Credit Scores, Social Capital, and Stock Market Participation

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Abstract

We introduce average credit scores as an indicator of a community's social capital and present evidence that this measure is consistent with, but richer than, those used in the existing literature. As an application of this indicator, we show that households residing in communities with higher social capital are more likely to invest in stocks, even after controlling for a rich set of socioeconomic, preferential, neighborhood, and demographic characteristics. Consistent with the notion that social capital and trust promote stock investment, we find that, first, this association is more pronounced among the lower educated; second, social capital levels of the county where one grew up has a lasting influence on future stock investment; and third, investors have a greater chance of entering the stock market in the years after they relocate to higher-social capital communities.

Keywords: Trust, Social capital, Stock market participation, Credit scores

JEL: D14, G10, O16

1 Introduction

The past quarter century witnessed a renaissance of research on social capital and trust. Since the seminal work of Putnam (1993), the influence of social capital and trust has been underscored in explaining economic outcomes in various contexts, such as economic growth and development (Knack and Keefer, 1997), performance of institutions (Fukuyama, 1995; La Porta, Lopez-de-Silanes, Shleifer, and Vishny, 1997), and the rise of public schools (Goldin and Katz, 1999). More recently, Guiso, Sapienza, and Zingales (henceforth GSZ) document that greater social capital promotes financial developments (GSZ, 2004).

While there is broad recognition that social capital and trust influences financial and economic activities, concrete, data-based measures have remained elusive.[1] In the existing literature, social capital is often approximated by social traits, such as electoral participation and blood donations. These measures have been primarily applied to European countries, leaving a void in our understanding of how social capital may affect household financial decisions in the U.S.

In this paper, we make two contributions to the measurement of social capital and trust and their effects on household financial decisions. First, we propose a novel measure of social capital and trust—the average credit score of the residents of a community. Second, we examine how social capital and trust may influence U.S. household investors' financial decisions, with a particular focus on stock investments.

Trust underlies financial interactions.[2] For lenders, information about the borrowers trustworthiness has always helped guide lending decisions. In the U.S., credit bureaus collect and maintain data about the characteristics and repayment history of formal credit transactions. Based on these data, a credit score is estimated for each borrower, designed to

[1]Indeed, as Putnam (1995) famously wrote, "Since trust is so central to the theory of social capital, it would be desirable to have strong behavioral indicators of trends in social trust and misanthropy. I have discovered no such behavioral measures."

[2]Arrow (1972) was among the earliest authors who noted that trust was essential to commercial transactions, and wrote: "...virtually every commercial transaction has within itself an element of trust."

predict the future risk that the borrower will default and not repay the loan. Credit scores also, to a certain extent, can reveal an individual's underlying trustworthiness beyond the likelihood of defaulting on financial obligations. For example, Dokko, Li, and Hayes (2015) show that individuals' credit scores are strong predictors of personal committed relationship outcomes, even after controlling for credit market experiences. Indeed, in recent years, credit scores are also increasingly being used in other settings—such as employment—where trustworthiness needs to be verified.

In addition, recent work has shown that financial experiences influence individuals' perceptions and expectations.[3] Past experience with credit markets—as summarized in a credit score—may also be informative of trust in financial markets. Consumers with lower credit scores, for example, may have had negative experiences with financial and credit markets, and may feel more distrustful toward these markets because of these negative experiences. Furthermore, an individual living in such a community would have a greater chance of interacting with less trusting people, which may make herself less trusting (Alesina and La Ferrrara, 2002). Consistent with the notion that trusting attitude can be influenced by the trustworthiness of the people one interacts with, Fowler and Christakis (2010) find that cooperative behaviors tend to cascade in social networks. Motivated by these theoretical and empirical findings, we argue that the average credit score of a community serves as an informative indicator of its level of social capital and trust.

We first examine the validity of using average credit score of a community as a social capital indicator and compare it with other social capital measures. We use a large proprietary dataset—the Federal Reserve Bank of New York Consumer Credit Panel/Equifax data—to estimate average community credit scores. Credit scores are correlated with income, demographics, and shocks, and our analysis conditions on these local area characteristics to isolate the part of credit score that is orthogonal to such characteristics. After controlling for

[3]Investors who experienced prolonged periods of low stock returns are less likely to later invest in stocks (Malmendier and Nagel, 2011), and past experiences with inflation influence subsequent inflation expectations (Malmendier and Nagel, 2016).

an extensive array of observable community characteristics, the average community credit score is positively correlated with other community-level social capital measures used in the literature: the presidential election participation rate, the Census response rate, the number of civic associations and nonprofit organizations, and the quantity of blood donations; it is also negatively correlated with the rate of consumer complaints filed with the Federal Communications Commission, which we introduce as a measure of social *distrust*.

While each indicator should convey at least some information about a community's social capital, we next employ a principal component analysis to condense that information into one indicator of the latent social capital variable. We show that the community average credit score has the highest correlation with the main latent factor derived from all social capital indicators. Furthermore, a unique advantage of our proposed social capital indicator is that the average credit score can be estimated for small geographies, such as a census tract or even a street block, which is particularly appealing because the effects of social capital are likely more pronounced in more granularly-defined communities.

We then apply our measure of social capital—community average credit score—to study the patterns of equity market participation. This analysis is intimately related to a recent strand of literature that underscores the influence of social trust on investment behaviors (GSZ, 2008; El-Attar and Poschke, 2011; Georgarakos and Pasini, 2011; Giannetti and Wang, 2016; Gurun et al 2017).[4] Notably, GSZ (2008) argue that as the perceived probability of being cheated increases, stock investment becomes less likely; empirically, they show that areas with more social capital display greater trust and thus tend to have higher stock market participation.

Our empirical strategy shares many similarities with GSZ (2008), and we extend and complement their work in several important aspects. First, instead of examining how self-

[4] Numerous other theories, such as participation costs (Vissing-Jorgensen, 2002; Briggs, Cesarini, Lindqvist, and Östling, 2016), information barriers (Hong, Kubik, and Stein, 2004; Li, 2014), and certain behavioral biases (Haliassos and Bertaut, 1995; Malmendier and Nagel, 2011) have been proposed to account for the lack of stock market participation.

reported trust affects stock ownership, we link the level of social capital of the community where an investor resides with her stock investment decisions.[5] Second, we study a broad array of measures of social capital, including the one we introduce here—the community's average credit score—in order to assess their relative merit in accounting for variations in the propensity to invest in stocks. Third, to the best of our knowledge, this paper is the first that studies the relationship between social capital and stock market participation at individual investor level using data from large U.S. household surveys.[6]

Specifically, we link household balance sheet information in the Survey of Consumer Finances (SCF) and the Panel Study of Income Dynamics (PSID) to various indicators of trust and social capital. We find that consumers residing in areas with higher average credit scores are more likely to own equities—defined here as stocks and mutual funds—and to invest a greater share of their portfolio in equities. For example, our baseline SCF analysis indicates that investors living in a census tract with a one standard deviation higher average credit score have a 20 to 30 percent higher probability of owning equities. Conditional on owning equities, the share of equities in an investment portfolio is also 10 to 15 percent higher. Such a relationship holds against a rich set of socioeconomic, preferential, neighborhood, and demographic characteristics. In particular, our estimates are robust to controlling for neighborhood average stock ownership, suggesting that it is a factor that goes beyond the information sharing channel that was also shown in earlier studies to have a positive effect on stock investment (Hong, Kubik, and Stein, 2004; and Li, 2014). Interestingly, average credit scores stand out from other community-level measures of social capital in the U.S., which are found to be only weakly associated with the likelihood of stock investment.

[5] As a robustness check, we also use an assessment of the trusting behavior of the household provided by survey interviewers. We find a similar positive correlation between household trust and stock market participation as in GSZ (2008).

[6] Balloch, Nicolae, and Philip (2015) and Duarte, Siegel, and Young (2012) are the only related studies of U.S. investors we find. Balloch, Nicolae, and Philip (2015) use an Internet panel that is likely not representative of the U.S. population as nearly 70 percent of the panel's respondents are stock owners, many times higher than observed in representative household surveys and administrative tax data. Duarte, Siegel, and Young (2012) study peer-to-peer lending, which is used only by a small, select subpopulation of U.S. households.

To examine if such a relationship is causal, we first show that the association between the propensity to own stocks and community average credit score is stronger for investors with lower educational attainment and weaker among the college educated, a finding similar to that in GSZ (2004, 2008). We also show that the social capital level of the county where an investor grew up appears to have a lasting influence on her future stock ownership even years after moving out of that county.

Furthermore, we leverage the longitudinal structure of the PSID data and study stock investment dynamics. We find that investors who did not own stocks previously have a greater chance of entering the stock market a few years after they relocate to higher-score communities relative to comparable investors who did not move. This trend is consistent with the narrative that relocating to a high-score community allows the investor to interact with more trustworthy individuals and thereby develop more trust in financial markets. Our exercise focuses on stock market entries that are subsequent, instead of simultaneous, to relocation, thereby circumventing the endogeneity concerns to a certain extent.

The remainder of the paper proceeds as follows. Section 2 briefly discusses the theoretical background of social capital and introduces the community average credit score as one of its measures. Section 3 describes various data sources used in the paper and presents key summary statistics. Section 4 compares average credit scores with other measures of social capital. Sections 5 and 6 present static and dynamic analyses, respectively, of the relationship between average credit scores and stock investment. Section 7 concludes.

2 Conceptual Framework and Related Literature

2.1 Trust and Social Capital

In a widely cited definition from Putnam (1993), social capital is the "features of social life, networks, norms and trust that enable participants to act together more effectively to pursue shared objectives." Accordingly, societies with greater social capital tend to be more trusting, and more trusting societies are able to have stronger social connections, positive social norms, and lower transactional costs in economic activities. A voluminous literature has studied cross-country variations in trust and social capital, and how they help explain differences in economic growth (Putnam, 1993; Fukuyama, 1995; Knack and Keefer, 1997; La Porta, Lopez-de-Silanes, Shleifer, and Vishny, 1997; Algan and Cahuc, 2010). Our paper will follow the tradition of interpreting trust as a crucial component of social capital.

More recently, GSZ (2004) study the diverging growth paths of the north and south of Italy (a celebrated example of social capital and economic development). While both areas had similar levels of economic development in the late 1800s, the north of Italy had stronger social capital, in the form of social cohesion and trust in institutions. By the 20th century, the high social capital areas were more likely to develop financially, and had higher economic growth.

In a similar spirit, GSZ (2008) demonstrate that lack of trust contributes to the low rate of participation in stock markets. Individuals who trust others are 50 percent more likely to invest in stocks; among stock investors, those who trust others have a 15 percent higher stock allocation than the mean. Investing in stocks often depends on trust and cooperation between an investor and a financial intermediary—a trusting relationship from which both parties can benefit.[7] However, if the subjective probability of being cheated in this market increases, cooperation between market participants becomes less likely.

In spite of the increasing appreciation of the role of social capital in financial and economic developments, its measurement has been elusive to students of the subject. In the existing literature, trust—a central element of social capital—is routinely measured from household survey responses to the question: "generally speaking, would you say that most people can be trusted or that you have to be very careful in dealing with people?". However, the proper interpretation of responses to such survey questions remains a subject of active

[7] Trust in the financial intermediary can also increase an investor's willingness to take risks (Gennaioli, Schleifer, and Vishny, 2015), though this is an avenue that we do not explore in this paper.

debate (Glaeser, Laibson, Scheinkman, and Soutter, 2000; Fehr, Fischbacher, von Rosenbladt, Schupp, and Wagner, 2003; Karlan, 2005; Sapienza, Toldra-Simats, and Zingales, 2013).

Civic activity at the community level as a measure of social capital was popularized by the book *Bowling Alone* (Putnam, 1995). More recently, GSZ (2004) propose electoral participation and blood donations as social capital measures. Rupasingha, Goetz, and Freshwater (2006) extend measurement to include the number of civic activities and organizations in United States counties. The availability of these data is often restricted to a certain geographical levels (the county or state-level).

Objective behavioral-based measures of trust and social capital remain elusive. Trust functions as a pillar of financial interactions, and the ability of measuring trustworthiness is valuable in this sector.[8] Accordingly, we look to the financial sector for such a measure, and propose using the average credit score in a community as an indicator of social capital and trust in that community.

2.2 Community Average Credit Scores as an Indicator of Social Capital

A loan is a type of mutually beneficial opportunity that depends on trust between a lender and a borrower. To measure the degree to which a borrower can be trusted to repay a loan, financial services firms typically rely on credit scores, estimated by credit bureaus. Credit scores are designed to evaluate credit quality and predict the default risk of potential borrowers; borrowers with higher credit scores, on average, have lower default rates. Debt payment history—and how reliably payments were made—remains the most important determinant of one's credit score.[9]

[8] "In the absence of trust...many opportunities for mutually beneficial cooperation would be foregone", leading to economic underdevelopment (Arrow 1969). Lins, Servaes, and Tamayo (2017) also rely on the financial sector to measure social trust and social capital, but use firm-level stock price data.

[9] In addition, credit scoring also takes into account other factors, such as levels of indebtedness, length of the credit history file, credit limit utilization, and public judgments, such as tax liens and wage garnishment (Avery, Brevoort, and Canner, 2009).

We argue that credit scores contain signals that reveal underlying trustworthiness of an individual. To see this, consider the following conceptual framework. Broadly speaking, a person's default probability is affected by her willingness to repay debts, which we denote with ω, and her ability to repay, which we denote with η. Thus, one's credit scores, as a (noisy) indicator of her default probability, can be represented as

$$score = f(\omega, \ \ \eta) \ + \ \mu, \tag{1}$$

where μ is an error term. The willingness to repay debts, in turn, is closely related to an individuals underlying trustworthiness. Historically, lenders have long recognized a borrower's general trustworthiness and personality as important factors influencing her debt payment history and default probability. For example, Dokko, Li, and Hayes (2015) report that the credit reports garnered in the 1930s, in addition to debt repayment history and other financial data, collected information on borrowers' characteristics, reputation, habits, morals, and even illegal liquor traffic activities.[10]

Indeed, besides loan underwriting and pricing, credit scores are used extensively in the rental, labor, and auto insurance markets. For example, survey evidence suggests that up to 60 percent of employers, including the federal government, use credit checks in their hiring decisions, while nearly all auto insurance providers take credit record information into account in estimating the risk of car accidents (Chen, Corbae, and Glover, 2013). Many cell phone and cable companies also use credit score information in contract-based plans.

Furthermore, the levels and match quality of credit scores of a couple at the onset of their relationship have a pronounced predictive power regarding future relationship outcomes, even after controlling for the credit events the couple encounters, such as new debt acquisitions and financial distress (Dokko, Li, and Hayes, 2015).

That said, it is important to remind ourselves that credit scores can be low for reasons that

[10] For example, one of the credit reports prepared by the Retail Credit Company in 1934 included the following questions: "Does his record show he has been a steady and reliable man?" "Is his personal reputation as to character, honesty, and fair dealing good?" "Do you learn any illegal liquor traffic activities or domestic difficulties?"

have little to do with individuals' general trustworthiness, and such factors are summarized in the term of ability to repay, η. For example, many families with low credit scores have gone through a negative financial event because of economic hardship brought on by severely adverse events or job loss. As noted above, though, families with these negative financial experiences will be less likely to trust financial markets and institutions, in general (Alesina and La Ferrera, 2002; Graeber and Zimmerman, 2016).[11]

The past experience of a community's residents with financial markets may shape their perceptions and attitudes towards the market, and influence the level of trust and social capital of the community. For example, Malmendier and Nagel (2011, 2016) show that individuals' stock investment and inflation expectations are significantly influenced by their previous stock return and inflation experiences. In addition, banking crises also have persistent negative effects on measured individual trust, especially trust in social institutions (Graeber and Zimmerman, 2016). Thus, because credit scores contain information about past experiences with financial and credit markets, residents of a community with lower average credit scores may be more distrustful toward these markets due to past negative experiences.

At the community level, the experiences of residents with each other may shape the community's social trust and social capital. For example, as one encounters more cheaters or feels unfairly treated in personal interactions and business transactions, her trust of the society will be undermined. Indeed, recent research has found that individuals with low trust are more likely to have experienced a recent traumatic event or to belong to a group that has traditionally experienced discrimination (Alesina and La Ferrrara, 2002). On the other hand, exposure to more trustworthy people may help others overcome adversity, especially those with low social standing (Helliwell, Huang, and Wang, 2016). More broadly speaking, Jackson, Rodriguez-Barraquer, and Tan (2012) propose a framework studying how

[11]SCF survey data suggest that consumers who are assessed by the survey interviewers as more suspicious to the survey interviews are indeed less likely to rely on advice from financial institutions but more likely to stick with advice from friends, family, or themselves.

social network and social capital promote trust and cooperative behaviors, and Fowler and Christakis (2010) find that cooperative behaviors tend to cascade in social networks in a laboratory setup.

To summarize, we argue that credit score, as an indicator of one's willingness and ability to repay financial debt, contains information on an individual's underlying trustworthiness and previous experience with and attitudes toward financial markets and institutions. Accordingly, a community's average credit score reveals information on the levels of both trustworthiness and trust of its residents. Trustworthiness and trust in a community may also interact with and reinforce each other. Community average credit scores therefore serve as a sound indicator of the community's social capital in general—a proposition that we test later in the paper.

3 Data Description and Summary Statistics

Our study takes advantage of a rich array of data sources. In this section, we discuss the data source that we use to estimate community-average credit scores. We also introduce a wide range of other social capital indicators used in previous studies. For information on household stock investment we use the Survey of Consumer Finances (SCF) and the Panel Study of Income Dynamics (PSID). We are able to use the internal version of the SCF and restricted geo-coded version of the PSID, so both datasets can be linked to measures of social capital of a community. In order to control for community characteristics other than social capital, such as demographic compositions and contemporaneous economic conditions, we use data from the Census Bureau, the Bureau of Labor Statistics (BLS), the American Community Survey, the Federal Bureau of Investigation (FBI), and CoreLogic. Finally, to control for local stock ownership, we take advantage of the ZIP Code Statistics of Income (SOI) data released by the Internal Revenue Service. This section will introduce the primary data sources we use and present statistics of the key variables of our study.

3.1 The Equifax CCP Data

The Equifax CCP is a large proprietary dataset that follows a 5-percent random sample of U.S. consumers with valid credit histories (about 11 million individuals in recent quarters) on a quarterly basis. The data include fairly detailed consumer residence location information down to the census block level and extensive credit history data, including a credit score. We calculate the average credit score at both the census tract and county levels. A census tract has an average population of 4,000 of all ages. Relative to earlier studies on the subject, which typically focus on cross-country or cross-province variations, working with much smaller communities like census tracts allows us to measure social capital and analyze its influence in a more zoomed-in, focused way. Our analysis removes the census tracts that have fewer than 20 individuals in the sample.[12] We compute the average credit score for each quarter from the first quarter of 2001 to the fourth quarter of 2015. We then average the quarterly mean of credit scores of each tract and county to filter out high-frequency variations that are not necessarily reflecting differences in social trust and social capital. As shown in the top panel of table 1, over the 2001–15 period, our sample has more than 655 million observations of individual credit scores, with a mean of 690 and a standard deviation of 107. The standard deviations of the tract and county level average scores are 41 and 46, respectively, which are smaller than that of the individual score distribution but remain quite sizable, suggesting wide geographical variations in community average credit scores across the country.[13]

3.2 Other Measures of Trust and Social Capital

Our goal is to compare the community-average credit score to a wide range of social capital indicators employed in the existing literature to evaluate if our proposed indicator is consis-

[12]Because the Equifax CCP is a 5 percent random sample, we are roughly removing census tracts with a population smaller than 400.

[13]In addition, not shown in the table, standard deviations of the residuals of regressing the tract and county level average scores on their respective socioeconomic and demographic characteristics remain sizable.

tent with these existing indicators and possesses other desirable properties. In the existing research, the most consistently available indicators of social capital are due to Rupasingha, Goetz, and Freshwater (2006). They collect data, for each county, of U.S. Census participation rate, presidential election voting rate, number of nonprofit organizations, and number of societies and associations as social capital indicators.[14] As shown in the middle-panel of table 1, an average of about two thirds of the population responded to the U.S. Census; nearly 60 percent of the eligible population voted in presidential elections; and there are 6.3 and 1.4 nonprofit organizations and associations per 1,000 residents, respectively.

In addition, we include two additional social capital indicators. First, we follow GSZ and include the quantity of blood donations—provided by the U.S. Red Cross—as an indicator of social capital. Second, we use the number of Federal Communication Commission (FCC) complaints as additional (negative) indicators of trust and social capital in an area.[15] Arguably, a neighborhood where residents are frequently harassed by fraudulent calls tends to have lower social trust and social capital. Both blood donation and FCC complaints data are aggregated up to the county level to facilitate comparison. The mean of these two indicators are presented in the lower panel of table 1. On average, about 46 units of blood were collected and 1.8 complaints were filed per 1,000 residents, respectively.

3.3 Survey of Consumer Finances

Our main focus is household stock investment decisions. Two large U.S. household surveys—the SCF and PSID—provide such data with detailed household level socioeconomic, demographic, and financial characteristics, including qualitative reports on risk aversion. Our data include information on the census tract and county where the households reside, thereby allowing a merge of individual household investment decisions with measures of the community's social capital and other socioeconomic and demographic characteristics.

[14]We thank Professor Robert Putnam for pointing this data source to us. The data can be downloaded at http://aese.psu.edu/nercrd/community/social-capital-resources

[15]The FCC filing data can be accessed at https://www.fcc.gov/consumer-help-center-data

The SCF is conducted by the Federal Reserve Board every three years and is widely regarded as one of the most comprehensive sources of data concerning U.S. household balance sheets. These data have information on stock market participation status and share of stocks in financial portfolio. We use three waves of the SCF data collected in 2004, 2007, and 2010. During these years, the survey sample was geographically stratified using the 2000 U.S. decennial census. Consumer location information in the Equifax CCP data is also coded using the 2000 census, ensuring a higher-quality match. During the sample period, as presented in the left column of the top panel of table 2, only a small fraction (23 percent) of households directly own corporate equities (stocks).[16] Among those who own stocks, the share of stocks in their financial assets portfolio is about 11 percent, with a fairly large dispersion in the sample. In addition, the mean of wealth in the pooled 2004–10 SCF is about $437,000 in 2003 dollars, and mean income is about $69,000 (not shown). Both are comparable with external aggregates.[17]

The SCF also collects information on attitudes toward taking financial risk and investing. Consistent with the apparently low levels of stock ownership, most families also report being unwilling to take financial risk (table 2).[18] Moreover, the SCF data are collected by a trained field interviewer, either in person or on the phone. At the end of each completed interview, the interviewer assesses how the respondent interacted with the survey. Among these questions, the interviewer evaluates how suspicious the respondent was about the survey before the interview began. We use this interviewer assessment to identify families that were "not at all suspicious" of the interview, effectively creating a proxy for trusting attitudes. Note that, in contrast to the World Value Survey or SCCS measures, this measure

[16] Another 28 percent of families only own equities indirectly through tax-preferred retirement accounts. At its broadest definition, then, equity ownership in the U.S. is slightly above 50 percent.

[17] See Bricker, Henriques, Krimmel, and Sabelhaus (2016) for a comparison of SCF income and wealth estimates relative to those from income tax data. See Dettling and others (2015) for a more general comparison of SCF aggregates with external sources.

[18] Families that are "willing to take financial risks" are those that are either willing to take substantial or above average financial risk when making investments. Families willing to take average financial risks and those unwilling to take any financial risks are counted as not willing to take risk.

of trusting attitude in the SCF is not self-reported but is assessed by a third party (the interviewer). We include this interviewer-assessed measure of trust later in the regression analysis for robustness. About 56 percent of SCF families are coded as “trusting” by the field interviewer.

3.4 Panel Survey of Income and Dynamics

The PSID, unlike the SCF, is a longitudinal survey. It follows a core sample of households and their offspring over nearly 50 years.[19] From 1999 onwards, the PSID routinely collects some basic household financial information, including stock and checking account ownership and values. The PSID stock ownership is defined as including mutual funds but not including IRAs and retirement accounts. We use the PSID data for both cross-sectional analysis of stock ownership and dynamic analysis of stock market entries and exit.[20]

In the statistics presented in the right column of table 2, we note that the PSID stock ownership is quite similar to that of the SCF. However, the stock share in financial assets is higher in the PSID, likely due to the less-complete coverage of financial assets in the PSID than in the SCF. In addition, about 6 percent of the households in the PSID sample that did not own stock in a given year became stock investors two years later, and about 23 percent of stock investors in a given year owned no stocks two years later. Moreover, regarding attitudes toward financial risks, the PSID provides a risk tolerance index estimated using lottery questions similar to those in Barsky, Juster, Kimball, and Shapiro (1997). A greater value of the risk tolerance index indicates lower risk aversion, and the sample average is slightly above 1. Because these questions were only included in the survey in 1996, the tolerance index is available for only a fraction of the sample. Finally, 24 percent of the households relocated to a different census tract within two years, and we focus on these

[19]The PSID was an annual survey from 1968 to 1997, biennial afterwards.

[20]For the cross-sectional analysis, we keep the first observation of a household in the longitudinal panel that shares the same combination of location (census tract or county) and stock market participation status. Therefore, the PSID sample constructed for cross sectional analysis is a somewhat younger than the SCF sample.

households in our stock market entry and exit analysis.

3.5 Other Data Sources

In addition to individual characteristics, we also take into account potential effects of community characteristics other than trust and social capital on stock investment decisions. For community demographic compositions, we use statistics of the 2000 U.S. Decennial Census that include median income and racial, education, and age compositions. For local economic conditions, we use the Bureau of Labor Statistics unemployment rates, the CoreLogic data of house price growth, and the American Community Survey's income inequality measurements, all available at the county level. In addition, we use the FBI's violent crime rate statistics in our social capital measurement analysis. We also use SOI ZIP Code-level data on dividend income as a proxy of local average stock ownership. These data are released by the Internal Revenue Service, and are computed as the ratio of the number of filers with ordinary dividend income (line 9a of Form 1040) to the total number of filers in a given ZIP Code.[21] We use the public releases of the 2004, 2007, and 2010 SOI ZIP Code files, and match these data to the SCF and PSID data of the closest waves.

4 Average Credit Scores as an Indicator of Social Capital

In this section, we implement a sequence of statistical analyses to validate average credit score as an indicator for social capital of a community and discuss the strength and appeal of this measurement.

4.1 Simple Correlations

To begin with, we show that average credit scores are correlated with a range of other measures of trust and social capital used in the literature—Census participation, presiden-

[21] There are almost certainly more filers in a ZIP Code than families (Bricker and others, 2016), but these data can give a useful first approximation of the family-level statistics.

tial election turnout, numbers of NPOs and associations, blood donations, and FCC fraud complaints—even after taking into account a host of community characteristics. Specifically, we estimate the following model:

$$Indicator_c^s = \alpha^s + \beta^s \overline{Score}_c + \gamma^s Q_c + \varepsilon_c^s, \qquad (2)$$

where $Indicator_c^s$ is social capital indicator s in county c. $\overline{Score}$ is the county average credit score, and Q is a vector of county-level characteristics that includes the inverse hyperbolic-sine transformation (I.H.S.) of median income, Gini coefficient of income, homeownership, population shares of various educational attainments, share of age 65 and above, a measure of racial diversity, and violent crime rates. The estimated coefficients of these regressions are presented in table 3.

First, we note that the correlation between average credit scores and each of the six measures of social capital and trust is economically and statistically significant, even after controlling for a range of characteristics of the community. Specifically, our estimates imply that, holding other factors constant, counties with a one standard-deviation (46 points) higher mean credit score, on average, have 5 to 6 percentage points higher participation rates in the U.S. Census and presidential elections, have 3 more NPOs, have 0.3 more associations, donate 35 more units of blood, and file 0.4 fewer FCC complaints, per 1,000 residents, respectively. The negative relationship between average credit score and the prevalence of FCC complaints likely indicate that communities with higher social capital are less prone to be the targets of telemarketing scams, financial frauds, and harsh debt collection treatments, and that residents in these communities are less suspicious and are more alerted, and therefore more trustful, to certain market activities.[22]

Finally, the uniformly significant relationships between average credit scores and other social capital indicators are even more notable when considering that none of the county characteristics included as control variables (such as median income, inequality, education

[22] See Raval (2016) for a discussion of the factors influencing the count of complaints to the Federal Trade Commission.

levels, racial diversity, and violent crime rates) have consistent statistical relationships with these alternate social capital indicators (columns 1–6 of table 3).[23]

4.2 Consistency among Social Capital Indicators

As a further test of consistency among the social capital indicators we consider, including average credit scores, we run a series of regressions whereby each social capital indicator is regressed against the others, with the same set of control variables as in equation (2). We run these regressions using a subset of counties where all four social capital indicators are available. The results are reported in the upper panel of table 4.

There are two notable observations in our estimates. First, consistent with our expectations, average credit scores, Census and presidential election participation, blood donations, and the number of NPOs are positively correlated with each other, with the majority of the estimated coefficients being statistically significant. By contrast, FCC complaints are negatively correlated with the other indicators. Second, with the exception of the number of associations, county average credit scores are always associated with the other social capital indicators in a fashion that is statistically significant and consistent with theoretical predictions, underscoring the statistical richness and robustness of this indicator.[24]

4.3 Principal Component Analysis

To the extent that they behave in a way consistent with our priors, each of the seven social capital indicators should convey information about a community's social capital. Social capital, though, is best interpreted as a latent variable. One common way of illustrating this latent factor is through a principal component analysis (PCA). Here, we implement a PCA of these seven social capital indicators to underscore that average credit score is a valid indicator of social capital and to illustrate that it accounts for the greatest amount of

[23]Even without controlling for average credit scores, the statistical associations between the other social capital indicators and the control variables remain noticeably weaker than that for average credit scores.

[24]The only exception is in column 2, the coefficient is economically large but imprecisely estimated.

variation in the latent factor among all indicators.

To do so, we first conduct a PCA on all seven social capital indicators considered here, including average credit scores. As shown in the first row of the lower panel in table 3, the indicator of average credit scores has the highest correlation with the first PC derived from this PCA. Here essentially the correlation between all social capital indicators and the first PC are statically significant, with the exception of FCC complaints, denoted in the table with superscript ℵ. Second, we construct seven sets of PCs using only six out of the seven indicators considered here (omitting one of the seven each time) and compared the correlation between the first PC and the omitted indicator. As shown in the bottom row, the average credit score indicator again has the higher correlation with the first PC.

In sum, the statistical evidence presented above indicate that average credit scores are consistent with most of the other social capital indicators employed in previous studies and potentially have statistical merit superior to other indicators.

5 Static Analyses on Stock Ownership

As illustrated in the previous section, communities with higher average credit scores tend to have a greater share of residents who are more trusting and a higher level of social capital (measured with various indicators). We now revisit the relationship between social capital and household financial decisions with an analysis of whether people living in such high average credit score areas are more likely to own stocks.

We begin with estimating a workhorse model used extensively in stock market participation research, augmented with an array of community characteristics, including average credit scores. In our baseline analysis, a community is defined as a census tract. As previously discussed, an attractive feature of using average credit scores to measure trust and social capital is that such an indicator can be constructed for much more granular communities than earlier research. We also estimate the model at the county level as a robustness check and to facilitate comparisons with the estimates of other social capital indicators.

Specifically, we estimate the following logit model:

$$Part_{i,t}^{y} = \alpha + \beta \overline{Score}_{t}^{y} + \gamma Z_{i}^{y} + \theta Q_{t} + \rho Year^{y} + \varepsilon_{i,t}^{y}, \tag{3}$$

where $Part_{i,t}^{y}$ is a zero-one indicator of stock ownership (directly held or in mutual funds) for household i that lives in county t in year y. $\overline{Score}_{t}^{y}$ is the mean credit score for county t in year y. A positive β coefficient would suggest that residents living in communities with higher credit scores are more likely to invest in stocks. Z is a vector of individual characteristics of the investor, which includes the inverse hyperbolic sine transformation of household income and wealth, a household head age polynomial, bins of head educational attainment, race, marital status, and a single male dummy.[25] Q_t is a vector of county-level community characteristics (median income, share of people with a college degree, share of people with lower education, defined as high school or below, and share of white residents) that may also affect investment decisions. $Year$ is a vector of yearly fixed effects.

5.1 The SCF Analysis

We first estimate the model using the SCF data and the results are presented in table 5; standard errors are clustered at the tract level and adjusted for multiple imputations in the SCF shown in parentheses. In addition, for parameters of key interest, we also report in brackets the implied odds ratio associated with a one-standard deviation change of the independent variables.

To begin with, the baseline estimates shown in column 1 suggest that higher levels of tract average credit scores are associated with greater stock ownership, and the relationship is statistically significant and economically appreciable—a finding that is consistent with earlier research. The estimated odds ratio indicates that residents living in a tract with an average credit score 41 points (one standard deviation of the average credit score distribution

[25]The household characteristics included in Z are very similar to the existing literature on stock market participation (see, for example, Haliassos and Bertaut, 1995; Campbell, 2006). We use the inverse hyperbolic sine transformation of household income and wealth to deal with zero and negative values. This transformation is otherwise very similar to log transformation for typical positive values (Pence, 2006).

across all communities) higher than an otherwise identical tract are nearly 30 percent more likely to own directly held equities in a given year, a margin similar to the estimates reported in GSZ (2004).

In addition, our estimated coefficients of the control variables are all statistically significant and mostly consistent with results reported in earlier research. For example, greater levels of normal income and total wealth, greater willingness to take financial risk, and higher educational attainments are all associated with greater stock ownership. In addition, not shown in the table, none of the tract characteristics included as controls has a significant positive relationship with equity ownership. We then conduct a series of extension and robustness analysis to further corroborate the baseline results.

First, we show that the association between social capital and stock ownership in the SCF is more pronounced among those with less education. As described in GSZ (2004, 2008), those with more education should have had more formal opportunities to understand the benefits of investing in stocks, so in a world where trust determines stock investing, we should see a larger effect for those with less education. That is exactly what we find when we include terms that interact average credit scores with years of education (column 2). The negative coefficient estimate on the interaction implies that the influence of social capital is highest among those with fewer years of education (and, conversely, lower amongst those with higher education levels).

Second, we exploit a unique feature of the internal SCF data: the interviewer's assessment of the individuals' trusting attitude observed during data collection. As described earlier, the interviewer who conducts the SCF in the field makes note of the responding family's degree of suspiciousness. Interestingly, there is a positive correlation between families rated to have low suspicion and the average credit score of the tract where the respondent lives (not shown), consistent with the notion that people living in higher social capital communities tend to more trustful. Furthermore, the estimated odds ratio for the SCF assessment of trust indicates that respondents who appeared to be more trusting of the survey are on average 22 percent more likely to invest in stocks, a margin that is also statistically significant. However, even after adding an alternative indicator of trustfulness to the model as an additional control, our baseline results do not change qualitatively, and the average credit score remains positively associated with stock ownership (column 3), underscoring the information merit of credit scores that are orthogonal to other measures of trust and social capital.

Third, if high credit score areas tend to have high stock ownership on average, then, instead of the effects of trust and social capital on stock investment, the estimated β coefficient may reveal the effects of more efficient information sharing regarding equity investment that leads to a higher probability of participation in the stock market for any given individual investor (Hong, Kubik, and Stein, 2004; Li, 2014). To isolate the trust effect from this potential information sharing channel, we add to the model the local share of stock ownership estimated using the SOI data. As shown in column 4, families living in areas that have a one standard deviation higher stock ownership are 30 percent more likely to own stocks themselves. Because an area's average stock ownership is positively correlated with average credit score, the estimated β coefficient is appreciably smaller in this specification, but the β estimate is still economically sizable and statistically significant.

Including the local share of stock ownership in our cross-sectional estimates does not fully address the potential endogeneity arising from local information sharing (as in Hong, Kubik, and Stein, 2004, and Li, 2014). But it is re-assuring that the β estimate in column 4 is similar to another attempt at a causal relationship presented in table 5.

Fourth, we re-run our analysis using county, rather than census tract, as a community. Our results (column 5) are qualitatively the same as those that use the tract as the community reference point (column 1). The smaller implied odds ratio for the county-level analysis relative to the census tract level analysis (29 percent versus 22 percent) potentially also speaks to the notion that the effect of social capital may be stronger for communities defined at more granular levels, which in turn underscores this appealing feature of average credit scores as such an indicator.[26]

Finally, we study the effect of trust on the share of stock investment in household financial asset portfolios by estimating a tobit model with the same controls as in column 1. The results, reported in column 6, imply that a one standard deviation increase in tract mean credit score is associated with a near 7-percentage-point increase in stock investment share (about 15 percent of the mean equity investment share, similar to GSZ (2008)).

5.2 The PSID Analysis

The PSID results, shown in table 6, are quite similar to the SCF results. Unlike the SCF, which consistently collected risk aversion information in the three waves of data we use, the PSID only asked for such information in a special module of 1996. As a result, we have risk tolerance information for only a fraction of the households in the PSID sample. Therefore, the PSID baseline regression, shown in column 1, does not include risk tolerance as a control. The baseline PSID estimates show that households residing in census tracts that have a one standard deviation higher average credit score, on average, are 22 percent more likely to invest in stocks—similar to the SCF estimates. Notably, all control variables also have rather similar coefficients estimated using the SCF and PSID data, adding confidence to the representativeness and consistency of both surveys and the empirical model we adopt.

Interacting average credit scores with years of education of household heads in the PSID sample (column 2) reveals that the association between our measure of social capital and propensity of investing in stocks is diminishing with educational attainment—the same as in the SCF analysis and consistent with GSZ (2004, 2008). Estimates in column 3 provide reassurance that adding risk tolerance as a control variable does not qualitatively alter the baseline results. While, as expected, investors with greater risk tolerance are more likely to invest in stocks, in this model estimated using a smaller sample, greater community average

[26]Though not shown in the paper, we also examined whether our variable of interest was picking up credit access in addition to social capital. However, our findings are the same qualitatively as in column (1) when we re-run our analysis including a household-level measure of constrained credit as a control variable.

credit scores remain associated with higher propensity of owning stocks. Also, while local average stock ownership is a powerful predictor of individual investors' stock investment, adding such a control does not void the baseline results—again, as in the SCF results (column 4). In addition, as in the SCF analysis, the results of census tract level analysis qualitatively largely hold at the county level (column 5).

Moreover, the geo-coded PSID data include unique information about the county in which one grew up. This information allows us to study how social capital of the community where one grew up and the community where one currently lives may both influence an investor's stock ownership. To do so, we add the average credit score of the county in which the household head grew up to the baseline model and estimate it using a sample of household heads who no longer live in the same county in which they grew up. To highlight such a contrast, we estimated the model using the gaps of average credit scores between the county one grew up in and the county one currently lives in as the weights. The results, reported in column 6 and consistent with GSZ (2004) and Brown, Ivković, Smith, and Weisbenner (2008), show that higher social capital levels in both communities may boost household investors' stock ownership, with the coefficient estimated for the grow-up county being substantially larger.

There are two important caveats regarding this exercise. First, we note that we are approximating the social capital one was exposed to while growing up (decades ago for some investors) using that county's current average credit score. While average credit score is largely stable over time for most communities, it is possible that a county's average credit score today does not accurately reflect its social capital in the past. Second, the county one relocated to is not necessarily independent of one's earlier life experience, which in turn bears the imprint of the county where one grew up. Thus, the social capital of the two counties can be correlated, which needs to be taken into account while interpreting the coefficients estimated from such a model. Finally, the PSID tobit regression results of stock share in a financial portfolio (column 7) are also consistent to those estimated using the SCF data.

5.3 Alternate Measures of Social Capital—A Horse-Race Test

We introduced community average credit scores as a measure of social capital in comparison with other indicators used in the literature, including Census and presidential election participation, numbers of NPOs and associations, blood donations, and FCC complaints. Of these social capital indicators, electoral participation and blood donations have been shown to have a positive effect on household financial decisions using European data (GSZ, 2004). Here we estimate how various measures of social capital help predict stock market participation using U.S. data and evaluate their respective significance and robustness. We will first replace $\overline{Score}$ in equation (3) with each of the other three social capital indicators. Then we estimate a variation of equation (3) that includes all seven indicators to assess their relative significance. The results are reported in table 7, with column 1 of the upper and lower panels of the table replicating the $\overline{Score}$ estimates in column 5 of tables 5 and 6, respectively.

Our analysis reveals that first, in both SCF and PSID analysis, average credit scores are the only social capital indicator that is consistently predictive of stock market participation. Of the other indicators, only Census response rate, election turnouts, and FCC complaints are associated with stock investment in the SCF analysis, suggesting the other social capital indicators' limited power in predicting household stock investment in the U.S. Second, as shown in column 8, when all seven social capital measures are included, the community average credit score remains a prominent predictor of stock market participation in both the SCF and the PSID sample. By contrast, though Census response and election turnout rates are still positively correlated with stock ownership in the SCF sample, the estimated coefficients become smaller and insignificant.

6 Dynamic Analysis of Stock Market Entries and Exits

While the results of cross-sectional analyses presented earlier are robust and strongly indicative regarding the potential effects of trust and social capital on household stock investment, concerns remain with respect to whether these results establish a causal relationship or are driven by stock investors being more likely to live in high credit score areas, holding other factors constant. To address this concern, we follow Li (2014) and exploit the longitudinal structure of the PSID and ask whether an investor who did not own stocks before will have a higher chance of entering the stock market *after* moving to a community with a higher average credit score. Specifically, for an investor who did not own stocks in year $y-2$, moved to a different community sometime between $y-2$ and y, and still owned no stocks in year y, we estimate the following logistic model of her probability of entering the stock market by year $y+2$.

$$entry_i^{y,\,y+2} = \alpha + \beta_b \overline{CS}_{t^{y-2}} + \beta_p \Delta^p \overline{CS}_{t^{y-2},t^y} + \beta_n \Delta^n \overline{CS}_{t^{y-2},t^y} + \gamma Z_i^y + \theta \Delta Q_{t^{y-2},t^y} + \rho Year^y + \varepsilon_{i,t}^y, \tag{4}$$

where $entry_i^{y,y+2}$ is an indicator of entering the stock market between year y and $y+2$, and t^{y-2} and t^y denote the tract one resided in during year $y-2$ and y, respectively. Accordingly, $\overline{CS}_{t^{y-2}}$ denotes the average credit score of the census tract investor i resided in during year $y-2$. $\Delta^p \overline{CS}_{t^{y-2},t^y}$ and $\Delta^n \overline{CS}_{t^{y-2},t^y}$ are the positive or negative changes of average score before and after the relocation, respectively, to allow for asymmetric effects on subsequent stock market entry decisions. Control variables in Z are defined similarly as in equation (3), but here we use the $y-2$, y, and $y+2$ average levels of wealth and income. In addition, we include the change of real income between $y-2$ and $y+2$ to take into account the potential effects of the factors that led to the relocation on stock market entry. Moreover, we control for the changes of community characteristics $\Delta Q_{t^{y-2},t^y}$ to address the potential effects on stock ownership of these factors. Investors who did not move between years $y-2$ and y are included as the control group.

We focus on the stock market entry dynamics observed after the move in order to isolate the stock market entries that are endogenous to the relocation decisions. Indeed, while we control for an extensive set of indicators of household financial and demographic condition changes, there might be unobserved factors that cause the household to decide to move to a new neighborhood and start investing in stocks at the same time. Focusing on the stock market entries after moving helps alleviate this endogeneity concern. Furthermore, similar to Li (2014), we examine whether relocating to a lower credit score neighborhood increases a current stock investor's odds of subsequently exiting the stock market. For stock investors in year $y-2$ and y, we estimate a similar model of stock market *exits* between y and $y+2$. Arguably, current stock owners' investment decisions (including exiting the stock market) are more determined by their investment experiences, financial conditions, and expected returns, but less influenced by trusting attitude changes.

The results are summarized in table 8. While the estimates in column 1 do not suggest that moving to a community of higher average credit scores has a significant effect on subsequent stock market entries, this appears to reflect the asymmetry of the potential effects of social capital. As shown in columns 2 and 3, an investor who did not own stock previously and moved to a census tract of higher credit score would have a higher chance of entering the stock market during the two years following the move. The estimated odds ratio suggests that the relocation-induced positive change in community average credit scores that is one standard deviation bigger implies an 11 percent higher chance of entering the stock market.[27] By contrast, while the effects on the likelihood of entering the stock market are negative for moving to communities with lower credit scores, they are not statistically significant and much smaller in magnitude. Furthermore, our estimates, as in the cross-sectional analysis, are not sensitive to the inclusion of changes in community average stock ownership as a control variable (column 4). Finally, as shown in columns 5–8, relocation-induced community average credit score changes do not appear to have any significant effect on current stock owners' decisions on exiting the market. The contrast between the estimates of market entry and exit, as we argued earlier, is consistent with the notion that current stock investors tend

[27] On average, 6 percent of households that did not invest in stocks entered the market within a two-year period.

to make investment decisions on objective, market related factors, and they are therefore less influenced by subjective perceptions, such as trusting attitudes. Consequently, such a contrast also lends additional support to a causal relationship between social capital and stock investment.

7 Conclusion

This paper achieves two goals. First, we introduce average credit scores as a novel measure of a community's social capital. We show that this measure is consistent with other social capital measures employed in previous research. Average credit score as a measure of social capital is appealing for several reasons. It is objective, data driven, and based on individual behavior. Various analysis we conduct in this paper suggest that this measure is richer and more robust than other indicators. Such an indicator can be constructed for very small communities, including census tracts or even street blocks, and the underlying data are available for essentially the entire country. It is more correlated with the latent factor derived from a host of measures of social capital.

Second, we revisit the relationship between social capital, trust, and investment in stocks using U.S. data. We find that while other measures of social capital do not consistently show such a relationship, average community credit scores consistently reveal that greater trust and social capital enhances stock market participation. Furthermore, such a relationship is more pronounced for lower-educated investors and manifests itself in both static and dynamic analysis, all suggesting a causal relationship.

This new measure pushes the frontiers of social capital research. Many questions on this subject that we were previously not able to answer due to measurement and data limitation can be revisited. There are also many directions in which this measure can be enriched. For example, the current indicator only focuses on the first moment of community credit score distribution. We can imagine that the dispersion and tail properties of the distribution may reveal new insights on the social capital of a community.

References

[1] Alesina, Alberto and Eliana La Ferrrara (2002). "Who Trusts Who?" *Journal of Public Economics*, vol. 85, pp. 207–34.

[2] Algan, Yann and Pierre Cahuc (2010). "Inherited Trust and Growth," *American Economic Review*, vol. 100 (December), pp. 2060–92.

[3] Arrow, Kenneth (1969). "The Organization of Economic Activity: Issues Pertinent to the Choice of Market versus Nonmarket Allocation. The Analysis and Evaluation of Public Expenditure: the PPB System", *A Compendium of Papers Submitted to the Subcommittee on Economy in Government of the Joint Economic Committee*, Congress of the United States 1, pp. 47–64.

[4] Arrow, Kenneth (1972). "Gifts and Exchanges," *Philosophy and Public Affairs*, vol. 1, pp. 343–362.

[5] Avery, Robert, Kenneth Brevoort, and Glenn Canner (2009). "Credit Scoring and Its Effects on the Availability and Affordability of Credit," *Journal of Consumer Affairs*, vol. 43 (September), pp. 516-37.

[6] Balloch, Adnan, Annamaria Nicolae, and Dennis Philip (2015). "Stock Market Literacy, Trust and Participation," *Review of Finance*, vol. 19, pp. 1925–63.

[7] Barsky, Robert, Thomas Juster, Miles Kimball, and Matthew Shapiro (1997). "Preference Parameters and Behavioral Heterogeneity: An Experimental Approach in the Health and Retirement Study," *Quarterly Journal of Economics*, vol. 112 (May), pp. 537–79.

[8] Bricker, Jesse, Lisa J. Dettling, Alice Henriques, Joanne W. Hsu, Kevin B. Moore, John Sabelhaus, Jeffrey Thompson, and Richard A. Windle (2014). "Changes in U.S. Family

Finances from 2010 to 2013: Evidence from the Survey of Consumer Finances," *Federal Reserve Bulletin*, vol. 100 (September), pp. 1–41.

[9] Bricker, Jesse, Alice Henriques, Jacob Krimmel, and John Sabelhaus (2016). "Measuring Income and Wealth at the Top Using Administrative and Survey Data," *Brookings Papers on Economic Analysis*, Spring.

[10] Briggs, Joseph, David Cesarini, Erik Lindqvist, and Robert Östling (2016). "Windfall Gains and Stock Market Participation." *working paper.*

[11] Brown, Jeffrey, Zoran Ivković, Paul Smith, and Scott Weisbenner (2008). "Neighbors Matter: Causal Community Effects and Stock Market Participation," *Journal of Finance*, vol. 63 (June), pp. 223–37.

[12] Campbell, John (2006). "Household Finance," *Journal of Finance*, vol. 61 (August) pp. 1553–604.

[13] Chen, Daphne, Dean Corbae, and Andrew Glover (2013). "Can Employer Credit Checks Create Poverty Traps? Theory and Policy," *working paper.*

[14] Dettling, Lisa J., Sebastian J. Devlin-Foltz, Jacob Krimmel, Sarah J. Pack, and Jeffrey P. Thompson (2015). "Comparing Micro and Macro Sources for Household Accounts in the United States: Evidence from the Survey of Consumer Finances," Finance and Economics Discussion Series 2015–086. Washington: Board of Governors of the Federal Reserve System, June.

[15] Dokko, Jane, Geng Li, and Jessica Hayes (2015). "Credit Scores and Committed Relationships," Finance and Economics Discussion Series 2015–081. Washington: Board of Governors of the Federal Reserve System, October.

[16] El-Attar, Mayssun and Markus Poschke (2011). "Trust and the Choice Between Housing and Financial Assets: Evidence from Spanish Households," *Review of Finance*, vol. 15 (October), pp. 727–56.

[17] Fowler, James and Nicholas Christakis (2010). "Cooperative behavior cascades in human social networks," *Proceedings of National Science Academy*, vol. 107 (March), pp. 5334-5338.

[18] Fukuyama, Francis (1995). "*Trust: The Social Virtues and the Creation of Prosperity*," New York: The Free Press.

[19] Duarte, Jefferson, Stephan Siegel, and Lance Young (2012). "Trust and Credit: The Role of Appearance in Peer-to-Peer Lending," *Review of Financial Studies*, vol. 25(8), pp. 2455–83.

[20] Fehr, Ernst, Urs Fischbacher, Bernhard von Rosenbladt, Juergen Schupp, and Gert Wagner (2003). "A Nation-Wide Laboratory. Examining Trust and Trustworthiness by Integrating Behavioral Experiments into Representative Surveys," CESifo Working Paper Series No. 866.

[21] Georgarakos, Dimitris and Giacomo Pasini (2011). "Trust, Sociability and Stock Market Participation," *Review of Finance*, vol. 15 (October), pp. 693–725.

[22] Giannetti, Mariassunta and Tracy Wang (2016). "Corporate Scandals and Household Stock Market Participation," *Journal of Finance*, vol. 71 (December), pp. 2591–636.

[23] Glaeser, Edward, David Laibson, Jose Scheinkman, and Christine Soutter (2000). "Measuring Trust," *Quarterly Journal of Economics*, vol. 115 (August), pp. 811–46.

[24] Gennaioli, Nicola, Andrei Schleifer, and Robert Vishny (2015). "Money Doctors," *Journal of Finance*, vol. 70 (February), pp. 91–114.

[25] Goldin, Claudia and Lawrence Katz (1999). "Human Capital and Social Capital: The Rise of Secondary Schooling in America, 1910 to 1940," *Journal of Interdisciplinary History*, vol. 29, pp. 683–723.

[26] Graeber, Thomas and Tom Zimmerman (2016). "The Legacy of Financial Crises – A Persistent Erosion of Interpersonal Trust?" mimeo.

[27] Guiso, Luigi, Paola Sapienza, and Luigi Zingales (2004). "The Role of Social Capital in Financial Development," *American Economic Review*, vol. 94 (June), pp. 526–56.

[28] Guiso, Luigi, Paola Sapienza, and Luigi Zingales (2008). "Trust the Stock Market," *Journal of Finance*, vol. 63 (December), pp. 2557–600.

[29] Gurun, Umit, Noah Stoffman, and Scott Yonker (2017). "Trust Busting: The Effect of Fraud on Investor Behavior" *Working paper.*

[30] Haliassos, Michael and Carol C. Bertaut (1995). "Why Do So Few Hold Stock?" *The Economic Journal*, vol. 105 (September), pp. 1110–29.

[31] Helliwell, John F., Haifang Huang, and Shun Wang (2016). "New Evidence on Trust and Well-being," *NBER Working Paper*, No. 22450.

[32] Hong, Harrison, Jeffrey D. Kubik, and Jeremy C. Stein (2004). "Social Interaction and Stock Market Participation," *The Journal of Finance*, vol. 59 (February), pp. 137–63.

[33] Jackson, Matthew, Tomas Rodriguez-Barraquer, and Xu Tan (2012). "Social Capital and Social Quilts: Network Patterns of Favor Exchange," *American Economic Review*, vol. 102 (August), pp. 1857-97.

[34] Karlan, Dean (2005). "Using Experimental Economics to Measure Social Capital and Predict Financial Decisions," *American Economic Review*, vol. 95 (December), pp. 1688-99.

[35] Knack, Stephen and Philip Keefer (1997). "Does Social Capital Have an Economic Payoff? A Cross-Country Investigation," *Quarterly Journal of Economics*, vol. 112 (November), pp. 1251–88.

[36] La Porta, Rafael, Florencio, Lopez-de-Silanes, Andrei Shleifer, and Robert Vishny (1997). "Trust in Large Organizations," *American Economic Review*, vol. 87 (May), pp. 333–8.

[37] Li, Geng (2014). "Information Sharing and Stock Market Participation: Evidence from Extended Families," *Review of Economics and Statistics*, vol. 96 (February), pp. 151–60.

[38] Malmendier, Ulrike and Stefan Nagel (2011). "Depression Babies: Do Macroeconomic Experiences Affect Risk Taking?" *Quarterly Journal of Economics*, vol. 126 (February), pp. 373–416.

[39] Malmendier, Ulrike and Stefan Nagel (2016). "Learning from Inflation Experiences," *Quarterly Journal of Economics*, vol. 131 (February), pp. 53–87.

[40] Pence, Karen (2006). "Foreclosing on Opportunity: State Laws and Mortgage Credit," *Review of Economics and Statistics*, vol. 88 (February), pp. 177–82.

[41] Putnam, Robert (1993). *Making Democracy Work: Civic Traditions in Modern Italy.* Princeton: Princeton University Press.

[42] Putnam, Robert (1995). "Bowling Alone," *Journal of Democracy*, vol. 6 (January) pp. 65-78.

[43] Raval, Devesh (2016). "What Determines Consumer Complaining Behavior?" mimeo.

[44] Rupasingha, Anil, Stephan Goetz, and David Freshwater (2006). "The production of social capital in US counties," *Journal of Socio-Economics*, vol. 35, pp. 83–101.

[45] Sapienza Paola, Anna Toldra-Simats, and Luigi Zingales (2013). "Understanding Trust," *The Economic Journal*, vol. 123 (June) pp. 1313–32.

[46] Vissing-Jorgensen, Annette (2002). " Limited Asset Market Participation and the Elasticity of Intertemporal Substitution," *Journal of Political Economy*, vol. 110 (August), pp. 825-53.

Table 1: Summary Statistics of Credit Scores and Measures of Social Trust and Capital

Credit score data are from the FRBNY Consumer Credit Panel/Equifax. Statistics are estimated by averaging quarterly mean data from 2001 to 2015 (60 quarters). Census response rates, presidential election turnout rates, and number of nonprofits and associations are from Rupasingha et al (2006, with updates). Blood donations data are from the American Red Cross (county-level statistics are aggregated from the ZIP Codes from which the Red Cross collected blood). The Federal Communications Commission complaints data can be accessed at https://www.fcc.gov/consumer-help-center-data, and is described in Raval (2016).

	Credit Scores		
	Individuals	Census tract average	County average
Mean	690	684	680
S.D.	(107)	(41)	(46)
N	655 million	74,434	3,856

	Rupasingha, Goetz, and Freshwater Social Capital Indicators			
	Census response rate	Presidential elections turnouts	Number of nonprofit org. per 1,000 residents	Number of associations per 1,000 residents
Mean	67.4%	58.6%	6.3	1.4
S.D.	(9.1%)	(9.3%)	(4.1)	(0.7)
N	3,108	3,108	3,105	3,108

	Other Social Trust and Social Capital Indicators	
	Units of blood donation collected per 1,000 residents	FCC complaints submitted per 1,000 residents
Mean	45.9	1.8
S.D.	(41.6)	(1.7)
N	2,054	3,043

Table 2: Summary Statistics of Stock Investment and Household Characteristics

Statistics are estimated using the 2004, 2007, and 2010 Survey of Consumer Finances data and the 1999–2013 Panel Study of Income Dynamics data.

Variable	SCF	PSID
Financial decisions		
Stockholder (%)	23.5	22.3
Stock portfolio share (%)	43.9	56.7
Enter stock market (%)	...	6.3
Exit stock market (%)	...	23.3
Rely on family/friends for fin. dec. (%)	20.0	...
Rely on formal source for fin. dec. (%)	32.8	...
Household characteristics		
Willing to take fin. risk (%)	18.8	...
Risk tolerance	...	1.2
Interviewer observed trust (%)	56.1	...
Relocated in past two years (%)	...	24.3

Table 3: Average Credit Scores and Indicators of Trust and Social Capital

This table reports regressions of indicators of trust and social capital studied in the existing literature on county average credit scores. Standard errors are clustered at the state level and presented in parentheses. *, **, and *** denote 90, 95, and 99 percent statistical significance, respectively. Control variables include the inverse hyperbolic sine transformation of median income, income Gini coefficient, share of homeowners, composition of educational attainment, share of senior population, Herfindahl index on racial diversity, and violent crime rate, all at the county level. Column 7 projects average credit scores on the control variables.

	Census response rate	Presidential election turnouts	Number of NPOs	Number of associations	Blood donations	FCC complaints	$\frac{\overline{Score}}{100}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\frac{\overline{Score}}{100}$	0.100***	0.123***	6.632***	0.556*	76.846***	-0.989**	
	(0.025)	(0.031)	(0.967)	(0.280)	(21.874)	(0.398)	
I.H.S. median income	0.109***	-0.125***	-8.042***	-0.669**	-52.511**	1.698***	0.313***
	(0.035)	(0.035)	(1.455)	(0.302)	(22.178)	(0.553)	(0.068)
Gini coeff.	-0.002	-0.001	-0.110***	-0.026***	-2.204***	-0.013	-0.012***
	(0.001)	(0.001)	(0.033)	(0.008)	(0.558)	(0.014)	(0.002)
Homeownership	0.528***	0.087	-5.923***	0.353	14.877	-1.455	-0.351***
	(0.067)	(0.055)	(2.192)	(0.385)	(21.104)	(0.874)	(0.073)
High school and below share	0.263***	-0.483***	-6.298**	0.076	26.988	-0.572	-0.042
	(0.084)	(0.075)	(2.833)	(0.579)	(41.954)	(0.955)	(0.117)
College graduate share	0.066	0.405***	16.132***	1.596**	42.056	8.352***	1.346***
	(0.091)	(0.096)	(2.757)	(0.630)	(41.283)	(1.554)	(0.130)
Senior population share	0.055	-0.068	14.692*	8.109***	46.559	0.948	2.108***
	(0.195)	(0.109)	(8.057)	(2.286)	(60.648)	(2.524)	(0.274)
Racial Herf. index	0.083***	-0.032	-3.065**	-0.299	-10.470	0.858	0.744***
	(0.028)	(0.038)	(1.405)	(0.265)	(19.628)	(0.543)	(0.056)
Violent crime rate	0.006***	-0.001	-0.050	-0.009	0.093	0.017	-0.019***
	(0.002)	(0.002)	(0.059)	(0.011)	(0.726)	(0.029)	(0.003)
N	2,940	2,940	2,937	2,940	1,963	2,884	2,955

Table 4: Consistency among All Social Capital Indicators

The upper panel of this table presents the consistency analysis among seven indicators of social capital, including the average credit score. Each of these social capital indicators is regressed on the other six indicators and the set of control variables in table 3. Standard errors are clustered at the state level and presented in parentheses. *, **, and *** denote 90, 95, and 99 percent statistical significance, respectively. In the upper panel, average community credit score is associated with the other social capital indicators in a fashion that is statistically significant and consistent with theoretical predictions (except in column 5). None of the other indicators are correlated with the others as consistently. The lower panel shows that the average credit score has the highest correlation with the first principal component extracted from the seven indicators (column 1). Moreover, in the row below, it also has the highest correlation with the first principal component extracted just from the other six indicators.

	Competing Regressions						
	$\frac{\overline{Score}}{100}$ (1)	Census response (2)	Election turnouts (3)	Number of NPOs (4)	Number of associations (5)	Blood donations (6)	FCC complaints (7)
$\frac{\overline{Score}}{100}$		0.117***	0.105***	3.605***	-0.427**	42.840**	-0.924*
		(0.026)	(0.035)	(0.864)	(0.208)	(15.922)	(0.484)
Census response	37.907***		-0.111	-1.857	1.689***	41.341*	-1.802***
	(8.618)		(0.071)	(1.457)	(0.259)	(21.846)	(0.601)
Election turnouts	31.519***	-0.103		3.852**	0.114	20.107	-0.471
	(10.603)	(0.063)		(1.667)	(0.342)	(31.887)	(0.818)
# of NPOs	1.132***	-0.002	0.004**		0.096***	2.367***	-0.034*
	(0.289)	(0.001)	(0.002)		(0.017)	(0.767)	(0.017)
# of associations	-2.772*	0.034***	0.002	1.977***		13.970***	-0.112
	(1.481)	(0.008)	(0.007)	(0.195)		(2.381)	(0.069)
Blood donations	0.041***	0.000*	0.000	0.007***	0.002***		-0.002
	(0.012)	(0.000)	(0.000)	(0.002)	(0.000)		(0.001)
FCC Complaints	-0.424	-0.003**	-0.001	-0.049	-0.008	-0.743	
	(0.291)	(0.001)	(0.001)	(0.034)	(0.007)	(0.828)	
Controlling for county chars.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1,942	1,942	1,942	1,942	1,942	1,942	1,942
	Correlations with Principal Components						
$First\ PC^7$	0.81	0.40	0.72	0.78	0.70	0.67	$0.01^{\aleph}$
$First\ PC^6$	0.63	0.27	0.55	0.60	0.52	0.51	$0.00^{\aleph}$

Table 5: Community Average Credit Scores and Stock Investment—SCF Analysis

Note: Standard errors are presented in parentheses. Odds ratios associated with a one standard deviation change of the key independent variables are presented in brackets. Data are 2004, 2007, and 2010 SCF, pooled together. Credit score averages are calculated using the FRBNY CCP/Equifax data. Standard errors are clustered at the census tract and county level, respectively, and corrected for multiple imputation. *, **, and *** denote 90, 95, and 99 percent statistical significance, respectively. Column 1 presents the results of the baseline specification. Column 2 tests if the coefficient estimated for average credit scores diminishes with years of schooling. Columns 3 and 4 test the robustness of baseline results when adding SCF-interviewer-observed trustfulness and neighborhood average stock ownership as controls. Column 5 estimates the baseline model using county level data. Column 6 studies the association between average credit scores and stock shares in household portfolios of financial assets.

	Logistic Analysis of Stock Ownership					**Tobit Analysis**
	Tract level				County level	Tract level
	(1)	(2)	(3)	(4)	(5)	(6)
$\frac{\overline{Score}}{100}$	0.621**	1.582**	0.630**	0.321**	0.853**	0.173**
	(0.137)	(0.515)	(0.135)	(0.147)	(0.216)	(0.041)
	[1.293]	[1.925]	[1.291]	[1.136]	[1.223]	
$\frac{\overline{Score}}{100}$ × Yrs. ed.		-0.067*				
		(0.034)				
		[0.972]				
SCF observed trusting			0.201**			
			(0.056)			
			[1.223]			
ZIP Code stock ownership				2.123**		
				(0.387)		
				[1.304]		
I.H.S. real income ($2002)	0.560**	0.561**	0.562**	0.562**	0.623**	0.127**
	(0.053)	(0.053)	(0.053)	(0.053)	(0.060)	(0.015)
I.H.S. real wealth ($2002)	0.092**	0.092**	0.092**	0.091**	0.092**	0.024**
	(0.012)	(0.012)	(0.012)	(0.012)	(0.013)	(0.003)
Head age	-0.041**	-0.040**	-0.039**	-0.040**	-0.045**	-0.007**
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.003)
Head age^2	0.000**	0.000**	0.000**	0.000**	0.001**	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Yrs. ed.	0.188**	0.658**	0.186**	0.188**	0.207**	0.056**
	(0.015)	(0.241)	(0.014)	(0.015)	(0.013)	(0.004)
Married	0.357**	0.358**	0.362**	0.365**	0.322**	0.132**
	(0.112)	(0.112)	(0.112)	(0.113)	(0.115)	(0.033)
Single male	0.176*	0.178*	0.164*	0.183*	0.140**	0.067**
	(0.099)	(0.099)	(0.099)	(0.099)	(0.088)	(0.030)
White	0.534**	0.530**	0.532**	0.524**	0.597**	0.170**
	(0.081)	(0.082)	(0.081)	(0.082)	(0.082)	(0.023)
Willing to take fin. risk	0.592**	0.590**	0.589**	0.594**	0.581**	0.185**
	(0.066)	(0.066)	(0.066)	(0.066)	(0.066)	(0.019)
Controlled for						
Family size dummies	Yes	Yes	Yes	Yes	Yes	Yes
Tract characteristics	Yes	Yes	Yes	Yes	Yes	Yes
County economic conditions	Yes	Yes	Yes	Yes	Yes	Yes
Yearly fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
N	14,122	14,122	14,122	14,113	14,137	14,122

Table 6: Community Average Credit Scores and Stock Ownership—PSID Analysis

Note: Standard errors are presented in parentheses. Odds ratios associated with a one standard deviation change of the key independent variables are presented in brackets. Data are 1999–2013 PSID (see the text for sample construction details). Credit score averages are calculated using the FRBNY CCP/Equifax data. Standard errors are clustered at the census tract and county level, respectively. *, **, and *** denote 90, 95, and 99 percent statistical significance, respectively. Column 1 presents the results of the baseline specification. Column 2 tests if the coefficient estimated for average credit scores diminishes with years of schooling. Columns 3 and 4 test the robustness of baseline results when adding indicators of risk aversion and neighborhood average stock ownership as controls. Column 5 estimates the baseline model using county-level data. Column 6 contrasts the estimates of the average credit scores of the current-residence county and the grow-up county. This model is estimated using the gaps of average credit scores between the county one grew up in and the county one currently lives in as the weights. Column 7 studies the association between average credit scores and stock share in the household portfolio of financial assets.

	Logistic Analysis of Stock Ownership						**Tobit Analysis**
	Tract level				County level		Tract level
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\frac{\overline{Score}}{100}$	0.465***	2.362***	0.290**	0.308***	0.474***	0.110***	0.156***
	(0.093)	(0.360)	(0.135)	(0.101)	(0.149)	(0.032)	(0.040)
	[1.235]	[2.920]	[1.147]	[1.150]	[1.106]	[1.139]	
County grew up $\frac{\overline{Score}}{100}$						0.362***	
						(0.023)	
						[1.601]	
$\frac{\overline{Score}}{100} \times$ Yrs. ed.		-0.136***					
		(0.024)					
Risk tolerance			0.032***				
			(0.011)				
ZIP Code stock ownership				1.037***			
				(0.235)			
I.H.S. real income ($2002)	0.614***	0.607***	0.558***	0.613***	0.632***	0.668***	0.239***
	(0.036)	(0.036)	(0.060)	(0.037)	(0.040)	(0.010)	(0.014)
I.H.S. real wealth ($2002)	0.071***	0.071***	0.097***	0.072***	0.063***	0.055***	0.027***
	(0.005)	(0.005)	(0.012)	(0.005)	(0.004)	(0.001)	(0.002)
Head age	-0.005	-0.003	-0.007	-0.003	0.007	-0.005**	0.003
	(0.006)	(0.006)	(0.014)	(0.006)	(0.007)	(0.002)	(0.003)
Head age^2	0.019***	0.018***	0.018	0.017***	0.008	0.017***	0.005*
	(0.006)	(0.006)	(0.014)	(0.006)	(0.007)	(0.002)	(0.003)
Yrs. ed.	0.185***	1.128***	0.131***	0.183***	0.171***	0.187***	0.077***
	(0.009)	(0.171)	(0.013)	(0.009)	(0.009)	(0.003)	(0.004)
Married	0.217***	0.221***	0.320***	0.207***	0.253***	0.325***	0.085***
	(0.057)	(0.057)	(0.096)	(0.057)	(0.057)	(0.018)	(0.025)
Single male	0.076	0.078	0.047	0.077	0.123**	0.147***	0.055***
	(0.059)	(0.059)	(0.096)	(0.059)	(0.062)	(0.019)	(0.025)
White	0.672***	0.663***	0.609***	0.672***	0.774***	0.842***	0.280***
	(0.055)	(0.055)	(0.085)	(0.055)	(0.059)	(0.016)	(0.024)
Controlled for							
Family size dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Tract characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County economic conditions	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Yearly fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	22,958	22,958	7,124	22,618	18,264	10,739	22958

Table 7: Other Measures of Social Capital and Stock Ownership

Note: Standard errors are presented in parentheses. Data used in estimation of the upper and lower panel are 2004, 2007, and 2010 SCF, pooled together, and a sample constructed using the 1999–2013 PSID, respectively. Control variables are the same as in tables 5 and 6. See table 1 for more information about each social capital indicator. Standard errors are clustered at county level and corrected for multiple imputation (SCF only). *, **, and *** denote 90, 95, and 99 percent statistical significance, respectively.

				SCF				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\frac{\overline{Score}}{100}$	0.853**							0.739**
	(0.216)							(0.231)
	[1.223]							[1.198]
Census response		1.700*						0.795
		(1.014)						(1.046)
		[1.120]						[1.059]
Election turnouts			1.773**					1.176
			(0.656)					(0.784)
			[1.139]					[1.072]
# of NPOs				-0.001				-0.013
				(0.016)				(0.015)
				[0.997]				[0.973]
# of associations					-0.079			0.018
					(0.117)			(0.150)
					[0.971]			[1.003]
Blood donations						0.016		0.007
						(0.015)		(0.017)
						[1.044]		[1.030]
FCC complaints							-0.344**	-0.187**
							(0.144)	(0.077)
							[0.937]	[0.965]

				PSID				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\frac{\overline{Score}}{100}$	0.474***							0.667***
	(0.149)							(0.179)
	[1.106]							[1.165]
Census response		-0.149						-0.221
		(0.465)						(0.567)
		[0.992]						[0.988]
Election turnouts			0.200					0.147
			(0.313)					(0.354)
			[1.018]					[1.013]
# of NPOs				0.012				0.000
				(0.009)				(0.015)
				[1.030]				[1.001]
# of associations					0.025			0.040
					(0.058)			(0.095)
					[1.010]			[1.016]
Blood donations						-0.001		-0.001
						(0.001)		(0.001)
						[0.980]		[0.976]
FCC Complaints							0.006	0.012**
							(0.008)	(0.006)
							[1.010]	[1.020]

Table 8: Dynamic Analysis

Note: Standard errors are presented in parentheses. Odds ratios associated with a one standard deviation change of the independent variables are presented in brackets. Data are 1999–2013 PSID (see the text for sample construction details). Credit score averages are calculated using the FRBNY CCP/Equifax data. Standard errors are clustered at the census tract level. *, **, and *** denote 90, 95, and 99 percent statistical significance, respectively. Columns 1–4 present the results of how, for those who do not own stocks, relocating to a community of different average credit score may affect the odds of entering the stock market in the years after the move. Columns 5–8 present the results of how, for those who currently own stocks, relocating to a community of different average credit score may affect the odds of exiting the stock market in the years after the move.

	Entry analysis				Exit analysis			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta \frac{\overline{Score}}{100}$	0.272				0.150			
	(0.252)				(0.270)			
	[1.046]				[1.020]			
$\Delta^{+} \frac{\overline{Score}}{100}$		0.516*	0.864**	0.871**		0.272	-0.214	-0.291
		(0.300)	(0.387)	(0.394)		(0.333)	(0.432)	(0.447)
		[1.064]	[1.111]	[1.110]		[1.029]	[0.978]	[0.970]
$\Delta^{-} \frac{\overline{Score}}{100}$		-0.071	-0.427	-0.407		-0.087	0.877	0.998
		(0.340)	(0.419)	(0.426)		(0.447)	(0.596)	(0.615)
		[0.992]	[0.956]	[0.958]		[0.993]	[1.072]	[1.082]
$\frac{\overline{CS_0}}{100}$	0.457***	0.460***	0.456***	0.458***	-0.374***	-0.370***	-0.369***	-0.355***
	(0.110)	(0.110)	(0.110)	(0.110)	(0.127)	(0.127)	(0.127)	(0.127)
	1.222	[1.224]	[1.222]	[1.222]	[0.885]	[0.885]	[0.886]	[0.890]
Controlled for								
Individual char.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Δ Local char. and econ conditions	No	No	Yes	Yes	No	No	Yes	Yes
Δ ZIP Code stock ownership	No	No	No	Yes	No	No	No	Yes
Yearly fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	19,880	19,880	19,880	19,880	4,539	4,539	4,539	4,539