out of the sample because they close the account in good standing or even stay current till the end of 3 years without being delinquent or declaring bankruptcy. We do not consider left censoring in our analysis (accounts that have already been delinquent or declared bankruptcy even before the observation of time begins).

Table 1
Summary statistics.

Variables	Mean	Std. dev.
Macro and "Trigger" event variables		
Unemployment$_t$	4.72	1.01
% With no health care coverage	14.63	4.29
House price appreciation index	158.35	31.94
Legal variables		
Property exemptions	$9824	$6887
Homestead exemptions	$205,456	$377,166
Garnishment	18%	10%
Change in property exemptions	$2285	$5394
Change in homestead exemptions	$24,947	$308,622
Change in garnishment	50%	77%
Borrower credit risk variables		
Income	$56,636	$110,222
income low	29%	39%
Income medium	50%	50%
Income high	21%	41%
Wealth low	31%	29%
Wealth medium	59%	53%
Wealth high	10%	21%
FICO	713	72
APR	18.16	6.41
Credit line	$7408	$3404
Debt	$2232	$2915
Spending	$235	$763
Total credit card balances (spending)	$9167	$13,563
Home equity balance	$2805	$14,102
Mortgage balance	$52,826	$91,273
Auto balance	$4541	$7892
Credit bureau balance (other debt)	$69,339	$98,166
Social capital variables		
Borrower age	48.71	13.95
Own home	48%	50%
Married	64%	47%
Live in the state where born	35%	48%
Distance moved (miles)	191	371
Move to rural area	26%	19%
Own home $*$ live in the state where born	31%	46%
Own home $*$ log(distance moved)	2.52	2.75
Bankruptcies	1.47%	
Defaults	5.44%	
Default to bankruptcy	1.33%	
Default to current	2.04%	
Number of observations	3.2 Million	
Number of accounts	170793	

tion of the state population without health coverage. Several studies have found that legal variables are predictive of bankruptcy, thus $L_{i,t}$ is a vector of state-specific legal characteristics associated with consumer bankruptcy, including homestead and property exemption as well as garnishment rate. Fay, Hurst, and White (2002) argue that controlling for exemption levels at the state level might be confounding other state-specific events that are correlated with bankruptcy filings. Using the Panel Study of Income Dynamics (PSID), Elul and Subramanian (2002) found some evidence of *forum shopping* – that an individual's decision to migrate to a state with higher bankruptcy exemption levels is influenced by his propensity to file for bankruptcy, although the impact is modest. To address these potential issues, we include the difference in the state bankruptcy exemption levels in a borrower's state of birth and the exemption levels in the current state of residence, after controlling for the zip code fixed effects.

As found in Domovitz and Sartain (1999), described in Sullivan et al. (2000), and captured in the theoretical household default model of Chatterjee et al. (2007), a debtor's decision to default or declare bankruptcy varies with his earnings, wealth, and/or debt. Hence, the vector $W_{i,t}$ represents income and wealth (reported at origination), and the vector $Y_{i,t}$ captures the time-varying patterns of credit limit, spending, credit card debt, interest rate charge (APR) and other debt (including auto, mortgage or home equity credit), as well as updated quarterly external credit risk score (see e.g., Gross & Souleles, 2002).

Finally, the main variables of interest are represented by the vector SC_i, which captures the individual social capital variables at the opening of the credit card account. We mainly follow the economic approach to social capital formation set forth by Glaeser et al. (2002), in which individuals accumulate social capital in the beginning of life as the return to such investment rises, but then reduce investment in social capital later in life as its return declines, thus our socioeconomic

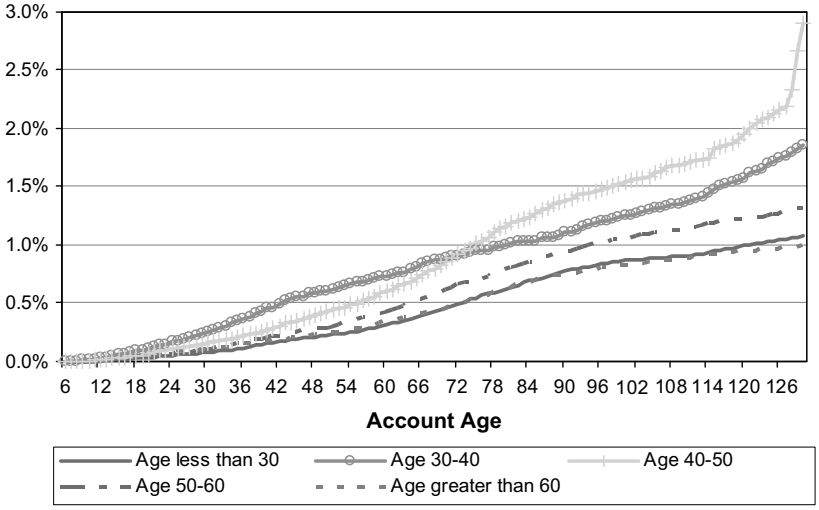

Fig. 1. Cumulative hazard function of bankruptcy by borrower age.

characteristic include the borrower's age and its square. Hence, we expect the risk of default or bankruptcy to decline in the early stage of life and then rise in the later stage of life – that is, we should find a U-shaped pattern of default or bankruptcy over the lifecycle. In addition, homeownership increases neighborhood social capital investment because high real estate transaction costs reduce mobility, and homeowners have a financial incentive to increase their property value (see also DiPasquale & Glaeser, 1999). Hence, the vector SC_i also includes an indicator variable denoting that the borrower is a homeowner, and another indicator variable denoting that the borrower is married. We expect the risk of default and bankruptcy to be lower for a debtor who owns a home or who is married.

Moreover, the vector SC_i also captures mobility of a borrower: We create three different measures of mobility. First, we create a spline function with knots at 50 miles, 250 miles, and 500 miles to measure the direct impact of mobility on borrower default and bankruptcy.[12] Next, we also create a dummy variables denoting whether the borrower still lives in the state of birth. Finally, we create an indicator variable denoting whether a borrower has moved to a rural area. Glaeser et al. (2002) argue that the return to social capital investment depreciates when one moves out of a community; thus, mobility reduces the individual's social capital investment in a community. Frequent mobility also weakens social connection (see e.g., Glaeser & Sacerdote, 2000; Putnam, 2000) and reduces reputational concerns (see e.g., Buckley & Brinig, 1998). Hence, we expect the risk of default or bankruptcy to be lower for a borrower who continues to live in the state of birth or who moves to a rural area, and we expect the risk of default or bankruptcy to be higher with greater distance of mobility.

4. Empirical results

4.1. Cumulative baseline hazard function

We first use the semi-parametric model to estimate the baseline cumulative hazard function to understand the average default and bankruptcy rate over time and across the various measures of individual social capital formation. The semi-parametric modeling does not make any assumption about the parametric distribution of the survival times. Our baseline cumulative hazard function represents the unconditional rate of bankruptcy over account tenure. Figs. 1–6 present the cumulative hazard functions by the various individual social capital variables.

Except for borrower age, the cumulative hazard functions indicate that the default/bankruptcy rate is higher over account tenure for borrowers with individual socialeconomic characteristics that are predicted by Glaeser et al. (2002) to have weaker incentive to invest in social capital. With respect to borrower age, the youngest (30 years or younger) and oldest (60 years or older) groups of consumers have the lowest bankruptcy risk, while the middle age group of consumers has the highest rate of bankruptcy (Fig. 1). This pattern is inconsistent to our expectation – that is, we expect lower risk of bankruptcy for the young and higher for the elders, given greater incentive to invest in social capital in the early stage of life and weaker incentive to invest in social capital in the later stage of life.

As expected, homeowners have a lower bankruptcy rate than non-homeowners across account tenure (Fig. 2), and married consumers also have a lower bankruptcy rate than single consumers (Fig. 3). Moreover, Fig. 4 indicates that consumers who continue to live in their state of birth have lower bankruptcy risk, while those who moved out of their state of birth have higher bankruptcy risk. Fig. 5 compares the cumulative hazard function by the distance of mobility. We categorize the

[12] The choice of the knots at 50, 250, and 500 miles may seem arbitrary; we tried several alternative specifications. The results suggest that these knot points are most suited to pick up the impact of distance moved on default and bankruptcy.

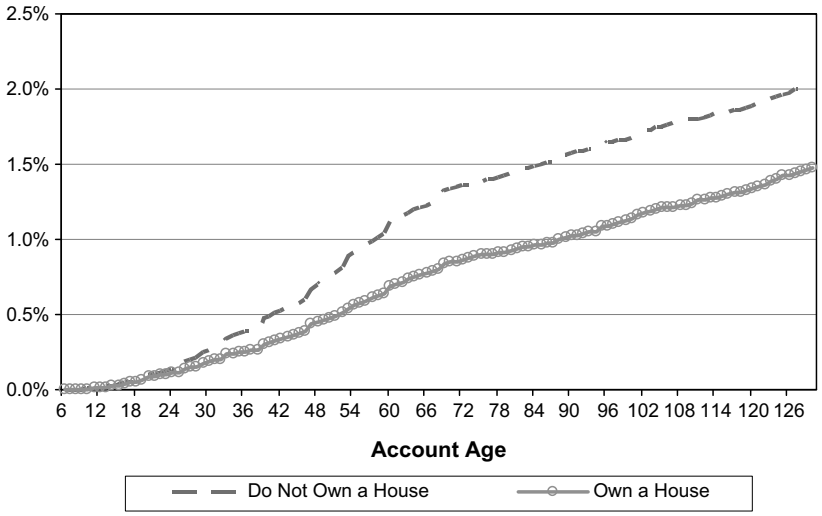

Fig. 2. Cumulative distribution of bankruptcy by homeownership.

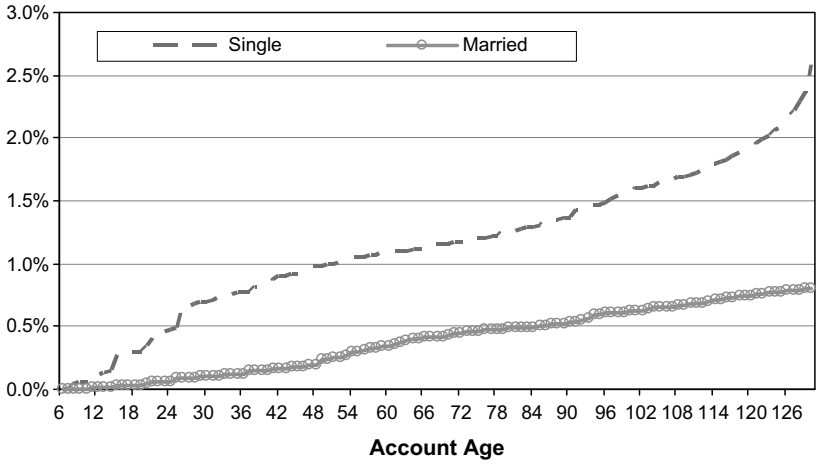

Fig. 3. Cumulative hazard function of bankruptcy by marital status.

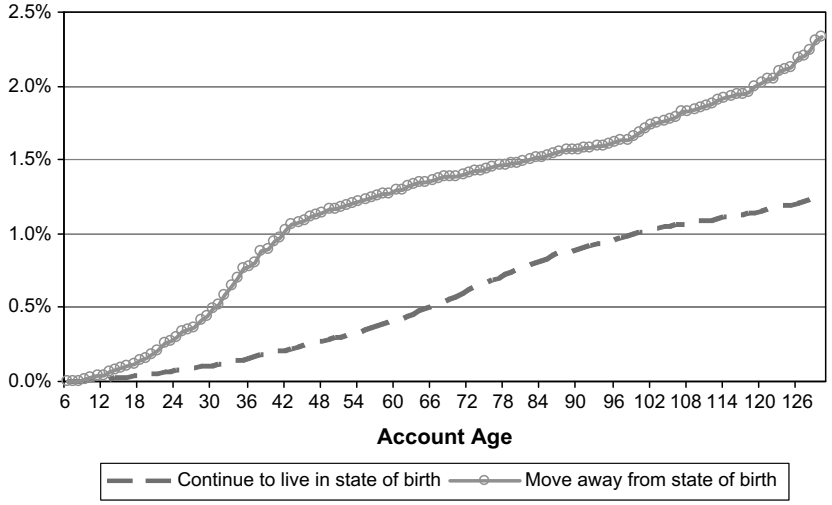

Fig. 4. Cumulative hazard function of bankruptcy by mobility.

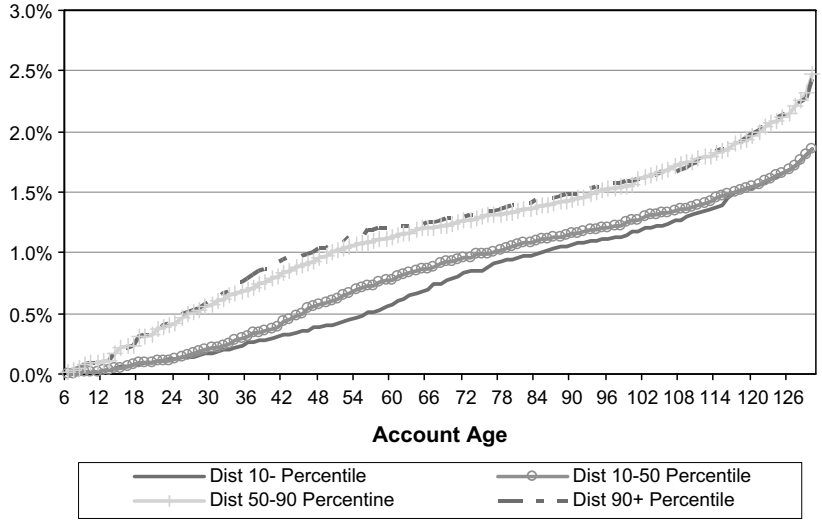

Fig. 5. Cumulative hazard function of bankruptcy by distance of mobility.

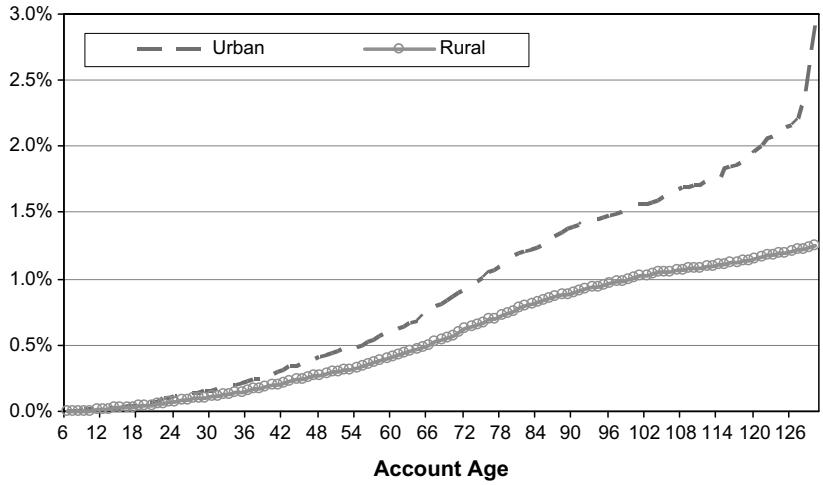

Fig. 6. Cumulative hazard function of bankruptcy by density of residence.

distance moved into percentile. Consumers who moved from their state of birth but are within relatively close proximity to their state of birth (below the 10th percentile distance) have lower bankruptcy risk, while consumers who move farther from their state of birth (above the 90th percentile distance) are more likely to file for bankruptcy. Furthermore, consumers who moved to a rural area have a lower rate of bankruptcy that those who move to an urban area (see Fig. 6), which we define using the metropolitan statistical area definition.

4.2. Semi-parametric estimation results

Table 2 presents the multivariate results of the estimated Cox-proportional hazard model testing the impact of individual social capital variables on the likelihood of consumer default or bankruptcy. Our results indicate that the risk of credit card default or bankruptcy is significantly higher for consumers living in a county with a higher unemployment rate,[13] as well as in a state with a higher fraction of its population with no health insurance. Holding all other covariates at their mean value, a 1% point increase in the county unemployment rate implies a 10 basis points increase in the likelihood of a borrower filing for bankruptcy. Equally important, the fraction of state population without health care coverage has a significantly positive but

[13] Agarwal and Liu (2003), who conduct an exhaustive analysis, also find county unemployment rates to be an important predictor of credit card default.

Table 2
Proportional hazard model of consumer default and bankruptcy.

Variables	Default				Bankruptcy			
	Coeff.	Std. err.	*P*-value	Marg. eff. (%)	Coeff.	Std. err.	*P*-value	Marg. eff. (%)
Macro and "Trigger" event variables								
Unemployment rate$_{t-6}$	0.06416	0.01027	0.0037	5.76	0.06088	0.00944	<.0001	6.15
% With no health care coverage$_{t-6}$	0.01527	0.02536	0.0104	0.53	0.01523	0.05065	<.0001	0.62
Change in unemployment rate$_{t-6}$	0.00519	0.00488	0.4738	0.04	0.00791	0.00524	0.4209	0.06
Legal variables								
Difference in property exemptions$_{t0}$	0.00000	0.00000	<.0001	0.00	0.00002	0.00001	0.0032	0.00
Difference in homestead exemptions$_{t0}$	0.00000	0.00000	<.0001	0.00	0.00000	0.00000	<.0001	0.00
Difference in garnishment$_{t0}$	−0.00046	0.00016	<.0001	−0.02	−0.00840	0.00509	<.0001	−0.03
Borrower credit risk variables								
Income medium$_{t0}$	−0.07238	0.03031	<.0001	−6.43	−0.06676	0.02681	<.0001	−6.37
Income high$_{t0}$	−0.17818	0.04936	<.0001	−14.98	−0.20296	0.05665	<.0001	−17.87
Wealth medium$_{t0}$	−0.08055	0.03642	<.0001	−7.23	−0.05424	0.02014	0.0010	−5.16
Wealth high$_{t0}$	−0.20800	0.04800	<.0001	−17.43	−0.11965	0.05764	<.0001	−10.85
House price appreciation$_{t0}$	−0.28966	0.04492	<.0001	−7.19	−0.26257	0.05824	<.0001	−5.78
FICO$_{t-6}$	−0.00260	0.00024	<.0001	−0.62	−0.00272	0.00045	<.0001	−0.46
APR$_{t-6}$	0.37023	0.02694	<.0001	5.82	0.56508	0.07339	<.0001	6.84
Credit line$_{t-6}$	−0.00019	0.00001	<.0001	0.00	−0.00031	0.00001	<.0001	0.00
Spending$_{t-6}$	0.00000	0.00000	<.0001	0.03	0.00000	0.00000	<.0001	0.03
Debt$_{t-6}$	0.00000	0.00000	<.0001	0.00	0.00000	0.00000	0.0097	0.00
Credit bureau balance$_{t-6}$	−0.00001	0.00000	0.0083	0.00	−0.00001	0.00000	<.0001	0.00
Social capital variables								
Borrower age$_{t0}$	0.06431	0.00501	<.0001	2.74	0.04555	0.01050	<.0001	2.96
Borrower age-sq$_{t0}$	−0.00054	0.00004	<.0001	−1.68	−0.00037	0.00009	<.0001	−1.00
Own home$_{t0}$	−0.14690	0.05470	<.0001	−13.02	−0.23967	0.04543	<.0001	−21.65
Married$_{t0}$	−0.19434	0.03526	<.0001	−17.39	−0.30139	0.06686	<.0001	−26.49
Live in the state where born$_{t0}$	−0.13849	0.07105	0.0488	−12.46	−0.19747	0.05822	<.0001	−9.09
Distance moved <50 Miles	0.06172	0.01303	<.0001	6.04	0.13739	0.02230	<.0001	4.71
Distance moved 50–250 miles	0.04840	0.01015	<.0001	17.66	0.12500	0.04637	<.0001	15.17
Distance moved 250–500 miles	0.00236	0.00187	0.1543	0.78	0.02699	0.02797	0.6841	0.48
Distance moved <500 miles	0.00024	0.00057	0.7668	0.04	0.00449	0.00369	0.9229	0.03
Urban dummy	0.00387	0.00103	0.0038	1.02	0.00385	0.00103	0.0038	1.03
Urban dummy * move to rural area$_{t0}$	−0.06946	0.03158	<.0001	−6.86	−0.07357	0.01543	<.0001	−6.77
Own home* live in the state where born$_{t0}$	−0.48135	0.08981	<.0001	−2.45	−0.26754	0.07158	<.0001	−2.62
Own home* log(distance moved)$_{t0}$	−0.54129	0.03712	<.0001	−5.88	−0.51440	0.07077	<.0001	−5.42
R-Sq	37.93%				34.47%			
Number of observations/defaults	3.2 Million				3.2 Million			
Time fixed effects (19 months)	YES				YES			
Zip code fixed effects (21127 zipcodes)	YES				YES			
Clustered standard errors	Individual				Individual			

Notes: The table reports results of a hazard model of consumer default using monthly account level data from June 2000 to June 2002. The results correct for robust standard errors at the individual account level. Explanatory variables include: legal factors (garnishment, property and homestead exemptions); macroeconomic risk factors (county unemployment, percentage of consumer without health insurance in a state); account-specific risk factors (income, wealth, FICO score, credit line amount, spending, credit card debt, and other debt which may include mortgage, home equity or auto); and individual social characteristics (borrower age, home ownership status, marital status, distance moved from the state of birth – we model this as a spline with knots at 50, 250, and 500 miles, living in state of birth indicator, and move to rural indicator); local risk factors – state dummies and calendar time dummies. Subscript $t-6$ represents the control variables 6 months prior to default and $t0$ represents control variable at June 2000.

non-linear effect on bankruptcy (see Fig. 7). Relative to an individual living in a state with only 5% of the state population without health care coverage, a borrower living in a state with 10% of its people not having health care coverage is 34 basis points more likely to file for bankruptcy. On the other hand, relative to someone living in a state with 25% of the people without health insurance, a borrower living in a state with 30% of its population without health coverage is 135 basis points more likely to file for bankruptcy. These results are consistent with Gross and Souleles (2002), as well as with Domovitz and Sartain (1999) and Sullivan et al. (2000) who document that unexpected medical debts is one of the most significant sources of financial distress propelling households to file for bankruptcy.

Consumers who moved to a state with higher homestead and property exemption than their state of birth are statistically more likely to default or file for bankruptcy, albeit the economic impact is negligible (Fig. 8 shows the relatively flat response of the predicted bankruptcy rate to changes in the difference of property exemptions). Consumers who moved to a state with lower garnishment rate than their state of birth are more likely to default or declare bankruptcy, but the marginal impact is small. Consistent with Elul and Subramanian (2002), our findings indicate that forum shopping has a trivial economic impact.

While our measures of both income and wealth are fairly noisy, given that income is self-reported at the time of credit card account opening, they have significant predictive power. For example, compared with cardholders with low income,

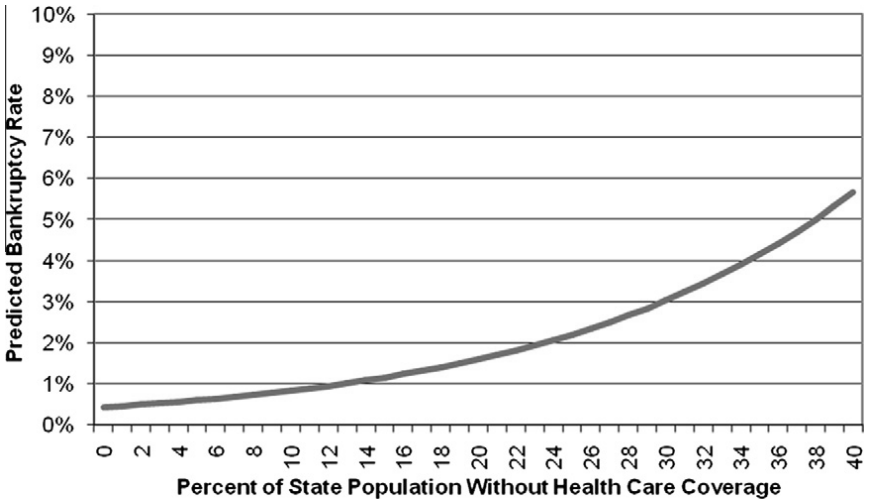

Fig. 7. Response of bankruptcy to no health care coverage.

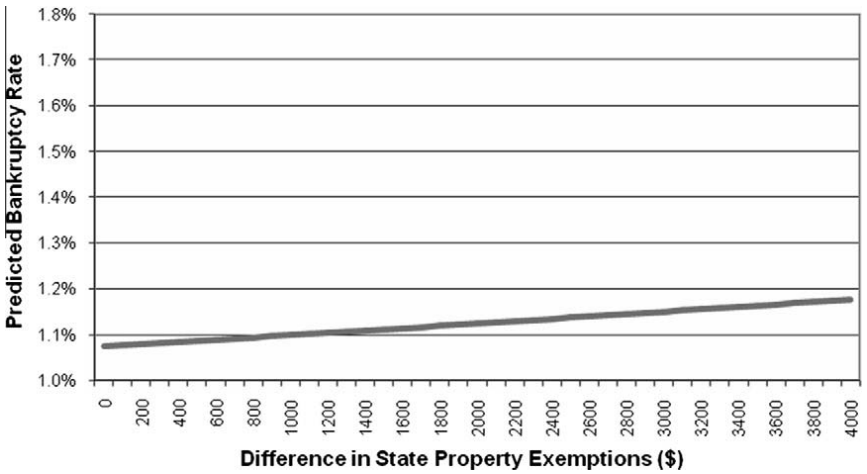

Fig. 8. Response of bankruptcy to difference in state bankruptcy exemptions.

those with high income and high wealth are 17% and 22%, respectively, less likely to default on their debt. Similarly, compared with borrowers with low wealth, those with high wealth are 19% and 14% less likely to default their credit card debt and declare bankruptcy, respectively. These results are consistent with the bankruptcy filing properties captured in the dynamic equilibrium model of household default of Chatterjee et al. (2007).

In addition, borrowers who are less creditworthy (lower FICO risk score) are more likely to default on their credit debt and more likely to file for bankruptcy, consistent with findings in Gross and Souleles (2002) and Agarwal, Chomsisengphet, Liu, and Souleles (2008). A 10-point drop in the FICO score implies a 4% point increase in the likelihood of default and bankruptcy, holding all other covariates constant at their mean value. However, the negative relationship between FICO score and bankruptcy seems to be non-linear (see Fig. 9), suggesting that the same 10-point drop of a FICO score of the less creditworthy borrowers (e.g., those with FICO $\leqslant$620) implies a larger increase in the risk of bankruptcy than the same point drop in the FICO score of the more creditworthy borrowers (e.g., those with FICO $\geqslant$740). For example, the bankruptcy risk of a borrower whose FICO score declines from 600 to 580 jumps 46 basis points, while the bankruptcy risk of a borrower whose FICO score drops from 800 to 780 increases only 13 basis points.

Moreover, we also find that cardholders with lower credit limits but higher interest charges (APR), spending or debt (on this credit card) are more likely to default or file for bankruptcy. The risk of bankruptcy is seven basis points higher when a borrower's APR increases from 15% to 25% and 32 basis points higher when the borrower's debt increases from $1000 to $5000 (see Fig. 10). The explanatory significance of credit card debt and APR on consumer default and bankruptcy is consistent with evidence found in Domovitz and Sartain (1999) and documented in Sullivan et al. (2000). On the other hand, our

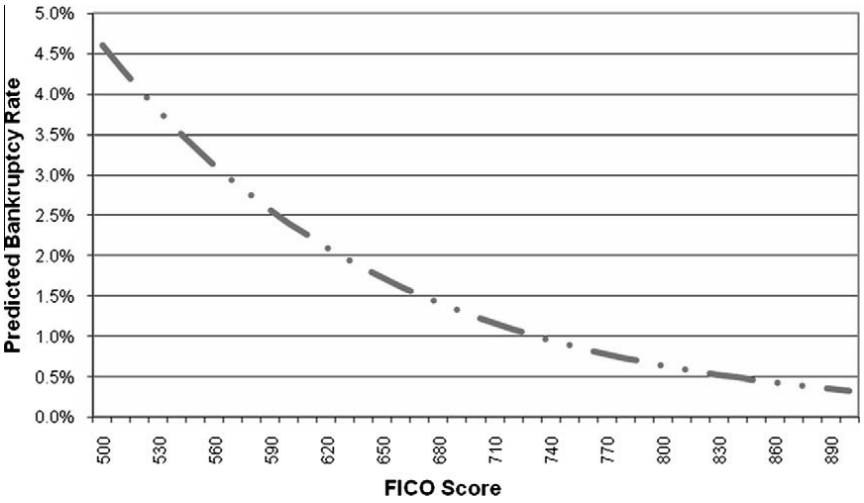

Fig. 9. Response of bankruptcy to FICO score.

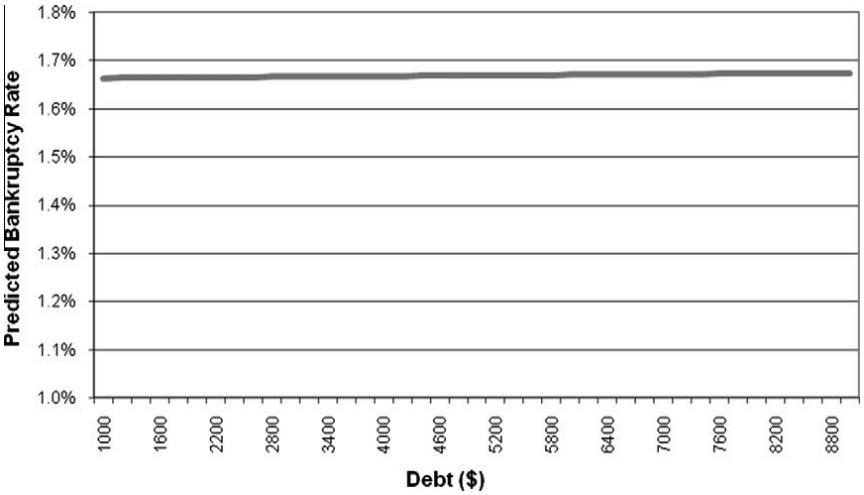

Fig. 10. Response of bankruptcy to debt.

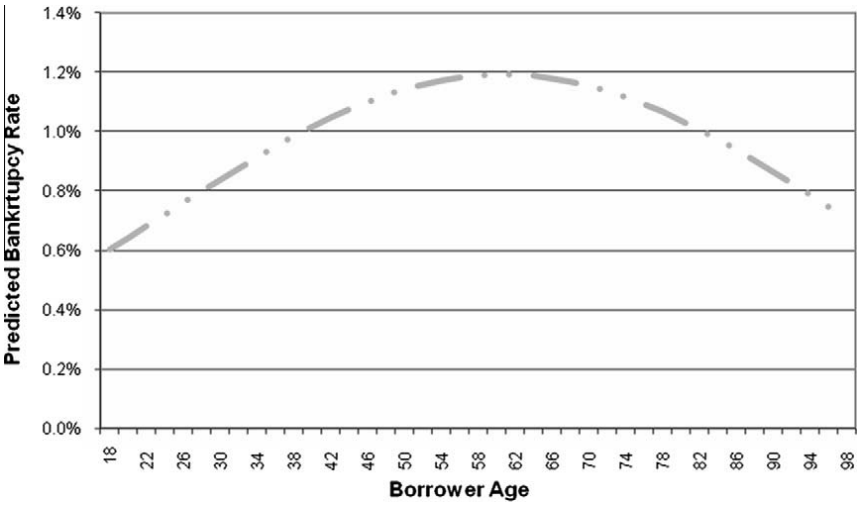

Fig. 11. Response of bankruptcy to borrower age.

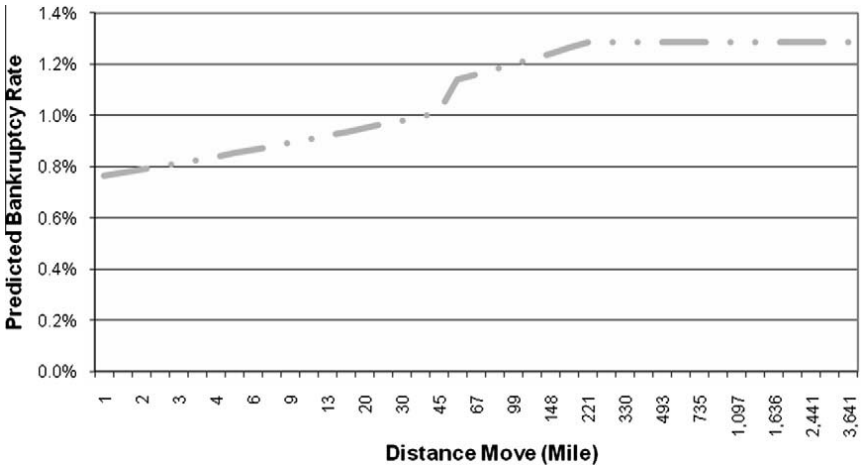

Fig. 12. Response of bankruptcy to mobility.

results also indicate that borrowers with higher other debt (including auto, mortgage, and home equity credit) are significantly less likely to default on credit card debt and less likely to file for bankruptcy.

Finally, we turn to the impact of individual social capital variables on consumer bankruptcy or default outcomes. First, we find that credit card default and bankruptcy rates vary over the lifecycle – that is, the likelihood of default or bankruptcy rises with age in the early stage of life but then declines with age in the later stage of life (see Fig. 11). While this inverted U-shaped pattern of bankruptcy over the lifecycle is inconsistent with our expectation based on the social capital framework of Glaeser et al. (2002), it is consistent with the pattern depicted in Livshits et al. (2007) and Agarwal, Driscoll, Gabaix, and Laibson (2009).[14] This is also consistent with the explanation offered by Zywichi (2005a, 2005b) that there may be a Baby Boom effect on consumer bankruptcy filings. Specifically, the baby boom generation has overturned traditional taboos of marriage, the role of women in society, etc., and these in turn could have influenced the social norms about personal financial decisions and the social stigma associated with personal bankruptcy (see Zywichi, 2005a). In addition, cardholders who own a home or are married are 17% and 24%, respectively, less likely to default on their credit cards, and 25% and 32%, respectively, less likely to declare bankruptcy. These results are consistent with findings in Domovitz and Sartain (1999).[15]

Moreover, we find that cardholders who continue to live in their state of birth have a 14% lower probability of defaulting on their credit card debt and a 10% lower probability of declaring bankruptcy. Meanwhile, individuals who move 190 miles from the state of birth are 17% more likely to default on their debt and 15% more likely to file for bankruptcy (see Fig. 12). Finally, individual moving to a rural area are 9% less likely to default on their debt and 7% less likely to file for bankruptcy. Given that the return to social capital investment declines with mobility (Glaeser et al., 2002), weakens social connection (see e.g., Glaeser & Sacerdote, 2000; Putnam, 2000) and reduces reputational concerns (see e.g., Buckley & Brinig, 1998), these results are consistent with our expectations based on the individual social capital formation economic model – that is, the risk of default or bankruptcy is lower for a borrower who has greater incentive to invest in social capital.

4.3. Extensions

In order to fully understand the underlying mechanism through which distance impacts social capital, we conduct additional tests on two hypotheses. If social networks play a role, then we would expect that borrowers living in the state of birth are more likely to cure their delinquency status. Under the first hypothesis, we test the impact of the various social capital variables on a borrower's propensity to become current after being 90 days delinquent. Similarly, a borrower who has greater mobility is likely to have less social stigma and more likely to declare bankruptcy. Under the second hypothesis, we test the impact of various social capital variables on a borrower's propensity to declare bankruptcy after being 90 days delinquent.

The results are reported in Table 3. The first set of results show that the probability of declaring bankruptcy subsequent to a default increases in the distance moved from the state of birth. However, the probability of becoming current after being 90 days delinquent is not affected by the distance moved from the state of birth, but is higher for borrowers who live in the state of birth.

[14] Agarwal et al. (2009) study various outcomes over the lifecycle and find that most of them show a U share pattern, expect for default which exhibits an inverted U shape pattern.

[15] Since we do not know the household income, it is not possible to completely rule out that cardholders who are married have a lower default rate due to the fact that married households have a larger household income and have the ability to share the risk across household members.

Table 3
Proportional hazard model of consumer default migration to bankrutpcy and current.

Variables	Default to bankruptcy				Default to current			
	Coeff.	Std. err.	*P*-value	Marg. eff. (%)	Coeff.	Std. err.	*P*-value	Marg. eff. (%)
Macro and "Trigger" event variables								
Unemployment rate$_{t-6}$	0.06432	0.01044	0.0036	5.78	−0.03086	0.02513	0.2692	−0.37
% With no health care coverage$_{t-6}$	0.01555	0.02553	0.0106	0.52	−0.00585	0.00404	0.4844	−0.13
Change in unemployment rate$_{t-6}$	0.00524	0.00492	0.4763	0.04	0.00189	0.00137	0.3218	0.02
Legal variables								
Difference in property exemptions$_{t0}$	0.00000	0.00000	<.0001	0.00	0.00002	0.00001	0.0032	0.00
Difference in homestead exemptions$_{t0}$	0.00000	0.00000	<.0001	0.00	0.00000	0.00000	<.0001	0.00
Difference in garnishment$_{t0}$	−0.00045	0.00016	<.0001	−0.02	−0.00836	0.00510	<.0001	−0.03
Borrower credit risk variables								
Income medium$_{t0}$	−0.07154	0.03043	<.0001	−6.48	0.06748	0.02715	<.0001	2.42
Income high$_{t0}$	−0.17907	0.04939	<.0001	−15.15	0.20451	0.05693	<.0001	6.20
Wealth medium$_{t0}$	−0.08171	0.03638	<.0001	−7.25	0.05468	0.02010	<.0001	3.21
Wealth high$_{t0}$	−0.20695	0.04774	<.0001	−17.30	0.11904	0.05766	<.0001	6.00
House price appreciation$_{t0}$	−0.28971	0.04556	<.0001	−7.22	0.16378	0.05830	<.0001	4.80
FICO$_{t-6}$	−0.00262	0.00024	<.0001	−0.62	0.00124	0.00145	0.4832	0.01
APR$_{t-6}$	0.37393	0.02701	<.0001	5.75	−0.17071	0.14045	0.6802	0.03
Credit line$_{t-6}$	−0.00019	0.00001	<.0001	0.00	0.00012	0.00014	0.3839	0.00
Spending$_{t-6}$	0.00000	0.00000	<.0001	0.03	0.00000	0.00000	<.0001	0.03
Debt$_{t-6}$	0.00000	0.00000	0.0004	0.00	0.00000	0.00000	0.0097	0.00
Credit bureau balance$_{t-6}$	−0.00001	0.00000	0.0084	0.00	−0.00001	0.00000	<.0001	0.00
Social capital variables								
Borrower age$_{t0}$	0.06445	0.00509	<.0001	2.78	0.03586	0.01051	<.0001	1.39
Borrower age-sq$_{t0}$	−0.00054	0.00004	<.0001	−1.69	0.00048	0.00009	<.0001	−1.50
Own home$_{t0}$	−0.14685	0.05430	<.0001	−13.15	0.63903	0.14566	<.0001	14.78
Married$_{t0}$	−0.19575	0.03531	<.0001	−17.59	0.14936	0.04730	<.0001	8.84
Live in the state where born$_{t0}$	−0.14121	0.07159	0.0488	−12.49	0.49819	0.13719	<.0001	−6.27
Distance moved <50 miles	0.08429	0.01315	<.0001	6.09	−0.06732	0.04828	0.6785	5.73
Distance moved 50–250 miles	0.06902	0.01029	<.0001	17.55	−0.04623	0.04738	0.7759	2.28
Distance moved 250–500 miles	0.01427	0.00184	0.1559	0.77	−0.02693	0.02811	0.6813	0.47
Distance moved <500 miles	0.00731	0.00058	0.7848	0.04	−0.00450	0.00371	0.9402	0.03
Urban dummy	0.00386	0.00102	0.0038	1.03	0.00385	0.00102	0.0038	1.03
Urban dummy * move to rural area$_{t0}$	−0.07033	0.03160	<.0001	−6.82	0.09373	0.03543	<.0001	−2.75
Own home * live in the state where born$_{t0}$	−0.48717	0.09047	<.0001	−2.46	0.47017	0.07176	<.0001	−4.67
Own home * log(distance moved)$_{t0}$	−0.54629	0.03767	<.0001	−5.87	0.21642	0.06998	<.0001	−3.40
R-sq	36.39%				31.13%			
Number of observations/defaults	3.2 Million				3.2 Million			
Time fixed effects (19 months)	YES				YES			
Zip code fixed effects (21127 zipcodes)	YES				YES			
Clustered standard errors	Individual				Individual			

Notes: The table reports results of a hazard model of consumer default using monthly account level data from June 2000 to June 2002. The results correct for robust standard errors at the individual account level. Explanatory variables include: legal factors (garnishment, property and homestead exemptions); macroeconomic risk factors (county unemployment, percentage of consumer without health insurance in a state); account-specific risk factors (income, wealth, FICO score, credit line amount, spending, credit card debt, and other debt which may include mortgage, home equity or auto); and individual social characteristics (borrower age, home ownership status, marital status, distance moved from the state of birth - we model this as a spline with knots at 50, 250, and 500 miles, living in state of birth indicator, and move to rural indicator); local risk factors – state dummies and calendar time dummies. Subscript $t-6$ represents the control variables 6 months prior to default and $t0$ represents control variable at June 2000.

4.4. Robustness

We also conducted exhaustive robustness checks on our analysis. First, we estimated the survival model with varying lag structure to alleviate any concerns that our results might be biased toward a particular lag length. Second, we also tried including state divorce rates (dropping three states that do not report divorce rate statistics). Third, we tried including homestead and personal property exemption levels as well as garnishment rates (instead of the difference between those of the borrower's state of birth and the state of residence as used in Table 2), dropping the zip-code dummy variables since they do not vary over time. Overall, the re-estimation results remain qualitatively consistent with the results reported in Table 2.

4.5. State-level social capital and household bankruptcy

To further assess whether there is a connection between social capital and consumer bankruptcy at the community level, we assess the correlation between Putnam's aggregate social capital index (Putnam, 2000) and state bankruptcy filing rates

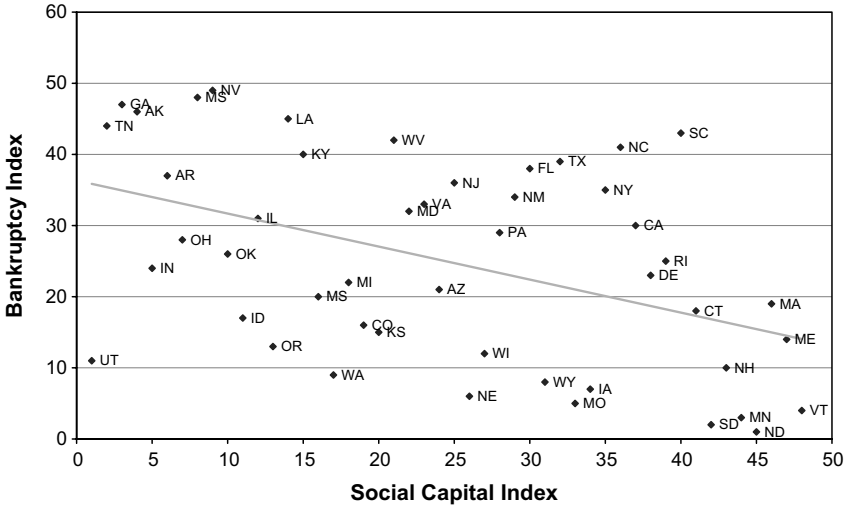

Fig. 13. Correlation between social capital index and state bankruptcy index in 2000.

Table 4
State bankruptcy rates and state social capital index in 2000.

Variables	Coeff.	Std. err.	*t*-Stat
Intercept	9.277720	4.798880	1.93
Social capital index	−0.300690	0.152520	−1.97
Homestead exemptions	−0.000003	0.000005	−0.52
Property exemptions	0.000007	0.000343	0.02
Garnishment	−0.370800	0.213680	−1.74
% With no health care coverage	1.203840	0.525100	2.29
Unemployment rate	3.825380	1.401090	2.73
Adjusted *R*-sq	36.96%		
Number of observations	48		

in 2000.[16] Putnam develops a social capital index based on 13 different measures of social capital, such as membership in voluntary associations, attendance at club meetings, turnout at presidential elections, trust among individuals, and philanthropic generosity.

We find a negative correlation of 0.4356 between Putnam's social capital index and the state bankruptcy index. We find that states that are ranked higher on Putnam's social capital index (e.g., Vermont and Minnesota) have lower bankruptcy filing rates, while states that are ranked lower on the social capital index (e.g., Georgia and Tennessee) have higher bankruptcy rates (see Fig. 13). We also regress the state bankruptcy rates on Putnam's social capital index, controlling for the state's economic and legal characteristics. Table 4 reports the OLS regression results. We find that a 1 point increase in the social capital index results in a 0.3 points reduction in the state bankruptcy rate.

Finally, we also measure the time series correlation between the various social capital variables and the consumer bankruptcy decision. In order to determine this correlation, we use the social capital index created by Rupasingha, Goetz, and Freshwater (2004) for the years 1994 to 2004 (see Appendix for a detailed data description) and merge it with the individual credit card over the same time period. This data set comes from a large national bank with a national credit card portfolio. We find that there is a negative correlation between bankruptcy and the following variables: bowling centers (0.9122), labor organizations (0.8573), civic and social organizations (0.4887), golf courses (0.6905), and recreation clubs (0.8159). These results confirm that social capital at the individual and social level in the cross section and over time is negatively correlated with consumer bankruptcy.[17]

[16] The state bankruptcy rate per capita comes from the Administrative Office of the US Courts and the US Bureau of the Census and is ranked.

[17] In order to separate out the effect of individual social capital investment decision from stigma effects, we compare the individual's decision to move from a high to a low social capital state versus an individual's decision to move from a high to a high social capital state. We should expect that people who move from a high to a low social capital state are driven by social capital investment decision. Our results do not confirm these predictions. The results are available upon request.

5. Conclusion

An individual's decision to maximize his investment in social capital is determined by his socioeconomic characteristics (Glaeser, Laibson, and Sacerdote, 2002). In this paper, we empirically test the role of individual social capital variables on personal bankruptcy and default outcomes in the consumer credit market. After controlling for a borrower's riskiness, spending, debt, and income and wealth, as well as legal and economic environments, we find that individual social capital variables, such as mobility, rural residency, homeownership, marital status, and borrower age play a statistically and economically significant role in consumer bankruptcy and default outcomes. These individual social capital variables collectively can affect the strength of a community's social networks and norms and, in turn, shape the community's attitudes toward certain socioeconomic behaviors or outcomes. Therefore, the explanatory significance of an individual's social capital variables on the need to default on debt or to file for bankruptcy could perhaps provide additional insights into the role of social stigma in consumer bankruptcy.

Acknowledgments

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Appendix A. Social capital data description

We use the social capital index created by Rupasingha, Goetz and Freshwater (the RGF index) for the years 1994 and 2004. One of the major sources of data used to construct their index was the County Business Patterns (CBP) dataset, an annual series created by the US Census Bureau, which breaks down economic data for each industry. This dataset contains variables that measure the number of various membership organizations within a given county and ultimately serves as a proxy for social capital as defined by Putnam (2000). For the years 1994–1997, we used the following variables that Rupasingha, Goetz and Freshwater pulled from the CBP dataset: bowling centers; civic and social associations; physical fitness facilities; public golf courses; religious organizations; sports clubs, managers and promoters; membership sports and recreation clubs; political organizations; professional organizations; business associations; labor organizations; and membership organizations not elsewhere classified. For the years 1998–2004, the Census Bureau started to classify its data based off of the North American Industry Classification System (NAICS) rather than the Standard Industrial Classification (SIC) System. The following variables were included in the social capital index for the years 1998 and later: scouting and related youth development organizations; sports teams and clubs; stadium operators; sports promoters; sports agents; public golf courses; membership recreation clubs with facilities; bowling centers; membership sports and recreation clubs without facilities; religious organizations; humane societies; civic and social organizations; business associations; professional organizations; labor unions and similar labor organizations; political organizations; and other similar membership organizations.

Since the bankruptcy data that we utilized is defined at the zip code level rather than county level, it became necessary to relate the two geographic units. In order to do this, we utilized MABLE/Geocorr, a web application created by the Missouri Census Data Center that generates geographic equivalency files. These equivalency files related counties to ZCTA's (ZIP Census Tabulation Areas) rather than ZIP Codes. As explained by the US Census Bureau, the ZCTA's are almost identical to ZIP Codes although a few differences exist between the two (http://www.census.gov/geo/ZCTA/zcta.html). The majority of the ZCTA's fell solely in one county and we just assigned the social capital properties of that county to the ZCTA. However there were cases in which the ZCTA's spanned over several counties (According to the Missouri Census Data Center, about 10% of ZIP Codes are in more than one county: http://mcdc2.missouri.edu/webrepts/geography/ZIP.resources.html). In those instances, we calculated the social capital index for the ZCTA by weighting the social capital indices of all of the counties in that ZCTA by their population as found by the 2000 Census.

A.1. Proportional hazard model of consumer default

Variables	Default – robustness spec. 1			
	Coeff.	Std. err.	*P*-value	Marg. eff. (%)
Macro and "Trigger" event variables				
Unemployment rate$_{t-6}$	0.06405	0.01036	0.0037	5.72
% With no health care coverage$_{t-6}$	0.01526	0.02540	0.0104	0.52
Change in unemployment rate$_{t-6}$	0.00518	0.00487	0.4735	0.04
Divorce rate$_{t-6}$	0.08204	0.02875	<.0001	0.48
Legal variables				
Difference in property exemptions$_{t0}$	0.00000	0.00000	<.0001	0.00
Difference in homestead exemptions$_{t0}$	0.00000	0.00000	<.0001	0.00
Difference in garnishment$_{t0}$	−0.00046	0.00016	<.0001	−0.02
Borrower credit risk variables				
Income medium$_{t0}$	−0.07254	0.03042	<.0001	−6.46
Income high$_{t0}$	−0.17904	0.04952	<.0001	−14.94
Wealth medium$_{t0}$	−0.08028	0.03618	<.0001	−7.25
Wealth high$_{t0}$	−0.20761	0.04797	<.0001	−17.37
House price appreciation$_{t0}$	−0.28797	0.04492	<.0001	−7.18
FICO$_{t-6}$	−0.00260	0.00024	<.0001	−0.62
APR$_{t-6}$	0.37246	0.02685	<.0001	5.81
Credit line$_{t-6}$	−0.00019	0.00001	<.0001	0.00
Spending$_{t-6}$	0.00000	0.00000	<.0001	0.03
Debt$_{t-6}$	0.00000	0.00000	<.0001	0.00
Credit bureau balance$_{t-6}$	−0.00001	0.00000	0.0083	0.00
Social capital variables				
Borrower age$_{t0}$	0.06458	0.00502	<.0001	2.73
Borrower age-sq$_{t0}$	-0.00054	0.00004	<.0001	−1.69
Own home$_{t0}$	−0.14667	0.05422	<.0001	−13.03
Married$_{t0}$	−0.19468	0.03541	<.0001	−17.39
Live in the state where born$_{t0}$	−0.13880	0.07111	0.0489	−12.51
Distance moved <50 miles	0.06199	0.01305	<.0001	6.06
Distance moved 50–250 miles	0.04820	0.01014	<.0001	17.71
Distance moved 250–500 miles	0.00237	0.00185	0.1542	0.77
Distance moved <500 miles	0.00024	0.00057	0.7695	0.04
Urban dummy	0.00384	0.00103	0.0038	1.02
Urban dummy $*$ move to rural area$_{t0}$	−0.06956	0.03147	<.0001	−6.86
Own home $*$ live in the state where born$_{t0}$	−0.47839	0.08969	<.0001	−2.45
Own home $*$ log(distance moved)$_{t0}$	−0.54104	0.03698	<.0001	−5.85
R-Sq	38.32%			
Number of observations/defaults	3.2 Million	9288	170793	
Time fixed effects (19 months)	YES			
Zip code fixed effects (21127 zipcodes)	YES			
Clustered standard errors	Individual			

A.2. Proportional hazard model of consumer default

Variables	Default – robustness spec. 2			
	Coeff.	Std. err.	*P*-value	Marg. eff. (%)
Macro and "Trigger" event variables				
Unemployment rate$_{t-6}$	0.06083	0.00947	<.0001	6.14
% With no health care coverage$_{t-6}$	0.01527	0.05059	<.0001	0.62
Change in unemployment rate$_{t-6}$	0.00788	0.00524	0.4208	0.06
Legal variables				
Property exemptions$_{t0}$	0.00002	0.00001	0.0032	0.00
Homestead exemptions$_{t0}$	0.00000	0.00000	<.0001	0.00
Garnishment$_{t0}$	−0.00840	0.00514	<.0001	−0.03
Borrower credit risk variables				
Income medium$_{t0}$	−0.06640	0.02688	<.0001	−6.38
Income high$_{t0}$	−0.20133	0.05630	<.0001	−17.86
Wealth medium$_{t0}$	−0.05431	0.02011	0.0010	−5.19
Wealth high$_{t0}$	−0.11987	0.05797	<.0001	−10.84
House price appreciation$_{t0}$	−0.26218	0.05827	<.0001	−5.80
FICO$_{t-6}$	−0.00274	0.00046	<.0001	−0.46
APR$_{t-6}$	0.56641	0.07359	<.0001	6.89
Credit line$_{t-6}$	−0.00031	0.00001	<.0001	0.00
Spending$_{t-6}$	0.00000	0.00000	<.0001	0.03
Debt$_{t-6}$	0.00000	0.00000	0.0097	0.00
Credit bureau balance$_{t-6}$	−0.00001	0.00000	<.0001	0.00
Social capital variables				
Borrower age$_{t0}$	0.04547	0.01052	<.0001	2.97
Borrower age-Sq$_{t0}$	−0.00038	0.00009	<.0001	−1.00
Own home$_{t0}$	−0.23969	0.04566	<.0001	−21.72
Married$_{t0}$	−0.30212	0.06652	<.0001	−26.51
Live in the state where born$_{t0}$	−0.19675	0.05797	<.0001	−9.09
Distance moved <50 miles	0.13801	0.02241	<.0001	4.70
Distance moved 50–250 miles	0.12548	0.04652	<.0001	15.14
Distance moved 250–500 miles	0.02681	0.02792	0.6813	0.48
Distance moved <500 miles	0.00447	0.00369	0.9249	0.03
Urban dummy	0.00387	0.00102	0.0038	1.02
Urban dummy $*$ move to rural area$_{t0}$	−0.07377	0.01545	<.0001	−6.75
Own home $*$ live in the state where born$_{t0}$	−0.26703	0.07147	<.0001	−2.63
Own home $*$ log(distance moved)$_{t0}$	−0.51445	0.07086	<.0001	−5.40
R-Sq	32.90%			
Number of observations/defaults	3.2 Million	2504	170793	
Time fixed effects (19 months)	YES			
Zip code fixed effects (21127 zipcodes)	NO			
Clustered standard errors	Individual			

A.3. Proportional hazard model of consumer default

Variables	Default – robustness spec. 3			
	Coeff.	Std. err.	*P*-value	Marg. eff. (%)
Macro and "Trigger" event variables				
Unemployment rate$_{t-3}$	0.06385	0.01029	0.0037	5.74
% With no health care coverage$_{t-3}$	0.01526	0.02547	0.0104	0.53
Change in unemployment rate$_{t-3}$	0.00518	0.00489	0.4748	0.04
Legal variables				
Difference in property exemptions$_{t0}$	0.00000	0.00000	<.0001	0.00
Difference in homestead exemptions$_{t0}$	0.00000	0.00000	<.0001	0.00
Difference in garnishment$_{t0}$	−0.00045	0.00016	<.0001	−0.02
Borrower credit risk variables				
Income medium$_{t0}$	−0.07255	0.03039	<.0001	−6.41
Income high$_{t0}$	−0.17878	0.04961	<.0001	−14.97
Wealth medium$_{t0}$	−0.08012	0.03615	<.0001	−7.26
Wealth high$_{t0}$	−0.20710	0.04787	<.0001	−17.34
House price appreciation$_{t0}$	−0.28927	0.04519	<.0001	−7.20
FICO$_{t-3}$	−0.00259	0.00023	<.0001	−0.62
APR$_{t-3}$	0.37165	0.02694	<.0001	5.79
Credit line$_{t-3}$	−0.00019	0.00001	<.0001	0.00
Spending$_{t-3}$	0.00000	0.00000	<.0001	0.03
Debt$_{t-3}$	0.00000	0.00000	<.0001	0.00
Credit bureau balance$_{t-3}$	−0.00001	0.00000	0.0083	0.00
Social capital variables				
Borrower age$_{t0}$	0.06442	0.00500	<.0001	2.72
Borrower age-sq$_{t0}$	−0.00054	0.00004	<.0001	−1.68
Own home$_{t0}$	−0.14706	0.05421	<.0001	−12.99
Married$_{t0}$	−0.19469	0.03543	<.0001	−17.54
Live in the state where born$_{t0}$	−0.13881	0.07104	0.0488	−12.46
Distance moved <50 miles	0.06187	0.01305	<.0001	6.10
Distance moved 50–250 miles	0.04831	0.01021	<.0001	17.65
Distance moved 250–500 miles	0.00236	0.00186	0.1544	0.78
Distance moved <500 miles	0.00024	0.00057	0.7663	0.04
Urban dummy	0.00384	0.00103	0.0038	1.02
Urban dummy $*$ move to rural area$_{t0}$	−0.06995	0.03156	<.0001	−6.85
Own home $*$ live in the state where born$_{t0}$	−0.47898	0.08980	<.0001	−2.45
Own home $*$ log(distance moved)$_{t0}$	−0.53880	0.03695	<.0001	−5.90
R-sq	39.32%			
Number of observations/defaults	3.2 Million	9288	170793	
Time fixed effects (19 months)	YES			
Zip code fixed effects (21127 zipcodes)	YES			
Clustered standard errors	Individual			

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