Finance and Economics Discussion Series

Federal Reserve Board, Washington, D.C.
ISSN 1936-2854 (Print)
ISSN 2767-3898 (Online)

Credit Scores, Social Trust, and Stock Market Participation

Jesse Bricker and Geng Li

2017-008

Please cite this paper as:
Bricker, Jesse, and Geng Li (2023). "Credit Scores, Social Trust, and Stock Market Participation," Finance and Economics Discussion Series 2017-008r1. Washington: Board of Governors of the Federal Reserve System, https://doi.org/10.17016/FEDS.2017.008r1.

Credit Scores, Social Capital, and Stock Market Participation

Jesse Bricker
Federal Reserve Board
20th & C St, NW
Washington, DC 20551
jesse.bricker@frb.gov

Geng Li *
Federal Reserve Board
20th & C St, NW
Washington, DC 20551
geng.li@frb.gov

Abstract

We propose the average credit score of a community as a metric of its social trust—a critical component of social capital. It is consistent with existing social capital indicators and can be constructed for more granular communities. We show that this social trust indicator has a strong association with stock investment of individuals living in the community, controlling for a rich set of investor and neighborhood characteristics. This association is more pronounced among the less educated, in areas with weaker law enforcement, and for stock investment through mutual funds, which requires delegation and relies more on trust. Furthermore, relocating to higher-social-capital communities predicts future stock market entries.

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

JEL: D14, G10, G41, G50

*We thank Robert Putnam for his encouragements and suggestions. We thank Matthew Jackson, David Laibson, Juhani Linnainmaa, Brigitte Madrian, Adair Morse, Luigi Pistaferri, Devesh Raval, Michael Ungeheuer, our Federal Reserve Board colleagues, and seminar and conference participants for helpful discussions. In addition, we thank Robert Fluegge for suggesting an additional analysis, Martin Caste, Vincent Yao, and the American Red Cross for sharing data, and Kendra Collins for charting help. Taha Ahsin, Sophia Campbell, Jessica Hayes, and Lucas Nathe provided excellent research assistance. The views presented herein are those of the authors and do not necessarily reflect those of the Federal Reserve Board or its staff.

"When you can measure what you are speaking about and express it in numbers you know something about it; but when you cannot measure it, when you cannot express it in numbers, your knowledge is of a meagre and unsatisfactory kind."

—Lord Kelvin

1 Introduction

Since the seminal work of Putnam (1993), the role of social capital has been shown to be important in understanding well-being, economic outcomes, and financial development (see Chetty et al (2022) and Guiso, Sapienza, and Zingales (2004) for recent examples). A crucial component of social capital is social trust, involving both trust among individuals and trust in institutions (Algan 2018). Regarding the specific role of trust, Guiso, Sapienza, and Zingales (2008, henceforth GSZ) show that more trusting individuals are more likely to invest in stocks.[1] Despite this advancement in empirical analysis, concrete, data-based measures of social trust have remained elusive. 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."

This paper makes two contributions to this broad research agenda. First, we propose a novel indicator of social trust—the long run average credit score of a community—and make it available to the research community.[2]. This measure can be constructed at locations as granular as the Zip Code or census tract levels. Second, equipped with this new indicator, we examine how social trust may influence U.S. households' stock investment. While GSZ (2004) show that extant measures of social capital are associated with stock investment among European households, such measures do not consistently predict stock ownership among U.S. households. By contrast, our proposed social trust indicator has a robust,

[1] Other notable contributions on the effects of social capital and trust include Knack and Keefer (1997), La Porta, Lopez-de-Silanes, Shleifer, and Vishny (1997), and Algan and Cahuc (2010), among others.

[2] The ZIP Code level average credit scores data can be downloaded from `https://www.federalreserve.gov/econres/feds/files/feds2017008_data.zip`

pronounced association with household stock ownership, reaffirming the role of social trust in the U.S. financial development context.[3]

Two considerations have motivated us to relate trust with credit scores. First, trustworthiness and creditworthiness are closely related.[4] Indeed, lenders have long recognized the critical importance of a borrower's trustworthiness in assessing credit risks and historically had collected extensive information on personality, reliability, and general trustworthiness when underwriting loans. Relatedly, Arrow (1972) set forth the notion that "...virtually every commercial transaction has within itself an element of trust." In the modern credit market, credit scores are designed to predict borrowers' default risks that reflect their ability and willingness to repay, the latter of which is influenced by an individual's broad, underlying trustworthiness. Accordingly, credit scores can be used to predict personal experiences outside the credit market. For example, Dokko, Li, and Hayes (2015) show credit scores are strong predictors of personal relationship outcomes. In addition, many employers run credit checks on applicants as part of the hiring process (Bos, Lieberman, and Breza 2018). Thus, a community's average credit score likely reflects its average trustworthiness. It is important to note that income is not used in credit scoring models, and Beer, Ionescu, and Li (2018) show that consumers' income and credit scores are only moderately correlated.

Second, recent work has documented that financial experiences influence individuals' perceptions and expectations.[5] Credit scores reflect past experiences with credit markets, as credit usage and repayment history are among the main inputs of credit scoring models. Consumers with lower credit scores due to previous difficulties of repaying debt, for example, may feel more distrustful toward financial and credit markets because of negative experiences

[3]One important question that we do not attempt to address in this paper is the origins of the variations in social trust across communities, which can reflect a myriad of historical and contemporary factors (Halpern 2005). However, we expect that the proposed improved measure will facilitate future research that enhances our understanding of social capital and trust.

[4]Becchetti and Conzo (2011) argue that the two terms are "almost synonyms," and they point out that "Guinnane (2005) reminds us that the Latin root of credit, *credere*, means, among other things, trust, whereas in the German word *gläubiger* the two meanings of credit and trust coincide."

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

in the past. Such a distrusting effect can be particularly strong if the debt repayment difficulty was due to misleading or deceptive information offered by financial advisors, loan brokers, or credit product sales representatives. Consistent with this hypothesis, we find that counties with lower average credit scores tend to report more complaints to the Consumer Finance Protection Bureau. Furthermore, an individual living in such a community would have a greater chance of interacting with people less trusting of financial and credit markets, making herself less trusting as well (Alesina and La Ferrrara, 2002).

We use a large proprietary dataset—the Federal Reserve Bank of New York Consumer Credit Panel/Equifax data—to estimate average community credit scores. We recognize that the formation and evolution of social trust is a slow moving process that may take a long time to solidify and, accordingly, use the time-series mean of community average credit scores over a period of more than 15 years to filter out the higher-frequency variations that do not necessarily reflect changes in social trust. Confirming the notion that trust is a crucial component of social capital, we show that this average community credit score is positively correlated with a broad array of social capital measures—such as the presidential election participation rate, the Census response rate, the number of civic associations and nonprofit organizations, and the quantity of blood donations—even after controlling for an extensive array of observable community characteristics, including income.

Notably, such consistency also hold for the recently introduced social capital measures based on Facebook data (Chetty et al 2022) at both the ZIP Code and county levels. Our proposed indicator are based on individuals' experience and behavior in the credit market, whereas the Chetty et al indicators are derived from people's interactions on social media. Their high-degree of consistency, in spite of being derived from distinct contexts, underscores that people's underlying personal traits may manifest in a wide range of activities—market- and nonmarket-based.

The relationship between stock market participation and trust/social capital has been examined using European survey data (GSZ, 2004, 2008; El-Attar and Poschke, 2011; Georgarakos and Pasini, 2011).[6] By contrast, evidence based on U.S. data is more scant.[7] Applying our proposed social trust indicator in testing this relationship, we underscore that the focus of our analysis is the linkage between a consumer's stock ownership and her community's *average* credit score, rather than her *own* credit score.

Our empirical strategy is similar in spirit to GSZ (2008), and we extend and complement their work in several important aspects. First, we link household investment information in representative U. S. household surveys—the Survey of Consumer Finances (SCF) and the Panel Study of Income Dynamics (PSID)—to the average credit scores of the investors' residence communities and find that consumers residing in areas with higher average credit scores are more likely to own equities, held directly or through mutual funds, and to invest a greater share of their portfolio in equities. In the baseline results, investors living in a census tract with a one-standard-deviation higher average credit score have about a 30 percent higher probability of owning equities; conditional on owning equities, the share of equities in an investment portfolio is 10 to 15 percent higher. Such a relationship holds against a rich set of socioeconomic and demographic characteristics, including total wealth and income; and it holds among households with high and low levels of wealth. In addition, the relationship is estimated to be more pronounced for census tract-average credit scores than the county-average, corroborating the notion that social capital effects are likely localized.

Second, we demonstrate that these results are robust against an array of alternative hypotheses and model specifications. In particular, our results are not driven by community average credit scores being, to some extent, correlated with individual credit scores. Moreover, an individual's own access to credit and financial services may also affect her stock invest-

[6]Besides the trust/social capital channel, 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.

[7]Balloch, Nicolae, and Philip (2015) and Duarte, Siegel, and Young (2012) are the only related studies of U.S. investors we find. Balloch et al (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, much higher than observed in representative household surveys and administrative tax data. Duarte et al (2012) study peer-to-peer lending, which is used only by a small, select subpopulation of U.S. households. Another strand of literature focuses on how Ponzi game and corporate scandals affect household investment decisions (see, for example, Giannetti and Wang, 2016; Gurun, Stoffman, and Yonker 2017).

ment decisions and may be correlated with the average credit score of her neighborhood. We address these potential confounding factors by adding self-reported credit constraint status and the number of local banking branches to the baseline model as additional controls, and our results are little changed. In addition, we show that the baseline results hold against alternative hypothesis concerning household expectations, measurement errors due to survey attentiveness, and financial literacy. Furthermore, we note that, through an Oaxaca-Blinder decomposition, the differences in stock participation between residents of high and low social trust communities are only partly accounted for by the observable differences among such investors.

In addition to social trust, average credit scores likely contain rich information related to other aspects of communities that also have a bearing on stock investment. To isolate the role of trust on promoting stock market participation, we use a two-sample instrument strategy to estimate a projected value of average credit score using other existing social capital indicators. We then estimate the baseline stock market participation model using the predicted value and the residual. We found that the two orthogonal terms both have significant, positive associations with stock ownership.

Furthermore, we conduct a sequence of analyses to shed light on nature of the link between social trust and stock investment. For example, the association between the propensity to own stocks and community average credit score is stronger for investors with lower educational attainment, for the ownership of equity mutual funds (which involve another layer of delegation), and in areas with weaker law enforcement—findings consistent with GSZ (2004, 2008). We also find such an association for social trust levels of neighboring communities, though of a smaller magnitude, which is consistent with social ties diminishing with distance. Moreover, the social trust level of the county where an investor grew up appears to remain associated with her future stock ownership even years after moving out of that county. Further, leveraging a unique variable in the SCF data, we show that the survey interviewer-assessed individual trustfulness is also positively associated with survey respondents' stock ownership. Notably, this relationship holds when we instrument the interviewer-assessed trustfulness attitude with community average credit scores.

Finally, we exploit the longitudinal structure of the PSID data and study stock market entries and exits. We find that investors who did not own stocks previously have a greater chance of entering the 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 its residents and thereby develop more trust in financial markets. Our exercise focuses on stock market entries that are subsequent, instead of simultaneous, to relocation and control for future income growth, on which the households may have some foresight as they relocate, thereby circumventing the endogeneity concerns to a certain extent.

In spite of these effort, we note that our research design does not exploit any specific exogenous shocks to the level of trust of a given area, which limits the extent to which a causal relationship can be established. In addition, we acknowledge that introducing a reliable indicator for latent factors, such as social trust, is tough, and our proposed indicator is no exception. Its validity and advantages can only be established through subsequent work from the research community. We hope that our paper provides a concrete, promising starting point for this process and that making the data publicly available facilitates this effort.

The remainder of the paper proceeds as follows. Section 2 briefly discusses the theoretical background of social trust 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 Social Trust and the Measurement Challenge

Trust is an essential element of social capital. 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). More recently, GSZ (2004) show that social capital differences can account for the diverging growth paths of the north and south of Italy and GSZ (2008) demonstrate that lack of trust also contributes to the low rate of participation in stock markets as stock investment often depends on trusting a financial intermediary. The potential effects of trust on personal finance appear to go beyond investment in risky assets. Jiang and Lim (2018), for example, show that individuals who demonstrate more trust tend to default less on their debt.

In spite of the increasing appreciation of the role of social trust in financial and economic developments, its measurement has remained elusive. In the existing literature, trust is often measured from responses to survey questions such as: "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 debate (Glaeser, Laibson, Scheinkman, and Soutter, 2000; Fehr, Fischbacher, von Rosenbladt, Schupp, and Wagner, 2003; Karlan, 2005; Sapienza, Toldra-Simats, and Zingales, 2013).

2.2 Community Average Credit Scores as an Indicator of Social Trust

Taking on this challenge in the literature, we introduce the average credit score as an indicator of the level of a community's social trust. Credit scores are designed to evaluate borrowers' credit quality, and borrowers with higher credit scores, on average, have lower default rates. Among other factors used in estimating credit scores, debt payment history—and how reliably payments were made—remains an important determinants of one's credit scores.[8] As discussed below, we argue that credit scores may reveal one's underlying trustworthiness and reflect past experiences and attitudes toward the credit and financial markets.[9]

Credit scores as an indicator of an individual's trustworthiness

Borrowers may choose to default on their debt even when they have the means and financial capacity to repay. For example, borrowers may choose to file for bankruptcy when the financial benefit of filing outweighs the cost (Fay, Hurst, and White 1999), and homeowners may choose to default on their mortgages if their houses are deeply underwater (Mayer, Morrison, Piskorski, and Gupta 2014). Conversely, Becchetti and Conzo (2011) show that receiving a loan signals the trustworthiness of the borrower. We argue that credit scores contain signals that reveal underlying trustworthiness of an individual.

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 individual's 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] More comprehensive historical evidence is

[8]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).

[9]As mentioned before, income and credit scores are only moderately correlated.

[10]For example, one of the credit reports prepared by the Retail Credit Company in 1934 included the

documented in the recent book Lauer (2017). For example, one interesting anecdote cited in the book is that at a congressional testimony, when asked whether credit was "based primarily upon money or property," J.P. Morgan answered, "No, sir; the first thing is character." Accordingly, while credit scoring in modern days no longer uses such "soft" information, to the extent that credit scores predict defaults, they may reveal information related to one's general trustworthiness and character. In addition, recent research suggests that individuals' credit scores are only moderately correlated with their income (Beer et al 2018).

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).[11] Many cell phone and cable companies also use credit score information in contract-based plans.

Credit scores as an indicator of experiences, perceptions, and attitudes

It is important to remind ourselves that credit scores can be low for reasons that 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 losses. Such negative financial experiences may lead these families to have less trust in financial markets and institutions.[12]

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?"

[11]The extent to which such information helps screening candidates and predict job performance remains an area of active research, and the results tend to vary with the type of credit information and the subpopulation studied. For example, Dobbie, Goldsmith-Pinkham, Mahoney, and Song (forthcoming) find that the removal of bankruptcy flag does not appear to affect employment and earnings outcomes. By contrast, Bos, Breza, and Liberman (2018) find that removal pawnshop loan default information leads to a 3 percentage point increase in employment in Sweden. Finally, Nelson and Bartik (2019) find that banning the use of credit reports in screening job applicants decreases job-finding rates for blacks by 2.4 percentage points.

[12]Relatedly, less trustful households tend to use the financial market less. The 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.

For example, 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 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). In a similar vein, consumers with lower credit scores due to previous difficulties of repaying debt may feel more distrustful toward financial and credit markets; and such a distrusting effect can be particularly strong if the debt repayment difficulty was due to misleading or deceptive information offered by financial advisors, loan brokers, or credit product sales representatives. Indeed, we find that counties with lower average credit scores tend to report more complaints to the Federal Communication Commission. While the higher volume of complaints may reflect such financially vulnerable communities more likely being targeted by frauds, it may also indicate residents in these communities being more suspicious toward marketing campaigns. Furthermore, Dokko, Li, and Hayes (2015), using data from the Social Capital Community Survey, document that residents in areas with higher average credit scores also tend to demonstrate higher trustfulness toward other people and the society.

Individual investors' trust may be affected by the community's social trust in two channels. First, as one encounters more fraud or feels unfairly treated in personal interactions and business transactions, her trust of the society will be undermined. 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). Second, exposure to more trustworthy people may help others overcome adversity, especially those with low social standing (Helliwell, Huang, and Wang, 2016). Conversely, residents of a community with lower average credit scores have a better chance of running into someone distrustful of the financial market and being influenced by that person's view.

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. Interactions among individuals in community may reinforce such (mis)trust perceptions and attitudes, thereby affecting the social trust within the community. Figure 1 provides an illustration of this conceptual framework. Thus, a community's average credit score reveals information on the levels of both trustworthiness and trust of its residents. Moreover, we find that residents of communities with lower average credit scores tend to have greater mobility, likely in part reflecting financial-distress related relocations.[13] It will be more difficult for strong social trust and capital to form and establish in such communities with greater residents turnover. 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 its social trust—a proposition that we test 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 consider 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 trust of a community. For other community characteristics, such as demographic compositions and contemporaneous economic conditions, we use data from the Census Bureau, the Bureau of Labor Statistics (BLS), and the American Community Survey. This section will introduce the primary data sources we use and present statistics of the key variables of our study.

[13]We correlate mobility with average credit score at the census tract-level. The correlation is negative and statistically significant even after controlling for residents' average age and other socioeconomic characteristics.

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 trust 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.[14] 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 potential high-frequency variations that are not necessarily reflecting differences in social trust.[15] 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.[16] Figure 2 illustrates the wide variations in average credit scores across states and across counties in the same state (with Arkansas as an example).

3.2 Other Measures of Trust and Social Capital

Because social trust is a critical element of social trust, a sound measure of social trust should be correlated and consistent with measures of social capital. Accordingly, we compare the

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

[15]The neighborhood average credit scores are fairly stable over time. The sample-beginning and sample-end correlation is above 0.9 across the census tracts in our sample.

[16]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.

community-average credit score to a wide range of social capital indicators employed in the existing literature as a validation analysis. 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.[17] 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.[18] 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 and demographic characteristics. 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 trust and other socioeconomic and demographic characteristics. One unique advantage of using both the SCF and PSID data is

[17]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

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

that the former oversamples high-income, high-wealth households and the latter oversamples low-income, low-wealth households. Using data from both surveys provides a more complete and balanced analysis of U.S. household stock investment.

The SCF is a cross-section survey 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, fewer than one quarter of households directly own corporate equities (stocks).[19] Among those who own stocks, the share of stocks in their financial assets portfolio is about 44 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. Both are comparable with external aggregates.[20]

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).[21] 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, effectively creating a proxy for individual trusting attitudes.

[19]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.

[20]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.

[21]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.

Note that, in contrast to the World Value Survey measures, this measure of trusting attitude in the SCF is not self-reported but is assessed by a third party (the interviewer). 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.[22] 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, taking advantage of its longitudinal structure.

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 who 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, 24 percent of the households relocated to a different census tract within two years, and we focus on these households in our stock market entry and exit analysis. Finally, unlike the SCF, the PSID does not systematically collect data on respondents' risk aversions and trusting attitude.[23]

[22]The PSID was an annual survey from 1968 to 1997, biennial afterwards. Some of the data used in this analysis are derived from Sensitive Data Files of the Panel Study of Income Dynamics, obtained under special contractual arrangements designed to protect the anonymity of respondents. These data are not available from the authors. Persons interested in obtaining PSID Sensitive Data Files should contact through the Internet at PSIDHelp@isr.umich.edu.

[23]The only wave that the PSID collected risk aversion related information was in 1996. In an additional robustness analysis (not shown), restricting the PSID sample to those who were surveyed in 1996 and including their self-reported risk tolerance in the model does not qualitatively change the results in the baseline analysis.

3.5 Other Data Sources

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 crime case clearance rates as an indicator of local law enforcement strength.

4 Average Credit Scores as an Indicator of Social Trust

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

4.1 Simple Correlations

Trust is an important factor influencing social capital. Therefore, a sound indicator for social trust should be consistent with measures of social capital. Accordingly, we show that average credit scores are indeed correlated with a range of other measures of trust and social capital used in the literature—Census participation, presidential election turnout, numbers of NPOs and associations, blood donations, and FCC fraud complaints. Because credit scores can reflect a number of factors not necessarily driven by trust or social capital, it is important to include a rich set of controls of community characteristics. Specifically, we estimate the following statistical model:

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

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.

We note that the correlation between average credit scores and each of the six existing measures of social capital and trust is economically and statistically significant, even after controlling for a range of characteristics of the community. 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, 3 more NPOs, 0.3 more civil associations, 35 more units of blood donations, and 0.4 fewer FCC complaints per 1,000 residents, respectively.[24]

4.2 Principal Component Analysis

Each of the seven indicators, including average credit scores, should convey some information about a community's social trust and social capital, which is best interpreted as a latent variable. We implement a principal component analysis (PCA) of these seven social capital indicators to evaluate information content of these indicators with respect to this latent variable.

To do so, we first conduct a PCA on all seven indicators considered here, including average credit scores. As shown in the first row of the table 4, average credit scores has the highest correlation, 0.81, with the first principal component. The first principal component correlations with Census participation, election turnout, the number of associations, and blood donations are smaller. Bootstrapping analysis also indicates that the differences in correlation coefficients are statistically significant at at least the 90-percent level. The first principal component correlation with the number of NPOs is more similar to that with average credit scores and the difference is not statistically significant. Finally, FCC complaints are not correlated with the first principal component but has the largest correlation with the second principal component.

Second, we construct seven sets of PCs using only six out of the seven indicators con-

[24]The implied changes correspond to 25–75 percent of their standard deviations across these alternative social capital indicators.

sidered here (omitting one of the seven each time) and compared the correlation between the first PC and the omitted indicator. This exercise illustrates the extent to which one indicator is consistent with the other indicators in general. As shown in the bottom row, the average credit score indicator has the highest correlation, with the number of NPOs again being the runner-up.

In sum, the statistical evidence presented above indicate that average credit scores are consistent with most of the other indicators employed in previous studies and have potentially more appealing statistical properties. Notably, average credit scores can be estimated for more granular communities whereas existing indicators are typically available only at the county level. In addition, consistent with the notion that social capital tends to be slow-moving, average credit scores are relatively stable over time. Other indicators, however, tend to be more volatile. For example, using general election data from 2000 to 2016 at the county level, we find the time series volatility of election turnouts to be substantially larger than that of county average credit scores of the same years. As a result, the Spearman rank correlation of voter turnouts of the same county across years is much lower than that of average credit scores.

4.3 Relationship with Social Capital Indicators Derived from Social Media Data

In addition to the indicators discussed above, Chetty et al (2022) introduced an array of social capital indicators derived from data on people's interactions on a social media platform. They demonstrate strong associations between economic mobility and some of these indicators. We correlate the average credit score with four major social capital indicators they introduced, namely, connectedness, clustering, volunteering, and civic organizations at the ZIP Code level. As shown in table 5, average credit score is highly correlated with the connectedness indicator, with correlation coefficient as high as 0.8. Moreover, volunteering and civic org. indicators' correlations with average scores are essentially the same as those with the connectedness indicator. Interestingly, while the connectedness and clustering indicators have a slight negative correlation, the clustering and average score indicators have a modest, positive correlation. These correlations also hold at the county level. In addition, the appendix table A1 shows the results of estimating equation (2) using these social capital indicators, which are broadly similar to those reported in table 3.

5 Social Trust and Stock Ownership

With detailed data on Italian families, GSZ (2004) show a robust positive relationship between voter turnout and blood donation and stock investment. However, in the U.S. data, while voter turnouts are correlated with stock market participation, blood donations are not. Moreover, experimenting with other social capital indicators, we find that U.S. Census responses predict stock investment, but the numbers nonprofit organizations, associations, and FCC complaints do not.

The mixed results prompt us to revisit the question and ask whether people living in communities of higher average credit scores are more likely to own stocks. We note that our approach does not exploit any exogenous shocks to the social capital level in a given area. Instead, we strive to demonstrate the role of social capital by including rich, exhaustive controls. Furthermore, we present a large array of corroborative, ancillary evidence that shows the robustness of the results, sheds light on the mechanisms of this relationship, and helps rule out alternative hypothesis.

We begin with estimating a workhorse model used extensively in stock market participation research, augmented with 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:

$$Part_{i,t}^{y} = \alpha + \beta \overline{Score}_t + \gamma Z_i^y + \theta M_c^y \rho Year^y + \varepsilon_{i,t}^y, \tag{3}$$

where $Part^y_{i,t}$ 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. $\overline{Score}_t$ is the mean credit score for tract t.[25] Because our credit score data come from a 5-percent random sample of U.S. consumers, the chance of individual i, the survey respondent, being included in the calculation of average score is low. Moreover, an average census tract has 4,000 people. Therefore the credit score of one individual has only a limited impact on the tract-average. 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.[26] M is a vector of local economic conditions that includes house price growth and unemployment rates, which are measured at the county level, indexed by c. $Year$ is a vector of yearly fixed effects.[27]

5.1 The Baseline Analysis

We estimate the model using the SCF and PSID data in our baseline analysis, and the results are presented in table 6; standard errors clustered at the tract level (and adjusted for multiple imputation in the SCF) are shown in parentheses.[28] In addition, for key parameters of interest, we also report in brackets the implied odds ratio associated with a one-standard deviation change of the average credit score.

To begin with, the baseline estimates shown in column 1 suggest that higher levels of

[25]In the baseline analysis, we average tract-mean credit scores over year. Using yearly tract-average credit scores as the social trust indicator does not change the results qualitatively.

[26]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).

[27]In addition to controlling for local economic conditions, we regress a county's annual average credit score on contemporaneous and three lags of local unemployment rates then average the residuals of these regression across years. Our results are qualitatively unchanged, indicating that the correlations between average credit scores and local economic trends are not driving our main results.

[28]Our results are not sensitive to the level of clustering. Clustering at the state or MSA level yields only slightly larger standard errors.

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 across all communities) higher than an otherwise identical tract have a 35 percent higher odds to own equities in a given year in the SCF and a 30 percent higher odds in the PSID, 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.

Next, we re-run our analysis using county-level, rather than census tract-level, average credit scores. Our results—column 3 for the SCF and column 7 for the PSID—show odds ratios smaller than those in the tract-level analysis, consistent with 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.

On the intensive margin of stock investment, we study the effect of social trust on stock shares in household financial assets portfolios by estimating a tobit model with the same controls as in columns 1 and 5. The tract-level results, reported in columns 2 and 6, imply that a one-standard-deviation increase in census tract mean credit score is associated with a 5 and 9 percentage-point increase in stock investment share in the SCF and the PSID sample, respectively. The increases are about 10 to 15 percent of the mean stock investment share, broadly consistent with GSZ (2008)).[29]

[29] Furthermore, GSZ (2008) argue that low levels of trust and social capital offer a potential explanation for the puzzlingly low stock market participation rate among the wealthy households. Following their approach, we find that the association between the propensity of investing in stocks and community average credit scores are similar and significant for households with below-median and above-median wealth, a result similar to GSZ (2008).

5.2 Robustness Analysis and Alternative Hypotheses

The baseline analysis reveals strong associations between the average credit scores of a community and its residents' propensity and portfolio share of stock investment. However, it is possible that such a correlation is driven by omitted variables, confounding factors, or specifications. We present an array of tests that may challenge the estimates in table 6 and show that the baseline results are robust to these alternative specifications and alternative hypotheses. For brevity, the results in table 7 are shown only for the SCF, though the PSID results are similar when applicable.

Alternative model specifications

In the first column, equation (3) is re-run with a linear probability model. The estimates are comparable to those in table 6: a one standard deviation change in community average credit score is associated with a nearly 50 percent increase in participation. Similarly, results of estimating a probit model (not shown) are similar to the baseline estimates. Moreover, including nonlinear controls for household income and wealth in the form of decile dummies(column 2) attenuates the baseline estimate a bit, but key coefficient remains sizeable and significant. Furthermore, the results are little changed when the sample is restricted to families with a prime-age (aged 25 to 60) household head (not shown).

As shown in table 3, the average credit score of a neighborhood is correlated with its socioeconomic and demographic characteristics, which may have some bearings on residents' stock ownership. We test if average credit scores predict stock investment conditional on these factors. Specifically, in column 3 of table 7 we include a vector of tract-level community characteristics (median income, racial and education compositions). Likewise, the estimates are only slightly attenuated relative to the baseline estimates. We also estimate the baseline model with MSA $\times$ year fixed effects to control for potentially time-varying omitted characteristics.[30] The results, shown in column 4, confirm the baseline estimates. Moreover, in results not shown, controlling housing and nonhousing wealth separately does

[30]Due to the survey sample size limitation, we are not able to control for county $\times$ year or tract $\times$ year fixed effects.

not change the results qualitatively.

Is average score an approximation of one's own?

Credit score plays a prominent role in one's personal finance. Individuals with high credit scores tend to have better access to credit at lower interest rates, which help such investors accumulate wealth and invest in risky assets such as stock. Does the baseline result mainly reveal the relationship between one's own creditworthiness and stock investment should community average credit be a proxy of an individual's own credit score? First, we note that the within-tract and within-county dispersion of credit scores is substantial, with standard deviations greater than 40 score points. Thus, for many residents, the community average credit score is not a reliable approximation for individual scores. Indeed, nearly all lenders request individual borrowers' credit scores, instead of relying on the average scores of borrowers' neighborhoods. Furthermore, we estimate the baseline model using a subsample of census tracts of largest (top quartile) within-tract dispersion of individual credit scores. The results, shown in column 5, suggest that the baseline results hold for tract where average credit scores are not good proxies of residents' individual scores.[31]

Individual credit constraints

Second, we also examine whether the correlation between community average credit score and stock ownership mainly reflects the former predicting individual residents' access to credit, which may in turn affect their stock investment decisions. To do so, we add the self-reported credit constraints information collected in the SCF to the baseline specification.[32] As shown in column 6, controlling for household-level access to credit does not qualitatively change the baseline results.

[31] Qualitatively similar results are found when we use the entire sample and interact a continuous measure of within-tract dispersion with community average credit score.

[32] The SCF asks respondents whether they were declined for credit or felt discouraged to apply for credit during the past twelve months, which have been frequently used as indicators of household credit constraints (see, for example, Jappelli (1990)).

Financial service access

Third, it is possible that higher average credit scores are associated with greater local access to financial services (such as banking) that facilitate stock investment. To test this hypothesis, we include in the baseline model the number of bank branches in the county as an additional control variable. As shown in column 7, the number of bank branches does not bear a significant association with the propensity of owning stocks and the estimated coefficient for average credit score is little changed.[33]

Household economic expectations

Fourth, it is possible that a neighborhood's socioeconomic characteristics, including average credit scores, may affect its residents' economic expectations, which in turn may influence their stock investment decisions. To parse out the direct association between social trust and stock ownership from that through economic expectations, we include an additional control variable of household economic expectations. Specifically, the SCF asks respondents whether they expect the economy will perform better, worse, or about the same over the next five years. Including these expectation variables in the baseline model we find that, while more upbeat expectations are positively correlated with stock ownership, the coefficient of average credit score is essentially unchanged (column 8).

Survey response carefulness

Fifth, if residents living in high-social trust areas are more trustful, they may be more cooperative when responding to surveys by providing more complete and careful answers, including their stock ownership. In such a scenario, the measurement error on stock ownership is correlated with social trust, leading to bias of our estimates. To address this potential bias, we take advantage of the SCF paradata that record whether survey respondents referred to their financial documents when answering questions. Households consistently referring to financial documents are categorized as careful survey respondents.[34] As shown in columns 9

[33]The coefficient of bank branches estimated using the PSID sample is statistically significant but similarly modest.

[34]The SCF data include respondents' trustfulness to the survey as observed by the interviewers. We will provide a more detailed treatment of this measure of trustfulness, which is positively correlated with survey

and 10, while the average credit score coefficient is estimated slightly larger among careful respondents, it is statistically and economically significant for both careful and not-careful households, indicating that the association we find between social trust and stock ownership is not entirely driven by such measurement errors.

Financial literacy

Finally, higher credit scores may be associated with greater financial literacy, which may in turn associated with greater stock investment. We do not have financial literacy indicators of the SCF and PSID households. Instead, we use data collected in the 2015 FINRA National Financial Capability Study to approximate the financial literacy levels of the areas where the SCF and PSID sample investors reside and include this indicator to the baseline model.[35] The results (column 11) indicate that controlling for average financial literacy levels at the county levels leaves the baseline results little changed. However, we note that because of the relatively small sample size of the FINRA study, our financial literacy indicator constructed at the county level may be noisy and better data are needed for more concrete analysis. To mitigate this concern, we compare stock investment returns as reported in the SCF among investors of low- versus high-social trust areas. Looking at both dividends and capital gains, we find no evidence suggesting that investors living in high-social trust areas consistently enjoy higher returns that those living in low-social trust areas. Thus, our baseline results is unlikely driven by potential differences in financial literacy or stock investment know-how across the social trust gradient.

5.3 A Blinder-Oaxaca Decomposition

Thus far we have shown that social trust has an association with participation distinct from other observables (tables 6 and 7). But to get a better sense of how the participation rate differs across social trust spectrum—and how observables (some of which can be correlated with trust measures) explain this difference—we follow Grinblatt, Keloharju, and Linnain-

response carefulness, later in the paper.

[35]For more information about the FINRA survey, see `http://www.usfinancialcapability.org/about.php`

maa (2011) and perform an Oaxaca-Blinder decomposition of the participation gap between residents of high- and low-social capital areas.

There is a 54-percentage point gap in the participation rate between the areas in the top decile of social trust—with a 61 percent participation rate—and those in the bottom decile—with a participation rate of 7 percent (table 8). About 30 percentage points of the 54-percentage point gap can be explained by observable differences in the neighborhood composition (about 11 percentage points), household income and wealth (about 10 percentage points), and other household differences (the remaining 9 percentage points). The 24 percentage points of unexplained difference in participation potentially reflect the trust effects that are orthogonal to these observables. It could also reflect the effect of other unobserved factors that are potentially correlated with social trust—such as participation costs (Vissing-Jorgensen, 2002; Briggs, Cesarini, Lindqvist, and Östling, 2016), and certain behavioral biases (Haliassos and Bertaut, 1995; Malmendier and Nagel, 2011)—that have been proposed to account for the lack of stock market participation. Quantifying the contribution of each of these factors will be a topic for future research when better data become available.

5.4 Social Trust vs. Other Effects

We argue average credit scores containing important information about social trust of a community. However, average credit scores may contain other information that also predict stock investment. To test whether the association between average credit scores and stock market participation established above reflects a trust effect, we implement a two-sample IV analysis. Specifically, projecting county-average credit scores on other social capital indicators (discussed in table 3) of the same county yields $\widehat{\overline{Score}}$ and Res, the predicted value and residual, respectively. We then replace $\overline{Score}$ in equation (3) with $\widehat{\overline{Score}}$ and Res. The estimated coefficients are 0.876 (0.189) for $\widehat{\overline{Score}}$ and 0.763 (0.177) for Res, respectively, and both are statistically significant.[36] The analysis indicates that both the social trust element and other information revealed in community average credit scores are

[36]Standard errors estimated with 1,000 bootstrapping iterations are reported in parentheses.

associated with individual residents' stock market participation.

5.5 Inspecting the Mechanism

Social trust's bearing diminishes with education

We now introduce several tests that shed light on the property of the relationship between trust and stock investment. To begin with, we show that the association between social trust and stock ownership is more pronounced among those with less education. As described in GSZ (2004, 2008), those with more education should have had more formal channels to understand the benefits of investing in stocks, so in a world where trust influences stock investing, we should see a larger effect for those with less education. To test such a difference, we add to the baseline model a term that interacts average credit scores with years of education (columns 1 and 8 of table 9). The coefficient of the interaction term is indeed negative and large in magnitude in both the SCF and the PSID sample, with the SCF estimate (column 1) having borderline significance and the PSID estimate (column 8) being highly significant. The negative coefficients imply that the influence of social trust is highest among those with lowest educational attainment and, conversely, lower amongst those with higher education levels.

Strong law enforcement mitigates the lack of trust

GSZ (2004) argue that the main reason why trust matters for economic decisions is the lack of high quality legal enforcement. An corollary of the theory is the association between social trust and stock market participation should be weaker in areas with stronger law enforcement. We test this corollary by including law enforcement, measured with crime case clearance rate, and an interaction term between average credit score and the clearance rate. The results, shown in column 2, indicate that stronger law enforcement (higher clearance rate) promote stock investment. However, in areas with stronger law enforcement, the association between social trust and stock market participation diminishes.

Mutual funds versus stocks

While trust in the financial market promotes stock market participation, investments through equity mutual funds involve an additional layer of delegation, and are thereby more sensitive to trust. For example, Gennaioli, Shleifer, and Vishny (2015) introduce a model where investors delegate portfolio management to professionals based on performance and trust. We test this implication by comparing the associations of social trust with propensities of owning stocks directly and of owning stocks through equity mutual funds.[37] The results, reported in columns 3 and 4, respectively, show the estimated coefficient for stock mutual funds is larger than that for direct stock ownership, and the difference therein is statistically significant. Consistent with the Gennaioli et al (2015) model, the odds ratio estimates (not shown) imply that a one standard-deviation increase in average credit score is associated with a 19 percent higher likelihood of owning stocks directly and a 27 percent higher chance of owning stocks through such mutual funds.

Survey interviewer observed trustfulness

We now exploit a unique feature of the internal SCF data—the interviewer's assessment of the individuals' trusting attitude observed during data collection—that allows us to examine how trusting attitudes may influence stock investment using an alternative indicator. As described earlier, the interviewer who conducts the SCF in the field makes note of the responding family's degree of suspiciousness. 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 (column 5). Furthermore, there is a correlation between interviewer-assessed degree of trustfulness and the average credit score of the tract where the respondent lives—consistent with the notion that people living in higher social trust communities tend to more trustful. Accordingly, we use this correlation as an instrument in the first stage of a two-stage least squares regression of stock market

[37] The first dummy is equal to one if the household owns stocks only directly and owns no equity mutual funds. The second dummy is equal to one if the household owns equity mutual funds, regardless whether it also owns stocks directly. The mutual funds analysis excludes the households owning stock only directly from the sample.

participation on household trusting attitudes. The coefficient of the second stage regression, reported in column 6, is considerably larger than the one in column 5, due to much smaller variations in the predicted interviewer-observed trustfulness obtained from the first-stage regression. However, the implied increase in stock investment propensity of a one-standard deviation increase in the predicted trustfulness has a similar magnitude as in column 5, around 23 percent.[38] This result thereby reveals that one important channel through which social trust potentially promote stock ownership is by influencing residents' trustfulness. Furthermore, because the interviewer-recorded degree of trustfulness may reflect a particular interviewer's idiosyncratic taste and perception, we rerun the analyses in columns 5 and 6 including interviewer fixed effects, and the results are qualitatively unchanged.

Distance gradient of the estimated association

Because families interact not just with their near neighbors but also with those in surrounding areas, we expect the trust level of neighboring communities—in addition to an investor's own community—to influence participation, but to a lesser extent. We test this hypothesis by adding in the baseline model the social trust indicator of the tracts connected to the residing tract of each family (column 2). For each census tract, we first calculate the average credit score of all connected tracts, weighted by tract population. Because average credit scores of connecting census tracts tend to be correlated, we first regress the average credit scores of adjacent tracts on that of the residing tract and include the residual in the model. The results, reported in columns 7, indicate that variations in average credit scores of adjacent tracts orthogonal to those of an investor's own residing tract are also correlated with his stock ownership, but to a lesser degree. The estimated odds ratios (not shown) indicate that a one standard-deviation increase of our measure of adjacent tracts' average credit scores imply a 10 percent increase in the likelihood of owning stocks, comparing with 35 percent implied by higher own-tract average credit score.

[38]Because our first stage correlation is relatively weak, we use the "plausibly exogenous" two-stage estimator that is due to Conley, Hanson, and Rossi (2012).

Social trust where one grew up matters

Finally, the geo-coded PSID data include unique information about the county in which one grew up. This information allows us to study how social trust of the community where one grew up may influence an investor's stock ownership. To do so, we add the average credit score of the county where the household head grew up to the baseline model. We estimate the model using a sample of household heads no longer living in the same county where they grew up. The results, reported in column 9, are consistent with GSZ (2004) and Brown, Ivković, Smith, and Weisbenner (2008) and indicate that early-lifecycle exposures to higher social trust levels appear to have a lasting effect on future stock investment.[39]

5.6 Do Other Social Capital Indicators Predict Stock Investment?

We introduced community average credit scores as a measure of social trust in comparison with other indicators used in the literature, including U. S. 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 six 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 10, with column 1 replicating the $\overline{Score}$ estimates in column 3 of table 6.

Our analysis reveals that first, of the other indicators, only Census response rate and election turnouts are associated with stock ownership with statistical significance, whereas the numbers of NPOs and associations, blood donations, and FCC complaints are not. Second, as shown in column 8, when all seven social capital measures are included, the

[39]A caveat regarding this exercise is that we approximate the social trust one was exposed to while growing up (decades ago for some investors) using that county's more recent 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 trust in the past.

community average credit score is estimated to be the only significant predictor of stock market participation. On balance, the results demonstrate other social capital indicators' limited power in predicting U.S. household stock investment, especially when contrasted with community average credit score as an indicator of social trust, using which one can infer its social capital.[40]

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 on household stock investment, concerns remain as stock investors are 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 average levels of wealth and income over $y-2$, y, and $y+2$. In

[40] In addition, the appendix table A2 shows the analysis using the social media data-based indicators (Chetty et al 2022), and the results are similar with those of table 10.

addition, we include the change of real income between $y - 2$ and $y + 2$, acknowledging expected income growth can be an important factors affecting relocation and stock market entry. Investors who did not own stock in year $y - 2$ and did not move between years $y - 2$ and y are included as the control group.

We focus on the stock market entries 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' decisions of exiting the stock market are more related to their investment experiences, financial conditions, and expected returns, but less influenced by trusting attitude changes.

The results are summarized in table 11. As shown in column 1, 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 a 6 percent higher chance of entering the stock market. By contrast, the coefficient for moving to communities with lower credit scores is 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 2). Furthermore, we note that relocation (between $y-2$ and y) and stock market entry (between y and $y+2$) decisions may both reflect the foresight of investors on their future income growth. To address this concern, we take advantage of the long-panel feature of the PSID data and include in eq.

(4) the observed income growth between $y+2$ and $y+4$, in addition to that between $y-2$ and $y+2$. While the estimated coefficient (not shown) suggests that income growth between $y+2$ and $y+4$ is positively correlated with stock market entry between y and $y+2$, including this additional income growth control does not alter the estimated coefficients on positive changes of community average credit scores (column 3).

Finally, as shown in columns 4–6, relocation-induced community average credit score changes do not appear to have any significant effect on current stock owners' decisions on exiting the market, and this result holds with respect to the variations experimented in columns 2 and 3. The contrast between the estimates of market entries and exits, as we argued earlier, is consistent with the notion that current stock investors tend to make investment decisions on objective, market related factors, and are therefore less influenced by subjective perceptions, such as one's trust of the stock market.

7 Concluding Remarks

This paper has two goals. First, we introduce average credit scores as a measure of a community's social trust and make this indicator available to the broad research community. We show that the average credit score as a measure of social trust, as a critical component of its social capital, is consistent with other measures employed in previous research, including those introduced in Chetty et al (2022) based on people's behavior on a social media platform. Relative to survey-base social trust measures, this new measure has several appealing features. It is objective, data driven, and based on individual economic behavior such as credit usage and debt repayment. In addition, 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. That said, we want to underscore that establishing this metric as a reliable indicator for social trust requires much more research and analysis beyond what is done here. We hope that the analysis herein provides a promising starting point for future research.

Second, we examine the relationship between social trust and investment in stocks using

U.S. data. We find that higher average community credit scores are consistently associated with higher likelihood of stock market participation of residents in the same community, a finding that manifests itself in both static and dynamic analysis. Furthermore, consistent with the theory of social trust and financial investment, we find that such a relationship is more pronounced for lower-educated investors, in areas with weaker law enforcement, and for stock investment through mutual funds, which require additional delegation.

Measuring latent factors like social trust and understanding how they affect household behaviors is difficult. This is particularly true when the latent factor is slow moving and researchers do not have easy means to shock or manipulate it. While we argue for the desirable properties of the proposed indicator, we acknowledge its own limitations. The merit of the new indicator will be examined and established when it is applied to various research context. There are also directions in which this measure can be further refined and enriched. For example, the proposed 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 trust 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] Algan, Yann (2018). "Trust and Social Capital," in Joseph Stiglitz, Jean-Paul Fitoussi, and Martine Durand ed. *For Good Measure: Advancing Research on Well-being Metrics Beyond GDP* , OECD, 2018.

[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] Becchetti, Leonardo and Pierluigi Conzo (2011). "Enhancing capabilities through Credit Access: Creditworthiness as a Signal of Trustworthiness under Asymmetric Information," *Journal of Public Economics*, vol. 95 (April), pp. 265–78.

[9] Beer, Rachael, Felicia Ionescu, and Geng Li (2018). "Are Income and Credit Scores Highly Correlated?" *FEDS Notes*. Washington: Board of Governors of the Federal Reserve System, August 13, 2018, https://doi.org/10.17016/2380-7172.2235.

[10] Bos, Marieke, Emily Breza, and Andres Liberman (2018) "The Labor Market Effects of Credit Market Information," *Review ofFinancial Studies*, vol. 31 (June), pp. 2005-37.

[11] 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.

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

[13] 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.

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

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

[16] Chetty, Raj, Matthew Jackson, Teresa Kuchler, Johannes Stroebel, and others (2022). "Social capital I: measurement and associations with economic mobility," *Nature* vol. 608, pp. 108–21.

[17] Conley, Timothy, Christian Hansen, and Peter Rossi (2012). "Plausibly Exogenous" *Review of Economics and Statistics*, vol. 94 (February), pp. 260-72.

[18] 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.

[19] 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.

[20] Dobbie, Will, Paul Goldsmith-Pinkham, Neale Mahoney, and Jae Song, "Bad Credit, No Problem? Credit and Labor Market Consequences of Bad Credit Reports," forthcoming *Journal of Finance*.

[21] 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.

[22] 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.

[23] Fay, Scott, Erik Hurst, and Michelle White (2002). "The Household Bankruptcy Decision," *American Economic Review*, vol. 92 (June), pp. 706-18.

[24] 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.

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

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

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

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

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

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

[31] Grinblatt, Mark, Matti Keloharju, and Juhani Linnainmaa (2011). "IQ and Stock Market Participation," *Journal of Finance*, vol. 66(November), pp. 2121-64.

[32] Guinnane, Timothy (2005). "Trust: A Concept Too Many," *Jahrbuch für Wirtschaftsgeschichte*, pp.77-92.

[33] 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.

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

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

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

[37] Halpern, David (2005). *Social Capital*, Cambridge: Polity Press.

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

[39] 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.

[40] Jappelli, Tullio (1990). "Who is Credit Constrained in the U.S. Economy," *Quarterly Journal of Economics*, vol. 105 (February), pp. 219-34.

[41] Jiang, Danling, Sonya Lim (2018). "Trust and Household Debt," *Review of Finance*, vol. 22 (March), pp. 783-812.

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

[43] 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.

[44] 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.

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

[46] Lauer, Josh (2017). "Creditworthy: A History of Consumer Surveillance and Financial Identity in America," Columbia University Press, New York, New York.

[47] Mayer, Christopher, Edward Morrison, Tomasz Piskorski, and Arpit Gupta (2014) "Mortgage Modification and Strategic Default: Evidence from a Legal Settlement with Countrywide," *American Economic Review*, vol. 104 (September) pp. 2830-57.

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

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

[50] Nelson, Scott , and Alexander Bartik (2019), "Deleting a Signal: Evidence from Pre-Employment Credit Checks," *working paper*.

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

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

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

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

[55] 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.

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

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

Figure 1: An Illustration to the Conceptual Framework

This figure illustrates how credit scores reflect certain personal traits and experiences and how communities with lower average credit scores may have lower levels of social trust and social capital. Two types of factors can lead to debt defaults and lower credit scores. The external factors (the blue box on the left) include personal financial shocks and negative experience with financial institutions or individuals that affect the ability to repay debt; the internal factors (the red box) include personal traits like lower willingness to repay debt. A community with a lower average credit score tends to have a larger share of residents of either or both types. Interactions among these residents and their interactions with other residents in the community may lead to or reinforce the lack of trust to institutions or individuals.

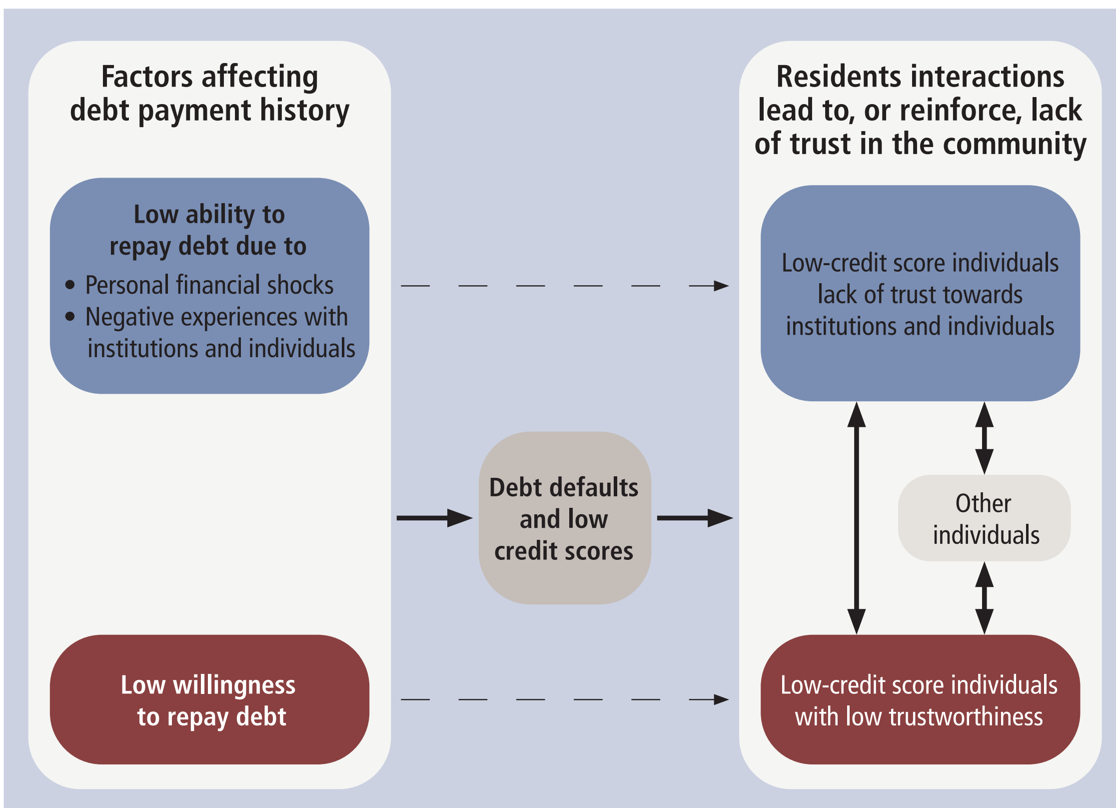

Figure 2: Average Credit Scores across U.S. States and Arkansas Counties

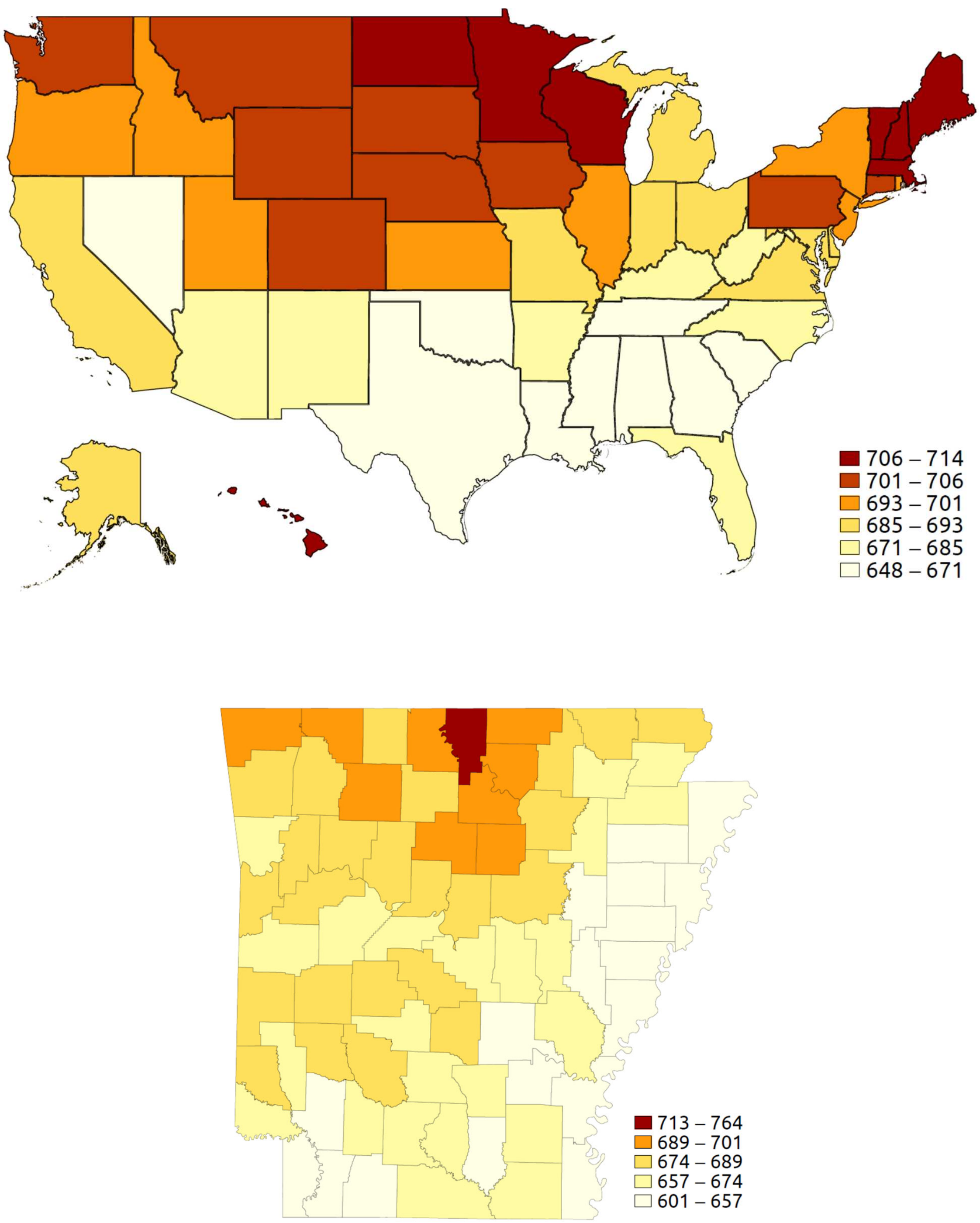

Table 1: Summary Statistics of Credit Scores and Measures of Social Trust and Capital

Note: 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 where 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

Note: 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
Household characteristics		
Head age	50.0	50.4
Yeas of schooling	13.3	13.1
Married (%)	58.2	51.3
White (%)	70.0	79.2
Real net worth (2002$)	437,828	280,710
Real normal income (2002$)	69,197	...
Real income (2002$)	...	60,557
Willing to take fin. risk (%)	18.8	...
Interviewer observed trust (%)	56.1	...
Relocated in past two years (%)	...	24.3

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

Note: This table reports regressions of indicators of social 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 Social Capital Indicators

Note: The table shows that the average credit score has the highest correlation with the first principal component extracted from the seven indicators (column 1). Moreover, it also has the highest correlation with the first principal component extracted just from the other six indicators. *** indicates that the difference between the correlation coefficient and that in column 1 is statistically significant at the 99-percent level.

	$\frac{\overline{Score}}{100}$	Census response	Election turnouts	Number of NPOs	Number of associations	Blood donations	FCC complaints
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Correlations with the Principal Components of All Seven Indicators						
$First\ \ PC^7$	0.81	0.40***	0.72***	0.78	0.70***	0.67***	0.01***
	Correlations with the Principal Components of the Other Six Indicators						
$First\ \ PC^6$	0.63	0.27***	0.55***	0.60	0.52***	0.51***	0.00***

Table 5: Consistency with Social Media-Based Indicators

Note: The table shows the population-weighted correlations between average credit scores and the social media-based indicators introduced in Chetty et al (2022) at the ZIP Code level.

	$\overline{Score}$	Connectedness	Clustering	Volunteering	Civic Org.
$\overline{Score}$	1.00	0.79	0.12	0.48	0.10
Connectedness		1.00	-0.02	0.47	0.10
Clustering			1.00	0.22	0.16
Volunteering				1.00	0.16
Civic Org.					1.00

Table 6: Community Average Credit Scores and Stock Ownership

Note: Control for household head age polynomial, family size dummies, yearly fixed effects and local economic conditions such as county-level unemployment and house price growth. Standard errors are clustered at the census tract and county levels, respectively, and are presented in parentheses. *, **, and *** denote 90, 95, and 99 percent statistical significance, respectively. Odds ratios associated with a one standard deviation change of the key independent variables are presented in brackets. Data are 1999–2013 PSID and 2004-2010 SCF (see the text for sample construction details). Credit score averages are calculated using the FRBNY CCP/Equifax data. Columns 1-4 present the SCF analysis results, and column 5-8 present the PSID analysis results. Columns 1-2 and 5-6 present the results of the baseline specification at the census tract level. Columns 3-4 and 7-8 estimate the baseline model at the county level.

	SCF				**PSID**			
	Tract		**County**		**Tract**		**County**	
	(1) Logisitic	(2) Tobit	(3) Logisitic	(4) Tobit	(5) Logisitic	(6) Tobit	(7) Logisitic	(8) Tobit
$\frac{\overline{Score}}{100}$	0.734***	0.127***	0.894***	0.130***	0.558***	0.232***	0.311***	0.083**
	(0.087)	(0.018)	(0.142)	(0.025)	(0.055)	(0.023)	(0.101)	(0.040)
	[1.348]		[1.233]		[1.288]		[1.073]	
I.H.S. real income ($2002)	0.587***	0.074***	0.651***	0.085***	0.632***	0.250***	0.646***	0.203***
	(0.052)	(0.009)	(0.059)	(0.009)	(0.036)	(0.014)	(0.035)	(0.014)
I.H.S. real wealth ($2002)	0.092***	0.012***	0.097***	0.013***	0.072***	0.028***	0.063***	0.022***
	(0.012)	(0.002)	(0.013)	(0.002)	(0.005)	(0.002)	(0.004)	(0.002)
Yrs. ed.	0.195***	0.031***	0.210***	0.034***	0.192***	0.080***	0.179***	0.062***
	(0.015)	(0.003)	(0.014)	(0.003)	(0.009)	(0.004)	(0.009)	(0.004)
Married	0.341***	0.084***	0.335***	0.085***	0.204***	0.079***	0.232***	0.063**
	(0.113)	(0.023)	(0.115)	(0.023)	(0.057)	(0.025)	(0.057)	(0.026)
Single male	0.164*	0.047**	0.142	0.044**	0.067	0.052**	0.115*	0.086***
	(0.099)	(0.021)	(0.088)	(0.021)	(0.059)	(0.026)	(0.062)	(0.028)
White	0.490***	0.076***	0.586***	0.095***	0.602***	0.249***	0.674***	0.223***
	(0.075)	(0.015)	(0.082)	(0.015)	(0.049)	(0.021)	(0.054)	(0.024)
Risk aversion	0.592***	0.097***	0.581***	0.096***	NA	NA	NA	NA
	(0.066)	(0.013)	(0.067)	(0.013)	NA	NA	NA	NA
R-squared					0.240	0.205	0.206	0.114
N	14,143	14,143	14,143	14,143	23,010	23,006	18,363	14,149

Table 7: Robustness Analysis and Alternate Hypotheses

Note: Control for household head age polynomial, family size dummies, yearly fixed effects and local economic conditions such as county-level unemployment and house price growth. Standard errors are clustered at the census tract level and are presented in parentheses. *, **, and *** denote 90, 95, and 99 percent statistical significance, respectively. Data are 2004-2010 SCF (see the text for sample construction details). Credit score averages are calculated using the FRBNY CCP/Equifax data. Column 1 presents the estimates of a linear probability model; column 2 the estimates allowing for nonlinear controls of household income and wealth; column 3 the estimates controlling for other neighborhood characteristics such as the census-tract level statistics of income, educational attainment, and racial composition; column 4 the estimates controlling for MSA × yearly fixed effects; column 5 the estimates using communities with high dispersion of credit scores; column 6 the estimates when including a measure of household credit constraints; column 7 include controls of household economic expectations; columns 8 and 9 present, respectively, estimates of the subsample of households that are more and less careful in their responses to the survey—approximated by their use of financial documents to guide responses; and column 10 includes controls of financial literacy approximations.

	Linear prob. (1)	Nonlinear controls (2)	Neighborhood controls (3)	MSA×Year FE (4)	High disp. communites (5)	Credit consts. (6)	Fin. service access (7)	Economic Expectation (8)	Careful households (9)	Not careful households (10)	Financial literacy (11)
$\frac{\overline{Score}}{100}$	0.121***	0.507***	0.621***	0.684***	0.677**	0.722***	0.741***	0.732***	0.798***	0.681***	0.680***
	(0.011)	(0.089)	(0.137)	(0.096)	(0.269)	(0.087)	(0.086)	(0.087)	(0.151)	(0.110)	(0.090)
Credit constrained						-0.398***					
						(0.095)					
Num. bank branches / 100							0.011				
							(0.008)				
Financial literacy											0.174***
											(0.058)
I.H.S. income ($2002)	0.076***		0.560***	0.604***	0.535***	0.579***	0.586***	0.587***	0.507***	0.623***	0.593***
	(0.007)		(0.053)	(0.052)	(0.117)	(0.051)	(0.052)	(0.052)	(0.100)	(0.059)	(0.052)
I.H.S. wealth ($2002)	0.007***		0.092***	0.092***	0.100***	0.088***	0.091***	0.092***	0.084***	0.094***	0.091***
	(0.001)		(0.012)	(0.012)	(0.025)	(0.012)	(0.012)	(0.012)	(0.022)	(0.015)	(0.012)
Yrs. ed.	0.025***	0.173***	0.188***	0.195***	0.212***	0.191***	0.171***	0.193***	0.182***	0.195***	0.195***
	(0.002)	(0.014)	(0.015)	(0.015)	(0.030)	(0.014)	(0.013)	(0.014)	(0.025)	(0.018)	(0.015)
Married	0.033***	0.262***	0.357***	0.363***	0.234	0.315***	0.350***	0.335***	0.223	0.401***	0.337***
	(0.011)	(0.118)	(0.112)	(0.114)	(0.214)	(0.113)	(0.112)	(0.113)	(0.203)	(0.138)	(0.114)
Single Male	0.019	0.117	0.176*	0.182*	0.138	0.157	0.163*	0.164*	-0.005	0.274**	0.132
	(0.013)	(0.104)	(0.099)	(0.101)	(0.185)	(0.099)	(0.099)	(0.099)	(0.183)	(0.117)	(0.100)
White	0.037***	0.464***	0.534***	0.517***	0.675***	0.471***	0.493***	0.498***	0.295**	0.496***	0.489***
	(0.009)	(0.078)	(0.081)	(0.079)	(0.155)	(0.075)	(0.076)	(0.075)	(0.142)	(0.090)	(0.075)
Risk Aversion	0.116***	0.574***	0.592***	0.581***	0.753***	0.591***	0.600***	0.587***	0.643***	0.543***	0.597***
	(0.011)	(0.067)	(0.066)	(0.067)	(0.137)	(0.066)	(0.066)	(0.066)	(0.113)	(0.084)	(0.067)
N	14,143	14,143	14,122	14,143	3,413	14,143	14,143	14,143	4,131	10,012	13,937

Table 8: Farlier-Blinder-Oaxaca Decomposition

Note: Data are 2004-2010 SCF (see the text for sample construction details). Credit score averages are calculated using the FRBNY CCP/Equifax data. The top decile of social capital census tracts have a stock market participation rate of 61 percent, while the lowest decile has a participation rate of 7 percent—a gap of 54 percentage points. A Oaxaca-Blinder decomposition—from Oaxaca (1978) and Blinder (1978)—shows that slightly more than half (30 percentage points of the 54 point gap) can be explained by observable differences, and slightly less than half of the gap is unexplained by observables. Thus, alternate explanations—such as social capital—can have a potentially large role in explaining the participation gap.

	Census tract average credit score distribution	
	Top decile vs. bottom decile	2nd decile vs. 9th decile
	(1)	(2)
Observable factors		
Household income	7.5	4.9
Household wealth	2.8	2.5
Education	2.8	4.9
Marital status	0.3	0.3
Other demo.	5.7	4.3
Neighborhood char.	11.2	4.5
Total diff. in participation rates	53.9	34.0
Explained diff.	30.2	21.3
Unexplained diff.	23.7	12.7

Table 9: Inspecting the Mechanism

Note: Control variables are the same as in tables 6. Standard errors are clustered at the census tract level and county level, respectively, and are presented in parentheses. *, **, and *** denote 90, 95, and 99 percent statistical significance, respectively. Columns 1-7 present the SCF analysis results; columns 8-9 present the PSID analysis results. Columns 1 and 8 tests if the associations between the average credit scores and stock investment propensity diminish with years of schooling. Column 2 estimates the associations between stock investment propensity and the average credit scores of both the residing and adjacent communities. The average credit scores of the adjacent census tracts are measured as the residual of projecting on the average credit score of own tracts. In column 3, the dependent variable is restricted to an indicator of direct holding of publicly-traded stocks only. In column 4, the dependent variable is an indicator of having stock mutual funds (including the households that also own stocks directly). Column 5 tests if the associations diminish in areas with higher legal enforcement norms (measured with crime investigation clearance rates). Column 6 estimates the association between a measure of SCF-interviewer-observed trustfulness and that survey respondent's stock investment propensity. Column 7 presents the two-stage analysis where the interviewer-observed trustfulness is instrumented using community average credit scores. Column 9 estimates the associations between stock investment propensity and the average credit scores of the county where one grew up and subsequently moved out from.

	SCF							**PSID**	
	Education interaction (1)	Crime clearance (2)	Stocks only (3)	Have stock mutual funds (4)	Survey trust measure (OLS) (5)	Survey trust measure (IV) (6)	Adjacent tracts (7)	Education interaction (8)	County grew up (9)
$\frac{\overline{Score}}{100}$	1.496***	1.184***	0.420***	0.597***			0.744***	2.412***	0.493**
	(0.508)	(0.211)	(0.082)	(0.086)			(0.087)	(0.358)	(0.225)
$\frac{\overline{Score}}{100}$ × Yrs. ed.	-0.053							-0.139***	
	(0.034)							(0.024)	
$\frac{\overline{Score}_{neighbor}}{100}$							0.645***		
							(0.195)		
SCF observed trusting					0.203***	3.467**			
					(0.056)	(1.603)			
Crime clearance		9.982*							
		(5.180)							
$\frac{\overline{Score}}{100}$ × Crime clearance		-1.452**							
		(0.734)							
$\frac{\overline{Score}_{grow-up}}{100}$									0.489**
									(0.212)
N	14,143	9,895	14,134	14,134	14,143	14,143	14,125	23,009	5,051

Table 10: Other Measures of Social Capital and Stock Ownership

Note: Standard errors are presented in parentheses. Data used in estimation are the 2004, 2007, and 2010 SCF data. Control variables are the same as in tables 6. See table 1 for more information about each social capital indicator considered. 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 Sample							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\frac{\overline{Score}}{100}$	0.894***							0.646**
	(0.142)							(0.203)
Census response		2.590**						0.649
		(0.629)						(0.963)
Election turnouts			1.516***					0.338
			(0.444)					(0.687)
# of NPOs				0.006				0.005
				(0.015)				(0.020)
# of associations					-0.069			-0.198
					(0.115)			(0.152)
Blood donations						0.014		0.009
						(0.014)		(0.016)
FCC complaints							-0.019	-0.114
							(0.140)	(0.103)

Table 11: Dynamic Analysis of Stock Market Entries and Exits

Note: Standard errors 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 1–3 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 4–6 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)
$\Delta^{+}\frac{\overline{Score}}{100}$	0.516*	0.568*	0.605**	0.272	-0.144	0.290
	(0.288)	(0.326)	(0.293)	(0.333)	(0.389)	(0.343)
	[1.064]	[1.070]	[1.075]	[1.029]	[0.985]	[1.031]
$\Delta^{-}\frac{\overline{Score}}{100}$	-0.074	-0.057	-0.300	-0.087	0.435	-0.376
	(0.339)	(0.366)	(0.350)	(0.467)	(0.513)	(0.481)
	[0.992]	[0.994]	[0.970]	[0.993]	[1.035]	[0.971]
$\frac{\overline{CS}_0}{100}$	0.460***	0.459***	0.431***	-0.370***	-0.354***	-0.374***
	(0.103)	(0.103)	(0.108)	(0.121)	(0.122)	(0.126)
	[1.224]	[1.223]	[1.207]	[0.885]	[0.890]	[0.885]
Controlled for						
Δ ZIP Code stock ownership	No	Yes	No	No	Yes	No
Future income growth	No	No	Yes	No	No	Yes
Individual char.	Yes	Yes	Yes	Yes	Yes	Yes
Yearly fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
N	19,880	19,880	17,631	4,539	4,539	4,267

Table A1: Average Credit Scores and Social Media Data-Based Social Capital Indicators

Note: This table reports regressions of social capital measures in Chetty et al (2022). 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.

	Connectedness	Clustering	Volunteering	Civic Org.
	(1)	(2)	(3)	(4)
$\frac{\overline{Score}}{100}$	0.326***	0.005**	0.037***	0.011***
	(0.016)	(0.002)	(0.005)	(0.001)
I.H.S. median income	0.025	-0.041***	-0.032***	-0.013***
	(0.018)	(0.003)	(0.005)	(0.001)
Gini coeff.	-0.007***	0.000	-0.000	-0.000***
	(0.001)	(0.000)	(0.000)	(0.000)
Homeownership	-0.052*	0.017***	-0.039***	-0.032***
	(0.027)	(0.004)	(0.008)	(0.002)
High school and below share	0.072*	-0.012**	-0.120***	-0.021***
	(0.038)	(0.006)	(0.011)	(0.003)
College graduate share	0.591***	-0.065***	-0.024	0.025***
	(0.055)	(0.008)	(0.016)	(0.004)
Senior population share	-0.153**	0.022**	-0.105***	0.025***
	(0.075)	(0.011)	(0.022)	(0.006)
Racial Herf. index	0.201***	-0.012***	0.024***	-0.005***
	(0.021)	(0.003)	(0.006)	(0.002)
Violent crime rate	-0.011***	-0.001***	-0.001**	-0.000***
	(0.001)	(0.000)	(0.000)	(0.000)
N	2,856	2,912	2,912	2,912

Table A2: Social Media Data-Based Measures of Social Capital and Stock Ownership

Note: Connectedness, clustering, volunteering, and civic organizations are social capital variables defined in Chetty et al (2022). Dependent and other control variables are the same as in tables 6. Standard errors are presented in parentheses and are clustered at county level and corrected for multiple imputation. *, **, and *** denote 90, 95, and 99 percent statistical significance, respectively.

	SCF Sample					
	(1)	(2)	(3)	(4)	(5)	(7)
$\frac{\overline{Score}}{100}$	0.931***					0.951***
	(0.095)					(0.149)
Connectedness		1.034***				0.046
		(0.142)				(0.220)
Clustering			2.440			-2.207
			(2.449)			(2.582)
Volunteering				2.592**		-1.405
				(1.061)		(1.069)
Civic org.					5.303***	3.742**
					(1.975)	(1.805)
N	14,125	13,738	13,918	13,918	13,918	13,738