Social Networks and Personal Bankruptcy[*]

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Abstract

While social networks have been examined in the context of many economic decisions, this study is the first to examine the role of social networks in a household's bankruptcy decision. Networks may affect a household's bankruptcy decision in many ways: they could provide information about the required paperwork, recommend an attorney, reduce the stigma associated with bankruptcy, or increase awareness of its benefits. Using data from the Panel Study of Income Dynamics (PSID), I exploit county and racial variation to identify network effects --- my empirical strategy asks whether being surrounded by others of the same race increases bankruptcy use more for those in racial groups with high filing rates. This methodology allows me to include both county-year and racial group fixed effects in my regressions. The results strongly confirm the importance of networks in a household's bankruptcy decision.

1. INTRODUCTION

A growing literature documents the impact of social networks on individual behavior. Prominent examples show, for example, that social networks impact welfare participation (Bertrand et al., 2000), publically funded prenatal care (Aizer and Currie, 2004), health care utilization (Deri, 2005), education (Calvo-Armengol, Pattacchini and Zenou, 2009; Aaronson, 1998), employment (Beaman, 2012; Topa, 2001), and investment decisions (Li, 2009; Duflo and Saez, 2003). In this paper, I show that social networks also have a significant impact on a household's decision to file for bankruptcy.

Using data from the 1991-1995 Panel Study of Income Dynamics (PSID), I define networks using a household's county and racial/ethnic group—this methodology is similar to Bertrand et al.(2000), Aizer and Currie (2004) and Deri (2005). My empirical strategy asks whether being surrounded by others of the same racial group increases bankruptcy use more for those in racial groups with high filing rates. Because my regressions include county-year and racial group fixed effects, I am able to eliminate omitted variable bias caused by unobserved neighborhood characteristics and unobserved household characteristics that are correlated with race. To test for remaining omitted variable bias I: 1) use an instrumental variables approach, 2) explore the effect of dropping covariates and 3) include household fixed effects. My results withstand all three tests.

Bankruptcy is one of the country's largest transfer of wealth programs. In 2010, over 1.5 million households filed for bankruptcy. As these 1.5 million households discharged more than $459 billion in debt, the bankruptcy system is now as large as Medicare (2010 Report of Statistics Required by the Bankruptcy Abuse Prevention and Consumer Protection Act of 2005, Table 1X). Yet despite its size, economists still have a limited understanding of a household's bankruptcy decision. The majority of the economic literature addressing bankruptcy has focused primarily on the financial factors that contribute to a household's bankruptcy decision, (for example: White, 2007; Fay, Hurst and White, 2002; Gross and Souleles, 2002; Domowitz and Sartain, 1999; Buckley, 1994; White, 1987). A smaller literature has examined the demographic factors (Lefgren and McIntyre, 2009) and legal factors (Dawsey and Ausubel, 2004; Miller, 2010) that contribute to bankruptcy. To date, however, no work has been done to examine whether social networks contribute to bankruptcy.

The presence of social networks may be able to explain several phenomena observed in the bankruptcy data. First, social networks, or the lack thereof, may explain why many households who would financially benefit from bankruptcy do not actually file for bankruptcy. White (1998) found that while at least 15 percent of households would benefit financially from bankruptcy, only about one percent of households actually files each year. The author argues that some households do not file, even though it is financially beneficial to do so, because creditors do not always attempt to collect. She argues that others choose not to file immediately because they gain from having the option to file in the future. My findings imply that some households may not file for bankruptcy because they have weak social networks. Social networks may provide information about the required paperwork, recommend an attorney, reduce the stigma associated with bankruptcy, or increase awareness of it benefits. Thus,

without strong social networks, some households may not file for bankruptcy, even though it is financially beneficial to do so.

In addition, social networks may be able to explain the vast regional variation in bankruptcy rates. As shown in Lefgren and McIntyre (2009), bankruptcy rates vary drastically across locations. While some of the variation can be explained by legal and demographic characteristics, much of the variation in bankrupt rates remains unexplained. My findings suggest that households in one area may be more likely to file because their social networks have either increased their knowledge of the bankruptcy system, reduced the cost of finding an attorney, reduced the stigma associated with bankruptcy, or increased awareness of the benefits of bankruptcy.

Finally, social networks may be able to explain why bankruptcy rates have risen so dramatically over time. During the first half of the twentieth century, bankruptcy was a rare event; on average, only 15,000 households filed for bankruptcy each year. But the number of households filing for bankruptcy has grown steadily. Indeed, in 2010, over 1.5 million households filed for bankruptcy. Current research, however, has been unable to explain why the bankruptcy rate has risen so dramatically over time. My results suggest that the bankruptcy rate may have risen because social networks have diffused knowledge about the bankruptcy process.

2. PERSONAL BANKRUPTCY IN THE UNITED STATES

The United States has two primary procedures for personal bankruptcy--- Chapter 7 and Chapter 13. Debtors can choose between these two procedures.[1]

In a Chapter 7 case, debtors liquidate *some* of their assets while retaining certain "exempt" property. Specifically, homestead exemption laws protect a debtor's home equity while personal exemption laws protect a debtor's personal property (such as vehicles, jewelry, and cash).[2] As seen in Table 1, these exemption levels vary dramatically across states.[3] For example, in 1995, debtors in Arkansas, Florida, Iowa, Kansas, Oklahoma, South Dakota, and Texas could keep an unlimited amount of home equity while households in Delaware and Maryland could not keep any home equity.[4] After the debtor's nonexempt assets are liquidated, the proceeds are used to repay creditors. The debtor's remaining unsecured debts can then be

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[1] The empirical analysis uses data from the 1991-1995 Panel Study of Income Dynamics (PSID). Prior to 2005, all households could choose between a Chapter 7 and a Chapter 13 bankruptcy. In 2005, the Bankruptcy Code was amended to include a "means test" which was intended to preclude households with high income levels from filing under Chapter 7. Specifically, the "means test" requires all households with income above the state median to file under Chapter 13 of the Bankruptcy Code.
It should be noted that relief under Chapter 11 is also available to individual debtors, but few debtors choose that option because of its significant cost.
[2] Personal property exemption laws are notoriously difficult to quantify. Like prior works, I collect information on the personal property exemption levels pertaining to automobiles, cash, near cash financial assets, and jewelry. I also collected information on wildcard exemptions.
[3] Where the law permits households to choose a federal exemption, I use the federal exemption if it is higher than the state exemption.
[4] For a further discussion of exemption laws and their impact on a household's bankruptcy decision, see Miller (2010).

discharged.[5] Under Chapter 7 of the Bankruptcy Code, the debtor may keep all of his future earnings.

As an alternative to Chapter 7, debtors may file for bankruptcy under Chapter 13 of the Bankruptcy Code. Under Chapter 13, the debtor retains all of his assets and instead agrees to repay some of his debts using his future earnings. Specifically, the debtor pays his projected monthly disposable income (the difference between his monthly income and monthly budgeted living expenses) into a Chapter 13 repayment plan. The proceeds of the Chapter 13 repayment plan are distributed among the debtor's creditors. After making payments for three to five years, the case is closed and any remaining debts are discharged.[6]

Aside from the financial benefit, bankruptcy has numerous non-pecuniary benefits. Most notably, when a debtor files under either bankruptcy chapter, creditors must stop all collection efforts; this means that creditors must cease all foreclosure proceedings and wage garnishments. In addition, creditors generally cannot send the debtor correspondence or telephone the debtor.

Bankruptcy, however, can be a costly endeavor--- debtors must pay both a court filing fee and attorney fees. These fees can be quiet high, considering that the typical debtor has limited funds and credit. As an example, filing fees are set by U.S. statute--- in 1995, debtors were required to pay a $140 filing fee when they filed for bankruptcy. Attorney fees, on the other hand, vary across location. When interviewing attorneys in four cities in 1990 and 1991, Braucher (1993) found that their fees averaged $1,025 for a Chapter 13 bankruptcy. And these fees have continued to rise over time--- it is estimated that the median attorney fee for a Chapter 13 bankruptcy was $2,000 in 2007 (U.S. GAO Report 2008).[7] In addition, to the filing fee and attorney fees, there are many non-pecuniary costs associated with filing for bankruptcy, including a future inability to obtain credit and emotional strain.

Networks may affect a household's bankruptcy decision in many ways: they could provide information about the bankruptcy system and provide insight into the necessary paperwork. In addition, discussing the bankruptcy process may decrease the stigma associated with bankruptcy. Moreover, social networks could alert households to all the benefits of bankruptcy--- both the monetary gain that can be associated with filing for bankruptcy as well as the non-pecuniary benefits. Finally, by recommending a lawyer, social networks may reduce the search costs associated with finding an attorney.

3. BACKGROUND LITERATURE

Social networks impact a wide array of behavior. For example, by defining networks using the individual's language spoken at home and PUMA, Bertrand et al. (2000) found that

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[5] Most unsecured debts, including credit card debts, installment loans, medical debts, unpaid rent and utility bills, tort judgments, and business debts, can be discharged under Chapter 7.
[6] Some debts which are not dischargeable under Chapter 7 including marital property settlements, debts from fraud and defalcation, embezzlement and larceny, can be discharged under Chapter 13 of the Bankruptcy Code. Thus, the Chapter 13 discharge is often referred to as a "super discharge."
[7] For additional information on attorney fees and chapter choice, see Lefgren et al. (2010).

social networks impact welfare participation. Similarly, by defining networks using a woman's racial group and zip code, Aizer and Currie (2004) found that social networks impact the use of publically funded prenatal care. Likewise, using language group and Census Sub-Division to define networks, Deri (2005) found that social networks impact the health care utilization rates. However, to date, no one has examined the impact of social networks on a household's bankruptcy decision.

Prior empirical works documented a positive correlation between a household's bankruptcy decision and its neighbors' bankruptcy decisions by regressing a household's bankruptcy decision on the lagged filing rate in the household's area. For example, using household level data from 1984-1995, Fay, Hurst, and White (2002) found that households are more likely to file for bankruptcy if they live in a district that had a higher filing rate in the previous year. Because their regressions included state and year fixed effect, the authors argued that their results likely reflected local differences in the level of bankruptcy stigma or the influence of information cascades. Using an analogous data set, Han and Li (2004) found that households are more likely to file for bankruptcy if they live in a state that had a higher filing rate in the previous year. Because their regressions included region and year fixed effects, the authors also argued that their results likely reflect stigma or network effects. Cohen-Cole and Duygan-Bump (2008) also showed that households are more likely to file for bankruptcy if they live in a neighborhood with a high bankruptcy rate. Their regressions included the filing rate within a mile of the respondent and the filing rate over a one to four mile radius of the respondent. Both factors were found to have a positive impact on a household's bankruptcy decision. However, as will be discussed in the following section, these regressions are plagued with omitted variable bias and therefore cannot accurately estimate the impact of social networks on a household's bankruptcy decision. As an example, the regressions could not distinguish the effect of networks from unobserved time varying neighborhood characteristics such as the number of advertisements for bankruptcy attorneys. Of additional concern is the broad definition of neighborhood; Fay, Hurst, and White (2002) and Han and Li (2004), define neighborhoods at the district and state level respectively.

This paper more accurately estimates the role of social networks on a household's bankruptcy decision. As described in more detail below, I employ an empirical strategy that is consistent with Deri (2005), Aizer and Currie (2004), and Bertrand, Luttmer, and Mullainathan (2000)--- I use county and racial variation to identify network effects. Thus, my empirical strategy asks whether being surrounded by others of the same racial group increases bankruptcy use more for those from racial groups with high filing rates. The richness of my dataset allows me to control for omitted variables to a greater degree than many other non-experimental studies. In particular, I include county-year fixed effects and racial group fixed effects. I also control for the direct effect of the density of the racial group in the county. To test for any remaining omitted variable bias, as described in section 6.1, I use an instrumental variables approach, I explore the effect of dropping covariates as well as adding household fixed effects. Finally, unlike previous bankruptcy papers in which neighborhoods were defined at the district or state level, in this paper, neighborhoods are defined at the county level--- while earlier works used the

lagged filing rate in a household's district or state level, I use the lagged filing rate in the household's county of residence.[8]

4. DATA

To estimate the impact of social networks on a household's bankruptcy decision, I use data from the 1991-1995 Panel Study of Income Dynamics (PSID). In 1996, the PSID asked respondents whether they had ever filed for bankruptcy, and if so, in what year(s). My data set is a combined cross-section, time-series sample of PSID households from 1991-1995.[9]

During each of these years selected, the PSID collected information on households' financial and demographic characteristics. For example, each year, the PSID collected data on a household's labor income, changes in the household's labor income, family size, age of the household head, education of the household head, marital status of the household head, and the race of the household head. In addition, the PSID collected data on homeownership and business ownership.

As discussed in the institutional background, a household's financial benefit from filing a Chapter 7 bankruptcy equals the amount of debt discharged less any nonexempt assets the household must give up. Therefore, for each year, I construct the financial benefit of a Chapter 7 bankruptcy in year t, which is given by:

$Financial\ Benefit_{it} = Debt_{it} - max[Assets_{it} - Exemption_{it},\ 0]$

where $Debt_{it}$ is the value of household i's unsecured debt in year t, $Assets_{it}$ include a household's home equity, equity in automobiles, and financial assets, and $Exemption_{it}$ is the applicable exemption level.[10,11]

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[8] Due to limitations in the court's data collection, I cannot use the lagged filing rate at a smaller geographic level. Bankruptcy filing rates, for example, are not available at the zip code or census tract level.

[9] This dataset is similar to that used in Fay, Hurst, and White (2002). In order for a particular household to be included by my sample, it must have answered the PSID questionnaire in 1996. Households that are in the sample for 1991-1995 are also included for any of the additional years for which data are available. I used the confidential PSID geocodes to assign households to their counties of residences in each year of the sample. Because I use PSID weights, the sample is representative of the general population. Finally, I utilize similar demographic and financial variables as Fay, Hurst, and White (2002).

[10] While the PSID collects information on home equity on an annual basis, it only collects information on unsecured debt and non-housing wealth every four years. As a result, like Fay, Hurst, and White (2002), I used the 1989 data to construct unsecured debt and non-housing wealth measures for each of the years 1991-1993 and the 1994 data to construct unsecured debt and non-housing wealth measures for 1994-1995. As a result, my measure of financial benefit is subject to measurement error. However, Fay, Hurst, and White (2002) note that this measurement error does not significantly alter the results.

[11] I collected information on the exemption levels in place in each year which pertained to equity in owner-occupied homes, vehicles, cash, near cash financial assets, and jewelry. The exemption levels are adjusted by the appropriate amount if the household contains a married couple. When state laws permit households to choose federal exemptions, I use federal exemptions if they are higher than the state exemptions.
Unlike Fay, Hurst, and White (2002), Fay, Hurst, and White (1998), and Elul and Subramanian (2002), I do not lump together homestead and non-homestead exemptions--- by lumping these exemptions together, earlier works assumed that households take advantage of the various bankruptcy exemptions by converting assets from nonexempt to exempt categories where possible. The Bankruptcy Code, however, specifically prohibits this type of behavior. Instead, my measure of nonexempt assets equals the household's non-exempt home equity, plus its non-exempt

Finally, in 1996, the PSID asked households if between 1991 and 1995, a creditor had ever called or come to see you to demand payment, their wages had been attached or garnished by a creditor, or a lien had been filed against their property because they could not pay a bill, and if so, in which year(s).

Table 2 shows summary statistics by race. Like Aizer and Currie (2004), I distinguish three racial groups: African-Americans (blacks), non-Hispanic whites (whites) and Hispanics.[12] The racial groups exhibit substantial variation in bankruptcy rates; blacks have the highest level of bankruptcy use followed by whites and then Hispanics. Hispanics, however, would gain the most, financially from filing for bankruptcy, followed by blacks and then whites. Finally, whites have the highest household labor income, followed by Hispanics and then blacks. In terms of demographic variables, Hispanic households are younger, while black households are less likely to be married. White households are more likely to own a business or a home.

5. EMPIRICAL STRATEGY

As mentioned above, previous works on personal bankruptcy used the state's lagged filing rate as a proxy for a household's social network. These works estimated regressions such as the following:

$$\Pr(Bankrupt_{i,s,t}) = \beta_1 \overline{Bankrupt}_{s,t-1} + \beta_2 X_{i,t} + \beta_3 Z_{s,t-1} + \beta_4 REGION_s + \beta_5 YEAR_t + \varepsilon_{i,s,t} \qquad (1)$$

where i indexes the household, s indexes the state, and t indexes the year. $Bankrupt_{i,s,t}$ is a dummy variable which equals one if the household filed for bankruptcy in year t, $X_{i,t}$ is a vector of household characteristics, $Z_{s,t-1}$ is a vector of time-varying state characteristics from the previous year, $REGION_s$ is a vector of region fixed effects, $YEAR_t$ is a vector of year fixed effects and $\overline{Bankrupt}_{s,t-1}$ is the filing rate in state s in the previous year.[13] In these regressions, $\overline{Bankrupt}_{s,t-1}$ serves as a proxy for the household's social network. This specification, however, is problematic as assumes that contacts are randomly distributed within a neighborhood. Thus, it suffers from the "reflection problem" (Manski, 1993) which asks whether individual behavior depends on the behavior of the group (social effects) or whether individuals in a group behave similarly because they are subject to the same shocks (correlated effects). The reflection problem is caused by two types of omitted variable bias: omitted personal characteristics that are correlated with $\overline{Bankrupt}_{s,t-1}$ and omitted state level characteristics that are correlated with $\overline{Bankrupt}_{s,t-1}$. As an example of the former, households living in a poorer area may be less financially savvy. As an example of the later, neighborhoods with numerous advertisements for bankruptcy attorneys may increase an individual's probability of bankruptcy as well as the bankruptcy filing rate in the neighborhood.

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personal property.
[12] Like Aizer and Currie (2004) I exclude household heads who are Asian, American Indian, or of "other" or unknown race. These households total less than 3 percent of my sample.
[13] Fay, Hurst, and White (2002) included state fixed effects and the lagged filing rate in the household's district in the previous year.

Like, Bertrand, Luttmer, and Mullainathan (2000), Aizer and Currie (2004), and Deri (2005), to measure the impact of social networks on a household's bankruptcy decision, I measure a household's network using the number of people the household interacts with in combination with the attitudes and knowledge of those people towards bankruptcy. Thus networks are defined as:

*NETWORK$_{c,r}$ = (Density of racial group r in county c in year t)$_{c,r,t}$ * (bankruptcy knowledge and attitudes of others from racial group r who live in county c in year t)$_{c,r,t}$*

The first component, termed by Bertrand et al. (2000) as "contact availability," measures the quantity of contacts. It is a proxy for the number of people the household interacts with; the more people of the same racial group who live in the county, the larger the available contacts.[14] Similar to prior works, the measure of contact availability is defined as follows:

$$CA_{c,r,t} = \ln\left(\frac{C_{c,r,t}/A_{c,t}}{R_{r,t}/T_t}\right)$$

where $C_{c,r,t}$ is the number of people in county c who belong to racial group r in year t, $A_{c,t}$ is the number of people who live in county c in year t, $R_{r,t}$ is the total number of people in the country who belong to racial group r in year t, and T is the total number of people in the country in year t. Dividing by $R_{r,t}/T$ prevents me from underweighting smaller racial groups. However, as shown in section 6.3, my results are robust to alternative measures of contact availability. The second component is my quality measure; the more people of the same race who have filed for bankruptcy, the greater the information provided. The above formula suggests that I proxy the knowledge and attitudes of others from the same racial group in county c with the filing rate of racial group r in county c (excluding household i) in year t, which I refer to as $\overline{Bankrupt}_{(-i)c,r,t}$.

However, $\overline{Bankrupt}_{(-i)c,r,t}$ may reflect unobserved characteristics that a household has in common with other households from the same racial group living in the same area. As a result, using this measure could introduce omitted variable bias. Therefore, like Bertrand et al. (2000) and Deri (2005), I use $\overline{Bankrupt}_r$ the bankruptcy filing rate of the racial group in the United States.[15]

Thus, my primary specification is given by:

$$Bankrupt_{i,c,r,t} = \beta_1 CA_{c,r,t} * \overline{Bankrupt}_r + \beta_2 CA_{c,r,t} + \beta_3 X_{i,t} + \beta_4 COUNTY_c * YEAR_t + \beta_5 RACE_{i,r} + \varepsilon_{i,c,r,t} \quad (2)$$

where i indexes the household, c indexes the county, r indexes the racial group, and t indexes the

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[14] Bertrand, Luttmer, and Mullainathan (2000), Aizer and Currie (2004), and Deri (2005) all define a household's social network in a similar manner. For example, Aizer and Currie (2004) use the number of people in one's racial group in one's zip code as their measure of "contact availability." Bertrand, Luttmer, and Mullainathan (2000) use the number of people in one's Public Use Microdata Area who speak one's language as their measure of "contact availability." Similarly, Deri (2005) uses the number of people in one's Census Sub-Division who speak one's language as her measure.

[15] The U.S. Bankruptcy Court does not collect information on race. Therefore, this variable is not available on an annual basis. I collect this information from the 2001 Consumer Bankruptcy Project (Warren, 2004), which estimates the bankruptcy rate by race. Studies by the Institute for Financial Literacy (2009, 2010, and 2011 Annual Consumer Bankruptcy Demographics Report) show that these rates do not vary significantly over time. As shown in section 6.2, my results are robust to alternative quantity measures.

year. *Bankrupt$_{i,c,r,t}$* is a dummy variable which equals one if the household files for bankruptcy in year *t*. Again, *CA$_{c,r,t}$* denotes contact availability and $\overline{Bankrupt}_r$ is the filing rate of racial group *r*. *X$_{i,t}$* is a vector of household characteristics, *COUNTY$_c$ *YEAR$_t$* is a vector of county-year fixed effects, and *RACE$_{i,r}$* is a vector of racial group fixed effects. I do not include $\overline{Bankrupt}_r$ in my regressions because it is subsumed by race fixed effects. By including *COUNTY$_c$ *YEAR$_t$* fixed effects, I can control for unobserved neighborhood characteristics. Similarly, by including *RACE$_{i,r}$* fixed effects, I can control for unobserved racial group characteristics, such as preferences. Finally, directly including *CA$_{c,r,t}$* controls for any omitted personal characteristics that are correlated with *CA$_{c,r,t}$*.

Two potential sources of omitted variable bias remain. The first potential source are omitted personal characteristics that are correlated with *CA$_{c,r,t}$**$\overline{Bankrupt}_r$. Such a correlation would arise if individually differentially self-select away from their racial group. I investigate this plausibility by instrumenting *CA$_{c,r,t}$* with the number of people from racial group *r* in the entire MSA. As seen in section 6.1, it is unlikely that my results are driven by this differential selection. Additionally, my results could be biased by unobservable household characteristics. If unobservable characteristics drive my results, then increasing the set of unobservables by treating observable characteristics as unobservable would have a large impact on the estimate of network effects. Additionally, if unobserved characteristics drive my results, adding household fixed effects would have a large impact on the estimate of network effects. In section 6.1, I also show that it is also unlikely that my results are driven by omitted household level characteristics.

6. ESTIMATION

6.1 The Probability of Bankruptcy

Table 3 presents the main results. As detailed in equation 2, I estimate a linear probability model for bankruptcy in which the independent variables include a measure of contact availability (*CA$_{c,r,t}$*), the interaction of *CA$_{c,r,t}$* with the bankruptcy filing rate of the household's racial group ($\overline{Bankrupt}_r$), household characteristics, racial group fixed effects[16], and county-year fixed effects. [17,18] The household characteristics include dummy variables that denote whether a creditor called to demand payment, whether wages were garnished, or whether a lien was placed on property, as well as the head's marital status. In addition, as in Fay, Hurst, and White (2002), I include the financial benefit of bankruptcy (*FinBen$_{it}$*)[19], *FinBen$_{it}^2$*, the

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[16] Households in the PSID are asked to self identify their racial group.

[17] Like Bertrand et al. (2000), Aizer and Currie (2004), and Deri (2005), I estimate a linear probability model instead of a logit or probit model. As explained in Bertrand et al. (2000), probits and logits become computationally infeasible in the presence of 9,000 county-year fixed effects. As a specification check, I estimate probit and logit models without the fixed effects and find similar results.

[18] As in Fay, Hurst, and White (2002), standard errors are corrected using the Huber/White procedure, which allows error terms for the same individual to be correlated over time.

[19] For computational ease, Financial Benefit is measured in $10,000.

household's labor income, the reduction in the household's labor income[20], age, age squared, years of education, family size, a dummy variable if the household owns a business, and a dummy variable if the household owns a home.

As seen in the first column of Table 3, the interaction term is significant and positive, showing that social networks are important in a household's bankruptcy decision. Other coefficients have the expected signs. Like Fay, Hurst, and White (2002), I find that having a higher financial benefit of bankruptcy increases the probability of filing for bankruptcy. This finding supports Fay, Hurst, and White's (2002) hypothesis that households respond to financial incentives in making their bankruptcy decisions. Additionally, like Fay, Hurst, and White (2002), my results indicate that adverse events do not affect the likelihood of bankruptcy; the variable that denotes the change in income is not statistically significant. As expected, results show that higher household labor income decreases the probability of filing for bankruptcy. Interestingly, however, households are only responsive to some collection methods. Before a household files for bankruptcy, a creditor may call or come to see the household to demand payment, garnish wages, or place liens on property.[21] Regression results show that wage garnishment and liens do not have an impact on the household's probability of bankruptcy. However, if a creditor calls or comes by to demand payment, a household is more likely to file for bankruptcy.

To interpret the network coefficients, I follow Bertrand et al. (2000). Consider the model

$$Bankrupt_{i,c,r,t} = \beta_0 + \beta_1 CA_{c,r,t} * \overline{Bankrupt}_r + \beta_2 CA_{c,r,t} + \beta_3 X_{i,t} + \beta_4 COUNTY_c * YEAR_t + \beta_5 RACE_{i,r} + \varepsilon_{i,c,r,t}$$

where β_0 is a measure of policies that influence welfare participation. It is scaled such that a one percentage point increases in β_0 leads to a one percentage point increase in bankruptcy *in the absence of network effects*. However, in equilibrium, changes in policy leads to both a direct effect on bankruptcy, β_0, and an indirect effect via networks. Taking the average of both sides by racial group and differentiating with respect to β_0 yeilds:

$$\frac{dBankrupt_r}{d\beta_0} = 1 + \overline{CA}_r * \frac{d\overline{Bankrupt}_r}{d\beta_0} \beta_1$$

where $\overline{CA}_r$ is the mean contact availability for racial group r. Solving this equation shows that the extra change induced by networks is $1/(1 - \beta_1 \overline{CA}_r) - 1$. To get the response for the economy as a whole, like Bertrand et al. (2000), I take the weighted means over all the racial groups. These computations show that for a policy change that increases bankruptcy use by one percentage point in the absence of networks, social networks may raise the responsiveness by an additional 23 percentage points.

Because it is impossible to know the exact reach of the network, as an alternative specification, in the second column, I estimate network effects when contact availability is

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[20] As in Fay, Hurst, and White (2002), this is calculated as the reduction in a household's income between year *t-2* and *t-1* if income fell, or else zero.
[21] Recall from section 2 that these collection measures must stop when a household files for bankruptcy.

measured as the larger Metropolitan Statistical Area (MSA).[22] The estimates are quiet similar to those found in the first column.

My results could be biased by omitted personal characteristics that are correlated with $CA_{c,r,t} * \overline{Bankrupt_r}$. Such a correlation would arise if individually differentially self-select away from their racial group. For example, living away from your racial group may signal success if you are in a racial group with a high bankruptcy rate whereas it may signal bankruptcy proneness if you are in a racial group with a low bankruptcy rate. Such differential selection would cause the coefficient on the interaction term to be positive although no network effect exists. In the third column of Table 3, I use an instrumental variables approach to assess whether the positive results seen in column one are caused by households differentially self-selecting away from their racial group. To test this possibility, I instrument the interaction term at the county level with the interaction term at the larger MSA level. Therefore, this instrumental variables approach should reduce any bias caused by choice of residence. OLS and IV estimates are similar in magnitude; thus there is little evidence that my results are driven completely by differential selection.

As an additional robustness check, I examine whether unobservable household characteristics drive my results. If unobservable characteristics drive my results, then increasing the set of unobservables by treating observable characteristics as unobservable would have a large impact on the estimate of network effects. In the fourth column of Table 3, I only include contact availability, racial group fixed effects, county-year fixed effects, and the interaction between CA and bankruptcy filing rate of the racial group. In the fifth column I also include demographic characteristics: family size, dummy variables for the head's marital status, the head's age, age squared, and the head's education. In both specifications, the coefficient on the interaction term is positive, significant, and of a similar magnitude to my primary specification. Similarly, to examine whether unobservable household characteristics drive my results, in the sixth column I include family fixed effects.[23] With the inclusion of family fixed effects, identification is based on changes over time. As seen in the sixth column, the magnitude of the coefficients remains similar even when these fixed effects are included. However, it should be noted that due to the decrease in sample size, the standard errors increase.

6.2 Parameter Heterogeneity

The impact of social networks may vary across households. In Table 4, I examine the heterogeneous responses across observable groups; all regressions control for household characteristics as well as racial group and county fixed effects.

The magnitude of my point estimate does not differ based on a state's laws. In the first row of Table 4, I include the interaction between my network variable and a dummy variable that

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[22] The United States Office of Management and Budget (OMB) has defined 366 Metropolitan Statistical Areas. The OMB defines an MSA as one or more adjacent counties or county equivalents that have at least one urban core area of at least 50,000 persons plus adjacent territory that has a high degree of social and economic integration with the core as measured by commuting ties.
[23] Recall that my data set is a combined cross-section, time-series sample of PSID households from 1991-1995. On average, households appear in the sample for three years.

equals one if the state has a high exemption level.[26] Similarly, in the second row, I include the interaction between my network variable and a dummy variable that equals one of the state does not allow wage garnishment. The coefficients on these interaction terms are insignificant, suggesting that my results are not driven by these state laws.

In the next four rows, I interact my network variable with the household's labor income, financial benefit of bankruptcy, assets, and debts. Again, the coefficients on these interaction terms are insignificant, suggesting that the impact of social networks does not vary based on these observable household characteristics.

6.3 Specification Checks

In Table 5, I show that my results are robust to different measures of contact availability. In the first row, I use the level version of the current log measure of contact availability, $\frac{C_{c,r,t} / A_{c,t}}{R_{r,t} / T_t}$. In the second row, I use the unadjusted faction in the area that is in one's racial group, $C_{c,r,t} / A_{c,t}$. In the third row, I use the log of this measure, $\ln(C_{c,r,t} / A_{c,t})$. All three measures produce positive and significant results.

My results are also robust to different measures of $\overline{Bankrupt}_{(-i)c,r,t}$. As noted above, $\overline{Bankrupt}_{(-i)c,r,t}$ may reflect unobserved characteristics that a household has in common with other households from the same racial group living in the same area. As a result, using this measure could introduce omitted variable bias. Therefore, like Bertrand et al. (2000) and Deri (2005), instead, I use $\overline{Bankrupt}_r$ the mean bankruptcy rate of the racial group in the United States. In row 4, as an alternative proxy, I use $\overline{Bankrupt}_{c,t-1}$. This alternative measure also produces a positive and significant result.

7. CONCLUSION

In this paper I use information on county and race to show that social networks have a positive impact on a household's bankruptcy decision. Households tend to interact with others from their racial group. Hence, households who live in a county with numerous households of their own racial group will have a larger pool of available contacts. Like Bertrand et al. (2000), Aizer and Currie (2004), and Deri (2005), I ask whether increased contact availability raises the probability of bankruptcy more for households from racial groups with high bankruptcy filing rates. In support of network effects, I find a positive and significant coefficient on the interaction between contact availability and the bankruptcy filing rate of one's own racial group.

Understanding the impact of social networks on a household's bankruptcy decision has important policy implications. For example, many recent papers have focused on assessing the

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[26] To determine whether a state has a high or low exemption level, I add the personal and homestead exemption levels together. For my analysis, I split total asset exemption levels in half.

impact of consumer credit regulations (including exemption levels, garnishment laws and usury laws) on a household's bankruptcy decision. My findings suggest that estimates put forth in those prior papers are too low--- social networks will increase these elasticities through multiplier effects.

In a broader context, this paper shows that households consult their social networks when making financial decisions. It raises the question: do households consult their social networks when making other financial decisions? Further work should be done to investigate whether some households purchased subprime loans because of their social networks. Similarly, further work should be done to investigate whether some households avoided foreclosure because their social networks showed them how to take advantage of the many government assistance programs. The findings put forth in this paper suggests that financial education programs may benefit more than those households directly being helped.

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Table 1: Exemption Levels by State, 1995

	Homestead Exemption Level	Personal Property Exemption Level
Alabama	5,000*	3,000*
Alaska	54,000	4,400*
Arizona	100,000	1,150*
Arkansas	unlimited	1,400^e
California	75,000	1,900*
Colorado	30,000	500*
Connecticut	75,0000*	2,500*
Delaware	0	500
District of Columbia	15,000*	3,425*
Florida	unlimited	2,000*
Georgia	5,000*	1,400*
Hawaii	20,000^a	1,000*
Idaho	50,000	1,500*
Illinois	7,500*	3,200*
Indiana	7,500*	4,000*
Iowa	unlimited	1,300*
Kansas	unlimited	20,000*
Kentucky	5,000*	3,500*
Louisiana	7,500*	0
Maine	12,500*	2,900*
Maryland	0	5,500*
Massachusetts	100,000	825*
Michigan	15,000*	0
Minnesota	200,000	2,000*
Mississippi	75,000*	10,000*
Missouri	8,000	2,250^f
Montana	40,000*	1,200*
Nebraska	25,000*	0
Nevada	125,000	15,000*

Note: Personal exemption levels apply to wildcard, automobiles, cash, near cash financial assets and jewelry exemptions.

* Exemption can be doubled if married
a. Exemption is 30,000 if married
b. Exemption is 33,000 if married
c. Exemption is 7,500 if married
d. Exemption is 10,000 if married
e. Exemption is 2,900 if married
f. Exemption is 3,900 if married
g. Exemption is 6,000 if married

Table 1 Continued: Exemption Levels by State, 1995

	Homestead Exemption Level	Personal Property Exemption Level
New Hampshire	30,000*	4,000*
New Jersey	15,000*	3,200*
New Mexico	30,000*	4,500
New York	10,000*	5,500*
North Carolina	10,000*	1,500*
North Dakota	80,000	1,200*
Ohio	5,000*	1,800*
Oklahoma	unlimited	3,000*
Oregon	25,000[b]	9,200*
Pennsylvania	15,000*	3,200*
Rhode Island	15,000*	3,200*
South Carolina	5,000*	2,200*
South Dakota	unlimited	4,000[g]
Tennessee	5,000[c]	4,000*
Texas	unlimited	30,000*
Utah	8,000[d]	1,500*
Vermont	75,000*	8,100*
Virginia	5,000*	2,000*
Washington	30,000	3,200*
West Virginia	15,000*	3,200*
Wisconsin	40,000	2,200*
Wyoming	10,000*	2,000*

Note: Personal exemption levels apply to wildcard, automobiles, cash, near cash financial assets and jewelry exemptions.

* Exemption can be doubled if married
a. Exemption is 30,000 if married
b. Exemption is 33,000 if married
c. Exemption is 7,500 if married
d. Exemption is 10,000 if married
e. Exemption is 2,900 if married
f. Exemption is 3,900 if married
g. Exemption is 6,000 if married

Table 2: Summary Statistics

	White	Black	Hispanic
Bankrupt	0.004	0.005	0.000
	(0.063)	(0.069)	(0.000)
Financial Benefit	-37,232.77	-6,901.66	-999.99
	(91,098.720)	(25,909.370)	(5708.751)
Creditor Called [a]	0.035	0.046	0.035
	(0.185)	(0.210)	(0.185)
Wages Garnished [a]	0.000	0.000	0.000
	(0.021)	(0.012)	(0.000)
Lien on Property [a]	0.002	0.001	0.000
	(0.042)	(0.030)	(0.000)
Household Labor Income	37,833.520	18,489.970	20,078.630
	(41,253.390)	(21,831.180)	(18950.970)
Reduction in Labor income [b]	-3,870.527	-2,215.858	-3,658.274
	(16,291.640)	(7,022.220)	(9017.738)
Age of Head	45.441	42.700	30.816
	(15.932)	(14.379)	(6.062)
Years of Education	13.148	11.792	10.342
	(2.777)	(2.733)	(3.610)
Family Size	2.501	2.496	3.056
	(1.421)	(1.565)	(1.278)
Single [a]	0.168	0.360	0.317
	(0.374)	(0.480)	(0.470)
Married [a]	0.550	0.244	0.526
	(0.498)	(0.430)	(0.504)
Divorced [a]	0.169	0.188	0.038
	(0.374)	(0.391)	(0.192)
Separated [a]	0.023	0.100	0.072
	(0.151)	(0.299)	(0.261)
Own Business [a]	0.167	0.034	0.023
	(0.373)	(0.181)	(0.152)
Own home [a]	0.563	0.269	0.381
	(0.496)	(0.444)	(0.491)
Sample Size	15,964	10,117	51

Note: Standard deviations are reported in parentheses

[a] Indicated a dummy variable (yes=1).

[b] The reduction in income equals the amount that household i's income fell, if income fell, or else zero.

Table 3: Regression Results

	(I)	(II)	(III)	(IV)	(V)	(VI)
CA Measure	County	MSA	County	County	County	County
Estimation Technique	OLS	OLS	IV	OLS	OLS	OLS
Contact Availability*	0.591**	0.717**	0.503**	0.621**	0.650**	0.669
Bankruptcy Filing Rate of Racial Group	(0.265)	(0.291)	(0.246)	(0.264)	(0.269)	(0.562)
Contact Availability	-0.006	-0.010**	-0.005	-0.006*	-0.007*	-0.012
	(0.004)	(0.005)	(0.003)	(0.004)	(0.004)	(0.009)
Financial Benefit	8.762E-05*	9.302E-05*	8.57E-05			3.850E-09
	(0.000)	(0.000)	(0.000)			(0.050)
Financial Benefit Squared	4.03E-07	3.57E-07	3.45E-07			-2.130E-07
	(0.000)	(0.000)	(0.000)			(0.042)
Creditor Called	0.022***	0.017**	0.018***			0.016
	(0.007)	(0.007)	(0.007)			(0.010)
Wages Garnished	-0.006	-0.004	-0.004			0.243
	(0.026)	(0.027)	(0.027)			(0.034)
Lien on Property	0.053	0.051	0.051			0.076
	(0.045)	(0.059)	(0.059)			(0.065)
Household Labor Income	-5.743E-08**	-7.010E-08**	-7.054E-08***			-2.130E-08
	(0.000)	(0.000)	(0.000)			0.000
Household Labor Income Squared	7.080E-14**	9.057E-14**	9.050E-14**			2.160E-14
	(0.000)	(0.000)	(0.000)			(0.000)
Reduction in Labor Income	0.000	0.000	0.000			-8.68E-09
	(0.000)	(0.000)	(0.000)			(0.000)
Own Business	-0.002	0.000	0.000			0.002
	(0.002)	(0.002)	(0.002)			(0.003)
Own Home	-0.001	-0.002	-0.001			0.003
	(0.002)	(0.002)	(0.002)			(0.003)
Demographic Characteristics	Yes	Yes	Yes	No	Yes	Yes
Racial Group Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
County-Year Fixed Effects	Yes	No	No	Yes	Yes	Yes
MSA-Year Fixed Effects	No	Yes	Yes	No	No	No
Household Fixed Effects	No	No	No	No	No	Yes

Standard errors are corrected using the Huber/White procedure, which allows error terms for the same household to be correlated over time.

All regressions use the PSID family weights.

Demographic characteristics include dummy variables for marital status, age, age squared, family size, and education.

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 4: Parameter Heterogeneity

	Coefficient on Network	Coefficient on Interaction Term
(1) High Exemption * Network	0.633**	-0.085
	(0.310)	(0.192)
(2) No Garnishment * Network	0.595**	-0.150
	(0.267)	(0.182)
(3) Income * Network	0.549**	0.000
	(0.264)	(0.000)
(4) Financial Benefit * Network	0.582**	-0.011
	(0.266)	(0.022)
(5) Assets * Network[a]	0.566**	0.000
	(0.264)	(0.000)
(6) Debts * Network[b]	0.568**	0.000
	(0.262)	(0.000)

Standard errors are corrected using the Huber/White procedure, which allows error terms for the same household to be correlated over time.

All regressions use the PSID family weights.

All regressions include the financial and demographic variables detailed in Table 3. In addition, all regressions include racial group and county-year fixed effects.

* significant at 10%; ** significant at 5%; *** significant at 1%

a. Regression also includes a variable which denotes the household's assets.

b. Regression also includes a variable which denotes the household's debts.

Table 5: Sensitivity of Results to Different Measures

	Coefficient on Interaction Term	Coefficient on Contact Availability
(1) Measure contact availability as $(C_{c,r,t}/A_{c,t})(R_{r,t}/T_t)^{-1}$	0.504**	-0.006*
	(0.238)	(0.004)
(2) Measure contact availability as $C_{c,r,t}/A_{c,t}$	2.425***	-0.014
	(0.930)	(0.009)
(3) Measure contact availability as $\ln(C_{c,r,t}/A_{c,t})$	0.574**	-0.005
	(0.275)	(0.004)
(4) Measure Bankrupt$_{(-i)c,r,t}$ as Bankrupt$_{c,t-1}$	0.002**	-0.008
	(0.001)	(0.005)

Standard errors are corrected using the Huber/White procedure, which allows error terms for the same household to be correlated over time.

All regressions use the PSID family weights.

All regressions include the financial and demographic variables detailed in Table 3. In addition, all regressions include racial group and county-year fixed effects.

* significant at 10%; ** significant at 5%; *** significant at 1%