Credit Scores, Social Capital, and Stock Market Participation

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Abstract

While a rapidly growing body of research underscores the influence of social capital on financial decisions and economic developments, objective data-based measurements of social capital are lacking. We introduce average credit scores as an indicator of a community's social capital and present evidence that this measure is consistent with, but richer and more robust than, those used in the existing literature, such as electoral participation, blood donations, and survey-based measures. Merging unique proprietary credit score data with two nationwide representative household surveys, we show that households residing in communities with higher social capital are more likely to invest in stocks, even after controlling for a rich set of socioeconomic, preferential, neighborhood, and demographic characteristics. Notably, such a relationship is robustly observed only when social capital is measured using community average credit scores. Consistent with the notion that social capital and trust promote stock investment, we find the following: first, the association between average credit score and stock ownership is more pronounced among the lower educated; second, social capital levels of the county where one grew up appear to have a lasting influence on future stock investment; and third, investors who did not own stocks before have a greater chance of entering the stock market a few years after they relocate to higher-score communities.

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

JEL: D14, G10, O16

1 Introduction

The past quarter century witnessed a renaissance of research on social capital and trust. Since the seminal work of Putnam (1993), the influence of social capital and trust has been underscored in explaining economic outcomes in various contexts, such as economic growth and development (Knack and Keefer, 1997), performance of institutions and judiciary efficiency (Fukuyama, 1995; La Porta, Lopez-de-Silanes, Shleifer, and Vishny, 1997), and the rise of public schools (Goldin and Katz, 1999).[1] More recently, Guiso, Sapienza, and Zingales (henceforth GSZ) document that greater social capital promotes financial developments (GSZ 2004).

While there is broad recognition that social capital influences financial and economic activities, concrete, objective, and data-based measures of social capital 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." In the existing literature, social capital is often approximated by the level of trust in a society, which in turn is often measured using self-reported trusting attitudes in household surveys.[2] 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). In this regard, GSZ (2004) propose electoral participation and blood donations as measures of social capital. However, these measures have been primarily applied to European countries, whereas empirical studies of how social capital may affect U.S. financial markets and household financial decisions remain largely a void.

In this paper, we make two contributions to the measurement of social capital and its

[1] Arrow (1969, 1972) was among the earliest authors who noted that trust was essential to commercial transactions.

[2] These questions are typically framed as "Generally speaking, would you say that most people can be trusted or that you have to be very careful in dealing with people?"

effect on household financial decisions. First, we propose a novel measure of social capital and trust—the average credit score of the residents of a community. Second, we examine how social capital and trust may influence U.S. household investors' financial decisions, with a particular focus on their stock investment.

Credit scores are designed to predict consumers' future default risks from their financial debt and are estimated using rich credit and payment history data. A community's average credit score can serve as a good indicator of its level of social trust and social capital for two reasons. First, credit scores reflect people's previous experiences with credit markets and personal finance. Many recent studies have revealed that people's perceptions and expectations are heavily influenced by their own past experiences. For example, Malmendier and Nagel (2011) document that investors who experienced prolonged periods of low stock returns are less likely to later invest in stocks. Malmendier and Nagel (forthcoming) show past experiences with inflation strongly influence subsequent inflation expectations. The neighborhoods with lower average credit scores tend to be economically downtrodden or hit particularly hard during financially hard times. Arguably, residents in such communities can feel more distrustful toward financial markets in general, including the stock market.

Second, credit scores, to a certain extent, may reveal an individual's underlying trustworthiness beyond the likelihood of defaulting on financial obligations. For example, Dokko, Li, and Hayes (2015) show that individuals' credit scores are strong predictors of personal relationship outcomes, even after controlling for credit market experiences. Thus, a neighborhood with higher average credit scores may also have higher levels of trustworthiness and social capital. Furthermore, an individual living in such a community has a greater opportunity to interact with more trustworthy people, which could make her more trustful herself.

We use a large proprietary dataset—the Federal Reserve Bank of New York Consumer Credit Panel/Equifax data—to estimate community average credit scores. We then examine the validity of average credit scores as an indicator for social capital and contrast its merit with other social capital measures in a number of statistical exercises. Specifically, we show that, controlling for an extensive array of observable community characteristics, the average community credit score is positively correlated with a survey-measured level of social trust (estimated using the Social Capital Community Benchmark Survey), the general election participation rate, and the quantity of blood donationsp; it is also negatively correlated with the rate of consumer complaints filed with the Federal Communications Commission (FCC), a possible measure of social *distrust*. Principal component analysis reveals that the average credit score has the highest correlation with the latent factor derived from all social capital indicators. Furthermore, a unique advantage of our proposed social capital indicator is that the average credit score can be estimated for small geographies, such as a census tract or even a street block, which is particularly appealing because the effects of social capital are likely more pronounced in more granularly-defined communities.

Our analysis on stock ownership contributes to a long line of research on the topic. The low level of stock market participation relative to what theory predicts has long been a puzzling phenomenon (Haliassos and Bertaut, 1995). Fewer than 25 percent of U.S. households directly own stocks (Bricker and others, 2014) even though stock investments earn a substantially higher risk-adjusted return than safer assets in the long run.[3] Numerous 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.

Our analysis, however, is intimately related to a recent strand of literature that underscores the influence of social trust on stock investment (GSZ 2008, El-Attar and Poschke, 2011; Georgarakos and Pasini, 2011). Notably, GSZ (2008) argue that as the perceived probability of being cheated increases, stock investment becomes less likely, whereas areas that

[3]Only about 50 percent own stocks even after including indirect equity ownership through retirement accounts. Throughout this paper we follow the literature and exclude indirect ownership (Brown, Ivković, Smith, and Weisbenner, 2008; Balloch, Nicolae, and Philip, 2015; GSZ, 2004, 2008).

have more social capital and display greater trust tend to have higher stock market participation. They find support for this hypothesis using individual level data of self-reported trust and stock ownership of Dutch households and cross-county evidence using the World Values Survey. More recently, Giannetti and Wang (2016) document that, in household survey data similar to what we use, household stock market participation decreases after the revelation of corporate fraud in the state of their residence.

While our empirical strategy shares many similarities with GSZ (2004), we extend and complement their work in several important aspects. First, instead of examining how self-reported trust affects stock ownership, we link the level of social capital of the community where an investor resides with her stock investment decisions.[4] Second, we study a broad array of measures of social capital, including the one we introduce here—the community's average credit score—and those adopted in the existing literature—such as electoral participation and blood donations—in order to examine the consistency among these indicators and assess their relative merit in accounting for variations in propensities of investing in stocks. Third, to the best of our knowledge, this paper is the first that studies the relationship between social capital and stock market participation at individual investor level using data from large U.S. household surveys.[5]

Specifically, we link household balance sheet information in the Survey of Consumer Finances (SCF) and the Panel Study of Income Dynamics (PSID) to various indicators of trust and social capital. We find that consumers residing in areas with higher average credit scores are more likely to own stocks and to invest a greater share of their portfolio in stocks. For example, our baseline SCF analysis indicates that investors living in a census tract

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

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

with a one standard deviation higher average credit score have a 7 percentage point higher probability of owning stocks. Conditional on owning stocks, the share of stocks in financial investment portfolio is about 60 percent higher.[6] Such a relationship holds against a rich set of socioeconomic, preferential, neighborhood, and demographic characteristics. In particular, our estimates are robust to controlling for neighborhood average stock ownership, suggesting that it is a factor that goes beyond the information sharing channel that was also shown in earlier studies to have a positive effect on stock investment (Hong, Kubik, and Stein, 2004; and Li, 2014). Interestingly, community electoral participation and blood donations are only weakly associated with the likelihood of stock investment. In a horse-race-style analysis in which household financial decisions are regressed on all social capital indicators at our disposal, average credit scores stand out as the winner for having the most sizable and significant estimated coefficient.

To examine if such a relationship is causal, we first show that the association between the propensity to own stocks and community average credit score is stronger for investors with lower educational attainment and weaker among the college educated, a finding similar to that in GSZ (2004, 2008). We also show that the social capital level of the county where an investor grew up appears to have a lasting influence on her future stock ownership even years after moving out of that county. Furthermore, we leverage the longitudinal structure of the PSID data and study stock investment dynamics. We find that investors who did not own stocks previously have a greater chance of entering the stock market a few years after they relocate to higher-score communities relative to comparable investors who did not move. This trend is consistent with the narrative that relocating to a high-score community allows the investor to interact with more trustworthy individuals and thereby develop a more trusting attitude himself. Our exercise focuses on stock market entries that are subsequent, instead of simultaneous, to relocation, thereby circumventing the endogeneity concerns to a certain extent.

[6] The average share of stock investment in financial portfolio is 11 to 16 percent in our samples.

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

2 Conceptual Framework and Related Literature

2.1 Trust and Social Capital

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

Trust also functions as a pillar of financial interactions. Arrow (1969) famously states that "it is useful for individuals to have some trust in each other's word. In the absence of trust it would become very costly to arrange for alternative sanctions and guarantees, and many opportunities for mutually beneficial cooperation would be foregone." More recently, GSZ (2004) study the diverging growth paths of the north and south of Italy (a celebrated example of social capital and economic development). Both areas had similar levels of economic development in the late 1800s, but the north of Italy had stronger social cohesion, trust in institutions, and social capital. GSZ document that by the 20th century, areas of

Italy with higher social capital were more likely to develop financially and had residents that were more likely to participate in financial equity markets. They also show that the higher levels of social capital in the north led to stronger use of financial institutions and economic growth.

In a similar spirit, GSZ (2008) demonstrate that lack of trust potentially contributes to the low rate of participation in stock markets. They show that individuals who trust others are 50 percent more likely to invest in stocks, and among stock investors, those who trust others have a 15 percent higher stock allocation than the mean. As GSZ point out, stock investment involves an investor sending assets to a financial intermediary (a broker, for example), who then invests the money in the market. If invested properly the broker makes money for both herself and the investor, and this cooperative endeavor benefits both parties. However, if the subjective probability of being cheated in this market increases, cooperation between market participants becomes less likely. Therefore, investing in stocks crucially depends on trust and cooperation.[7]

The experience of a community's residents, including their interactions with fellow members of the community, may shape their perception of and attitude towards the market and the society to a great extent, and thereby influence the level of trust and social capital of the community. For example, Malmendier and Nagel (2011, forthcoming) show that individuals' stock investment and inflation expectations are significantly influenced by their previous stock return and inflation experiences. In general, as one encounters more cheaters or feels unfairly treated in personal interactions and business transactions, her trust of the society will be undermined. Indeed, recent research has found that individuals with low trust are more likely to have experienced a recent traumatic event or to belong to a group that has traditionally experienced discrimination (Alesina and La Ferrrara, 2002). In addition, banking crises also have persistent negative effects on measured individual trust, especially trust

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

in social institutions (Graeber and Zimmerman, 2016). In a similar vein, the composition of a community can affect the trust levels therein. On the one hand, exposure to more trustworthy people may help others overcome adversity, especially those with low social standing (Helliwell, Huang, and Wang, 2016). On the other hand, lower levels of trust are observed among those exposed to less-trustworthy people or to conflicting social norms (Alesina and La Ferrrara, 2002).

In spite of the increasing appreciation of the role of social capital in financial and economic developments, its measurement has been elusive to students of the subject. In the existing literature, trust, a central element of social capital, is routinely measured with survey responses, which by design are only available for a small sample of individuals. More recently, GSZ (2004) propose electoral participation and blood donations as social capital measures. However, the implications of these measures of social capital have been studied primarily in European countries and have not been systematically explored using U.S. data. Moreover, the availability of these statistics is often restricted to a certain geographical levels. The search for an objective behavioral-based measure of social capital remains a high research priority.

2.2 Community Average Credit Scores as an Indicator of Social Capital

With this motivation, we propose using the average credit score in a community as an indicator of social capital in that community. Credit scores are designed to evaluate credit quality and predict the default risk of potential borrowers. Generally, borrowers with higher credit scores are deemed more creditworthy and have, on average, lower default rates. Broadly speaking, a person's default probability is affected by her willingness to repay her debt, which we denote with ω, and her ability to repay, which we denote with η. It is therefore helpful to represent one's credit score as a (noisy) indicator of her default probability such that

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

where μ is an error term.

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.[8]

Although modern credit reports no longer collect such soft information on borrowers' personality and characteristics, debt payment history remains the most important determinant of one's credit score.[9] As a result, one's credit score contains signals that potentially reveal underlying trustworthiness. 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). Also, many cell phone and cable companies use credit score information in contract-based plans. Furthermore, Dokko, Li, and Hayes (2015) document that the levels and match quality of credit scores of a couple at the onset of their relationship have a pronounced predictive power regarding future relationship outcomes, even after controlling for the credit events the couple encounters, such as new debt acquisitions and financial distress.

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

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

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

have little to do with individuals' general trustworthiness, and such factors are summarized in the term of ability to repay, η. For example, many families with low credit scores have gone through a negative financial event because of economic hardship brought on by severely adverse events or job loss. The families with these negative financial experiences, though, will be less likely to trust the advice of an institutional source (Alesina and La Ferrera, 2002; Graeber and Zimmerman, 2016) or trust the financial market and institutions in general.[10]

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

3 Data Description and Summary Statistics

Our study takes advantage of a rich array of data sources. Our proposed measure of social capital—the average credit score of a community—is estimated using the Federal Reserve Bank of New York Consumer Credit Panel/Equifax (henceforth FRBNY/Equifax CCP) data. To establish this statistic as a valid indicator of social capital, we compare it with a host of measures of trust and social capital used in the existing literature that include the following: (1) self-reported trusting attitude in the 2000 Social Capital Community Benchmark Survey (SCCS); (2) electoral participation in the 2012 U.S. general election by

[10] SCF survey data suggest, for example, 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.

county from the *Guardian* newspaper; (3) blood donation data provided by the American Red Cross; and (4) the number of consumer complaint filings at the FCC.

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

3.1 The FRBNY/Equifax CCP Data

The FRBNY/Equifax CCP is a large proprietary dataset that follows a 5-percent random sample of U.S. consumers with valid credit histories (about 11 million individuals in recent quarters) on a quarterly basis. The data include fairly detailed consumer residence location information down to the census block level and extensive credit history data, including a credit score. We calculate the average credit score at both the census tract and county levels. A census tract has an average population of 4,000 of all ages. Relative to earlier studies on the subject, which typically focus on cross-country or cross-province variations, working with much smaller communities like census tracts allows us to measure social capital and analyze its influence in a more zoomed-in, focused way. Our analysis removes the census tracts that have fewer than 20 individuals in the sample.[11] We compute the average credit score for each quarter from the first quarter of 2001 to the fourth quarter of 2015. We then average

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

the quarterly mean of credit scores of each tract and county to filter out high-frequency variations that are not necessarily reflecting differences in social trust and social capital. As shown in the top panel of table 1, over the 2001–15 period, our sample has more than 655 million observations of individual credit scores, with a mean of 690 and a standard deviation of 107. The standard deviations of the tract and county level average scores are 41 and 46, respectively, which are smaller than that of the individual score distribution but remain quite sizable, suggesting wide geographical variations in community average credit scores across the country.[12]

3.2 Other Measures of Trust and Social Capital

The 2000 SCCS samples 375 to 1,500 adults in 41 communities and asks the respondents trust-related questions such as "whether most people can be trusted or you can't be too careful." These trust-related questions greatly overlap with those from the World Value Survey and General Social Survey, which are used extensively in studies of trust and trustworthiness. Each community in the survey is a county or a combination of several counties, and we are able to map 38 out of the 41 communities to proper counties. We construct a trust index that is equal to 100 times the share of survey respondents in a community who reply that "most people can be trusted." As shown in the lower panel of table 1, averaging across all communities, 47 percent of the SCCS respondents in a community indicated that they feel most people can be trusted, with a standard deviation of 8 percent.[13]

In addition, we collect data of electoral participation and blood donations as indicators of social capital, which are introduced in GSZ (2004). Specifically, we use county-level 2012 presidential election participation data that cover over 2,700 U.S. counties. As shown in the lower panel of table1, averaging across all counties, 42 percent of the total population in a

[12] 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.

[13] The 2000 SCCS data used in this study were collected by Professor Robert D. Putnam of the Saguaro Seminar Civic Engagement in America, a project of the Kennedy School of Government at Harvard University and numerous community foundations nation-wide, and made available through the Roper Center for Public Opinion Research.

county voted in the 2012 general election, with a standard deviation of 8 percent.[14]

For blood donations, we use data provided by the American Red Cross. In 2015, the American Red Cross collected blood from more than 13,300 Zip codes in more than 2,000 counties. These Zip codes cover more than 60 percent of the U.S. population. For consistent comparisons, we aggregate the data to the county level. As shown in the lower panel of table 1, on average, 3.6 units of blood were collected per 100 people, with a standard deviation of 3.2 units.

Finally, we use the number of FCC complaints as additional (negative) indicators of trust and social capital in an area.[15] Similarly, we aggregate the number of complaints at the county level. Statistics regarding the number of complaints per 100 population in each county are presented in the lower panel of table 1. On average, about 0.14 complaints were filed to the FCC per 100 residents, with considerable cross-county variations.

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 along with detailed household level socioeconomic, demographic, and financial characteristics, along with qualitative reports on preferences. Our data include information on the census tract and county where sample households reside, thereby allowing a merge of individual household investment decisions with measures of the community's social capital and other socioeconomic and demographic characteristics.

The SCF is conducted by the Federal Reserve Board every three years and is widely regarded as one of the most comprehensive sources of data concerning U.S. household balance sheets. These data have information on stock market participation status and share of stocks in financial portfolio. We use three waves of the SCF data collected in 2004, 2007, and 2010. During these years, the survey sample was stratified using the 2000 U.S. decennial census.

[14] Note that 42 percent is computed using *total* population in each county as the denominator and total voters in each county as the numerator. Because about 25 percent of the population is under 18, our estimate of total national eligible voter turnout is 57 percent, which matches the national share.

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

Consumer location information in the FRBNY/Equifax CCP data is also coded using the 2000 census, ensuring a higher-quality match. During the sample period, as presented in the left column of the top panel of table 2, only a small fraction (23 percent) of households own corporate equities (stocks).[16] Among those who own stocks, the share of stocks in their financial assets portfolio is about 11 percent, with a fairly large dispersion in the sample. In addition, the mean of wealth in the pooled 2004–10 SCF is about $437,000 in 2003 dollars, and mean income is about $69,000(not shown). Both are comparable with external aggregates.[17]

The SCF also collects information on attitudes toward taking financial risk and investing. Consistent with the apparently low levels of stock ownership, most families also report being unwilling to take financial risk (table 2).[18] Moreover, the SCF data are collected by a trained field interviewer, either in person or on the phone. At the end of each completed interview, the interviewer assesses how the respondent interacted with the survey. Among these questions, the interviewer evaluates how suspicious the respondent was about the survey before the interview began. We use this interviewer assessment to identify families that were "not at all suspicious" of the interview, effectively creating a proxy for trusting attitudes. Note that, in contrast to the World Value Survey or SCCS measures, this measure of trusting attitude in the SCF is not self-reported but interviewer assessed. We include this interviewer-assessed measure of trust later in the regression analysis for robustness. About 56 percent of SCF families are coded as "trusting" by the field interviewer.

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

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

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

3.4 Panel Survey of Income and Dynamics

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

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

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

[20]For the cross-sectional analysis, we keep the first observation of a household in the longitudinal panel that shares the same combination of location (census tract or county) and stock market participation status. Therefore, the PSID sample constructed for cross sectional analysis is a somewhat younger than the SCF sample. Some of the PSID data used in this analysis are derived from Restricted Data Files, 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 Restricted Data Files should contact PSIDHelp@isr.umich.edu.

3.5 Other Data Sources

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

4 Average Credit Scores as an Indicator of Social Capital

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

4.1 Simple Correlations

To begin with, we show that average credit scores are correlated with a range of other measures of trust and social capital used in the literature—a survey-based trust indicator, blood donations, electoral participation, and fraud complaints—even after taking into account a

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

host of community characteristics. Specifically, we estimate the following model:

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

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

First, we note that the correlation between average credit scores and each of the four measures of social capital and trust is economically and statistically significant, even after controlling for a range of characteristics of the community. Specifically, our estimates indicate that counties with higher credit scores, on average, have a larger share of trusting residents, who are more likely to participate in elections and blood drives, and file fewer FCC complaints.

Putting the estimates in perspective, consider two otherwise comparable counties H and L, where county H has an average credit score 46 points (one standard deviation) higher than county L. Our estimates imply that in county H, 12 percentage points *more* of its residents would believe "most people can be trusted," 3 percentage points *more* of its residents would vote in general elections, 3.7 *more* unites of blood (about the all-county mean) would be collected, and 0.05 fewer FCC complaints per 100 residents (about half of the all-county mean) would be filed. The negative relationship between average credit score and the prevalence of FCC complaints likely indicate that communities with higher social capital are less prone to be the targets of telemarketing scams, financial frauds, and harsh debt collection treatments, and that residents in these communities are less suspicious and are more alerted, and therefore more trustful, to certain market activities.[22]

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

Further, the explanatory power of the model in equation (2) increases when average credit score ($\overline{Score}$) is included. For self-reported trustfulness in the SCCS and blood donations, adding average credit scores to the model boosts R-squared by a large margin (12 and 33 percent, respectively); for general election participation and FCC complaints, the increases in R-squared are a more modest 2 to 3 percent ("memo" row of table 3). Finally, the uniformly significant relationships between average credit scores and other social capital indicators are even more notable when considering that none of the county characteristics included as control variables (such as median income, inequality, education levels, racial diversity, and violent crime rates) have consistent statistical relationships with these alternate social capital indicators (columns 1–4 of table 3).[23]

4.2 Consistency among Social Capital Indicators

As a further test of consistency among the social capital indicators we consider, including average credit scores, we run a series of regressions whereby each social capital indicator is regressed against the others, with the same set of control variables as in equation (2).[24] We run these regressions using a subset of counties where all four social capital indicators are available. The results are reported in the upper panel of table 4.

There are two notable observations in our estimates. First, consistent with our expectations, average credit scores, electoral participation, and blood donations are positively correlated with each other, though the estimated coefficients are not all statistically significant. By contrast, FCC complaints are negatively correlated with the other three indicators. Second, county average credit scores are almost always associated with the other social capital indicators in a fashion that is statistically significant and consistent with theoretical predictions, underscoring the statistical richness and robustness of this indicator.[25]

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

[24] We omit the survey-reported SCCS trusting attitude for which we only have observations of 38 counties.

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

4.3 Principal Component Analysis

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

The PCA allows us to use our four observed county-level (c) social capital indicator variables to model $n(< 4)$ traits (Y_n):

$$\begin{aligned} Y_1 &= \varepsilon_{11}\overline{Score}_c + \varepsilon_{21}DonateBlood_c + \varepsilon_{31}Voting_c + \varepsilon_{41}Complaints_c, \\ Y_2 &= \varepsilon_{12}\overline{Score}_c + \varepsilon_{22}DonateBlood_c + \varepsilon_{32}Voting_c + \varepsilon_{42}Complaints_c, \\ &\quad ..., \end{aligned} \tag{3}$$

The first principal component is Y_1, the second principal component is Y_2, and so forth. As shown in equation (3), the principal components are a linear combination of observed social capital variables and estimated ε_{nk}s.[26] Each principal component is, by design, uncorrelated with the other principal components.

The principal components are not defined *a priori* but each is interpreted based on commonalities in the variables that predict the component. As seen in the lower panel of table 4, credit scores, electoral voting, and blood donation are all highly correlated with the first principal component, indicating that they are all signaling a similar trait.[27]Notably, among all the potential social capital measures, average credit score has the highest correlation with the first principal component (column 1, lower panel).

[26]The ε_{11} to ε_{k1} are estimated by maximum likelihood. Essentially, the PCA finds the variable or variables that explain the most variation in principal component Y_1—these variables have the largest values of ε_1—then finds the variables that explain the most variation in principal component Y_2, and so forth (Jolliffe, 2002).

[27]The first principal component explains about 45 percent of the variation in all the variables.

Because these principal components are derived from four series, a relatively small number, the correlation between each of the series and the principal components should be interpreted with caution. To address this concern, we calculate the principal components using three of the four social capital indicators and examine their correlations with the excluded series. The idea is that if a principal component derived from three indicators does a good job in capturing underlying variations in social capital, this latent factor should be correlated with the other indicators of social capital. Indeed, we find that average credit score has the highest correlation with the first principal components derived from the other three social capital measures (columns 3 and 4, lower panel), further reassuring its merit as a valid indicator of social capital that is potentially richer and more robust than other indicators exploited in the literature.

5 Static Analyses on Stock Ownership

As illustrated in the previous section , communities with higher average credit scores tend to have a greater share of residents who are more trusting and a higher level of social capital (measured with various indicators). We now revisit the relationship between social capital and household financial decisions with an analysis of whether people living in such high average credit score areas are more likely to own stocks. We begin with estimating a workhorse model used extensively in stock market participation research, augmented with an array of community characteristics, including average credit scores. In our baseline analysis, a community is defined as a census tract. As previously discussed, an attractive feature of using average credit scores to measure trust and social capital is that such an indicator can be constructed for much more granular communities than earlier research. We also estimate the model at the county level as a robustness check and to facilitate comparisons with the estimates of other social capital indicators. Specifically, we estimate the following logit model:

$$Part_{i,t}^{y} = \alpha + \beta \overline{Score}_{t}^{y} + \gamma Z_{i}^{y} + \theta Q_{t} + \rho Year^{y} + \varepsilon_{i,t}^{y}, \tag{4}$$

where $Part_{i,t}^{y}$ is a zero-one indicator of stock ownership (directly held or in mutual funds) for household i that lives in county t in year y. $\overline{Score}_{t}^{y}$ is the mean credit score for county t in year y. A positive β coefficient would suggest that residents living in communities with higher credit scores are more likely to invest in stocks. Z is a vector of individual characteristics of the investor, which includes the inverse hyperbolic sine transformation of household income and wealth, a household head age polynomial, bins of head educational attainment, race, marital status, and a single male dummy.[28] Q_t is a vector of county-level community characteristics (median income, share of people with a college degree, share of people with lower education, defined as high school or below, and share of white residents) that may also affect investment decisions. $Year$ is a vector of yearly fixed effects.

5.1 The SCF Analysis

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

To begin with, the baseline estimates shown in column 1 suggest that higher levels of tract average credit scores are associated with greater stock ownership, and the relationship is statistically significant and economically appreciable—a finding that is consistent with earlier research. The estimated odds ratio indicates that residents living in a tract with an average credit score 41 points (one standard deviation of the average credit score distribution across all communities) higher than an otherwise identical tract are nearly 30 percent more likely to own directly held equities in a given year, a margin similar to the estimates reported in GSZ (2004).

[28]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).

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

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

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

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

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

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

[29]Though not shown in the paper, we also examined whether our variable of interest was picking up credit

Finally, we study the effect of trust on the share of stock investment in household financial asset portfolios by estimating a tobit model with the same controls as in column 1. The results, reported in column 6, imply that a one standard deviation increase in tract mean credit score is associated with a 7 percentage point increase in stock investment share (about 60 percent of the mean equity investment share, similar to GSZ (2008)).

5.2 The PSID Analysis

The PSID results, shown in table 6, are quite similar to the SCF results. Unlike the SCF, which consistently collected risk aversion information in the three waves of data we use, the PSID only asked for such information in a special module of 1996. As a result, we have risk tolerance information for only a fraction of the households in the PSID sample. Therefore, the PSID baseline regression, shown in column 1, does not include risk tolerance as a control. The baseline PSID estimates show that households residing in census tracts that have a one standard deviation higher average credit score, on average, are 24 percent more likely to invest in stocks—similar to the SCF estimates. Notably, all control variables also have rather similar coefficients estimated using the SCF and PSID data, adding confidence to the representativeness of both surveys and the empirical model we adopt.

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

access in addition to social capital. However, our findings are the same qualitatively as in column (1) when we re-run our analysis including a household-level measure of constrained credit as a control variable.

adding such a control does not void the baseline results—again, as in the SCF results (column 4). In addition, as in the SCF analysis, the results of census tract level analysis qualitatively largely hold at the county level (column 5).

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

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

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

We introduced community average credit scores as a measure of social capital in comparison with other indicators used in the literature, including blood donations, electoral participation, and FCC complaints. Of these social capital indicators, blood donations and electoral participation 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 (4) with each of the other three social capital indicators. Then we estimate a variation of equation (4) that includes all four indicators to assess their relative significance.

Following GSZ (2004) and because of the availability of electoral participation data, we implement these analyses using county level average credit scores.[30] Accordingly, in the upper and lower panels of table 7, column 1 replicates the $\overline{Score}$ estimates in column 5 of tables 5 and 6. A notable observation from the table is that electoral participation and blood donations appear to have a significant bearing on stock ownership in the SCF or the PSID. Moreover, fewer FCC complaints are associated with greater propensity of investing in stocks only in the SCF sample. Finally, when all four social capital measures are included, as shown in column 5, the community average credit score remains a prominent predictor of stock market participation.

6 Dynamic Analysis of Stock Market Entries and Exits

While the results of cross-sectional analyses presented earlier are robust and strongly indicative regarding the potential effects of trust and social capital on household stock investment, concerns remain regarding whether these results establish a causal relationship or are driven by stock investors being more likely to live in high credit score areas, holding other factors

[30] More precisely, GSZ (2004) use Italian provincial data. They note that provinces in Italy are similar to U.S. counties.

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 $y+2$.

$$entry_i^{y,\,y+2} = \alpha + \beta_b \overline{CS}_{t^{y-2}} + \beta_p \Delta^p \overline{CS}_{t^{y-2},t^y} + \beta_n \Delta^n \overline{CS}_{t^{y-2},t^y} + \gamma Z_i^y + \theta \Delta Q_{t^{y-2},t^y} + \rho Year^y + \varepsilon_{i,t}^y, \tag{5}$$

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 (4), but here we use the $y-2$, y, and $y+2$ average levels of wealth and income. In addition, we include the change of real income between $y-2$ and $y+2$ to take into account the potential effects of the factors that led to the relocation on stock market entry. Moreover, we control for the changes of community characteristics $\Delta Q_{t^{y-2},t^y}$ to address the potential effects on stock ownership of these factors. Investors who did not move between years $y-2$ and y are included as the control group.

We focus on the stock market entry dynamics observed after the move in order to isolate the stock market entries that are endogenous to the relocation decisions. Indeed, while we control for an extensive set of indicators of household financial and demographic condition changes, there might be unobserved factors that cause the household to decide to move to a new neighborhood and start investing in stocks at the same time. Focusing on the stock market entries after moving helps alleviate this endogeneity concern. Furthermore, similar to Li (2014), we examine whether relocating to a lower credit score neighborhood increases a current stock investor's odds of subsequently exiting the stock market. For stock investors in year $t-2$ and y, we estimate a similar model of stock market *exits* between y and $y+2$. Arguably, current stock owners' investment decisions (including exiting the stock market) are more determined by their investment experiences, financial conditions, and expected returns, but less influenced by trusting attitude changes.

The results are summarized in table 8. While the estimates in column 1 do not suggest that moving to a community of higher average credit scores has a significant effect on subsequent stock market entries, this appears to reflect the asymmetry of the potential effects of social capital. As shown in columns 2 and 3, an investor who did not own stock previously and moved to a census tract of higher credit score would have a higher chance of entering the stock market during the two years following the move. The estimated odds ratio suggests that the relocation-induced positive change in community average credit scores that is one standard deviation bigger implies an 11 percent higher chance of entering the stock market.[31] By contrast, while the effects on the likelihood of entering the stock market are negative for moving to communities with lower credit scores, they are not statistically significant and much smaller in magnitude. Furthermore, our estimates, as in the cross-sectional analysis, are not sensitive to the inclusion of changes in community average stock ownership as a control variable (column 4). Finally, as shown in columns 5–8, relocation-induced community average credit score changes do not appear to have any significant effect on current stock owners' decisions on exiting the market. The contrast between the estimates of market entry and exit, as we argued earlier, is consistent with the notion that current stock investors tend to make investment decisions on objective, market related factors, and they are therefore less influenced by subjective perceptions, such as trusting attitudes. Consequently, such a

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

contrast also lends additional support to a causal relationship between social capital and stock investment.

7 Conclusion

This paper achieves two goals. First, we introduce average credit scores as a novel measure of a community's social capital. We show that this measure is consistent with other social capital measures employed in previous research. Average credit score as a measure of social capital is appealing for several reasons. It is objective, data driven, and based on individual behavior. Various analysis we conduct in this paper suggest that this measure is richer and more robust than other indicators. Such an indicator can be constructed for very small communities, including census tracts or even street blocks, and the underlying data are available for essentially the entire country. It is more correlated with the latent factor derived from a host of measures of social capital. Second, we revisit the relationship between social capital, trust, and investment in stocks using U.S. data. We find that while other measures of social capital do not consistently show such a relationship, average community credit scores consistently reveal that greater trust and social capital enhances stock market participation. Furthermore, such a relationship is more pronounced for lower-educated investors and manifests itself in both static and dynamic analysis, all suggesting a causal relationship.

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

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

Credit score data are from the FRBNY/Equifax CCP data. Statistics are estimated by pooling quarterly data from 2001 to 2015 (60 quarters). Self-reported trust indicator is estimated using the Social Capital Community Benchmark 2000 Survey. Electoral participation statistics are estimated from the November 2012 general election. Blood donations data are from the American Red Cross. County-level statistics are aggregated from the Zip codes from which the Red Cross collected blood. The Federal Communications Commission complaints data can be accessed at https://www.fcc.gov/consumer-help-center-data.

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

	Other Social Trust and Social Capital Indicators			
	Self-reported trust	Electoral participation	Blood donations	FCC complaints
Units	Share reporting trust	Share voted	Units collected per 100 residents	Complaints submitted per 100 residents
Mean	47.1%	42%	3.6	0.14
S.D.	(8.1%)	(8%)	(3.2)	(0.14)
N	38	2,712	2,054	3,043

Table 2: Summary Statistics of Stock Investment and Household Characteristics

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

Variable	SCF	PSID
Financial decisions		
Stockholder (%)	23.5	22.3
Stock portfolio share (%)	11.1	16.0
Enter stock market (%)	...	6.3
Exit stock market (%)	...	23.3
Rely on family/friends for fin. dec. (%)	20.0	...
Rely on formal source for fin. dec. (%)	32.8	...
Household characteristics		
Willing to take fin. risk (%)	18.8	...
Risk tolerance	...	1.1
Interviewer observed trust (%)	56.1	...
Relocated in past two years (%)	...	24.3

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

This table reports regressions of indicators of trust and social capital studied in the existing literature on county average credit scores. Standard errors are clustered at the state level and presented in parentheses. *, **, and *** denote 90, 95, and 99 percent statistical significance, respectively. Control variables include the inverse hyperbolic sine transformation of median income, income Gini coefficient, share of homeowners, composition of educational attainment, share of senior population, Herfindahl index on racial diversity, and violent crime rate, all at the county level. The "memo" row shows the percent increase of R-squared when adding average credit scores to the estimation. Column 5 projects average credit scores on the control variables.

	Self-reported trust	Electoral participation	Blood donations	FCC complaints	$\frac{\overline{Score}}{100}$
	(1)	(2)	(3)	(4)	(5)
$\frac{\overline{Score}}{100}$	0.267*	0.070*	8.054***	-0.094**	...
	(0.141)	(0.041)	(2.217)	(0.044)	
I.H.S. median income	-0.040	-0.051	-4.274*	0.184***	0.290***
	(0.150)	(0.047)	(2.263)	(0.059)	(0.062)
Gini coeff.	-0.043	0.011*	-0.519	0.004	-0.041***
	(0.039)	(0.006)	(0.357)	(0.012)	(0.009)
Homeownership	-0.316	0.110*	1.799	-0.141	-0.295***
	(0.275)	(0.059)	(2.194)	(0.087)	(0.074)
High school and below share	-0.340	-0.351***	1.483	-0.082	-0.171
	(0.466)	(0.103)	(4.276)	(0.111)	(0.134)
College graduate share	0.113	0.262***	-0.435	0.784***	1.277***
	(0.342)	(0.088)	(4.008)	(0.186)	(0.129)
Senior population share	-0.921	0.292*	-0.149	0.071	1.782***
	(0.830)	(0.159)	(6.064)	(0.255)	(0.293)
Racial Herf. index	0.345	-0.018	-0.987	0.087	0.751***
	(0.250)	(0.058)	(2.000)	(0.053)	(0.068)
Violent crime rate	0.010	-0.003	-0.012	0.001	-0.020***
	(0.013)	(0.002)	(0.080)	(0.003)	(0.003)
N	38	2,571	1970	2,898	2,973
Memo					
ΔR-Squared (%)	11.7	2.8	33.3	2.1	...

Table 4: Consistency among All Social Capital Indicators

The upper panel of this table presents the consistency analysis among four indicators of social capital, including the average credit score. Each of these social capital indicators is regressed on the other three indicators and the set of control variables in table 3. Standard errors are clustered at the state level and presented in parentheses. *, **, and *** denote 90, 95, and 99 percent statistical significance, respectively. We found that average credit scores, blood donations, and electoral participation are positively correlated among themselves, while all are negatively correlated with FCC complaints (though not all coefficients are statistically significant). The lower panel shows that the average credit score has the highest correlation with the first principal component extracted from the four indicators (column 1). Moreover, it has the highest correlation with the first principal component extracted from the other three indicators (column 3).

	Competing Regressions			
	$\frac{\overline{Score}}{100}$ (1)	Electoral participation (2)	Blood donations (3)	FCC complaints (4)
$\frac{\overline{Score}}{100}$	...	0.057	8.864***	-0.092**
		(0.055)	(2.301)	(0.045)
Electoral participation	0.145	...	3.584	-0.023
	(0.145)		(3.949)	(0.092)
Blood donations	0.008***	0.001	...	-0.003*
	(0.001)	(0.001)		(0.002)
FCC complaints	-0.004	-0.040	-1.427	...
	(0.016)	(0.026)	(1.172)	
Controlled for county chars.	Yes	Yes	Yes	Yes
N	1,687	1,687	1,687	1,687

	Correlations with Principal Components			
	$First\ PC^4$ (1)	$Second\ PC^4$ (2)	$First\ PC^3$ (3)	$Second\ PC^3$ (4)
$\frac{\overline{Score}}{100}$	0.85***	0.09***	0.53***	0.19***
Electoral participation	0.73***	0.09***	0.39***	0.03
Blood donations	0.68***	-0.39***	0.33***	-0.18***
FCC complaints	0.13***	0.94***	0.05**	-0.12***

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

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

	Logistic Analysis of Stock Ownership					**Tobit Analysis**
	Tract level				County level	Tract level
	(1)	(2)	(3)	(4)	(5)	(6)
$\frac{\overline{Score}}{100}$	0.621**	1.582**	0.630**	0.321**	0.861**	0.173**
	(0.137)	(0.515)	(0.135)	(0.147)	(0.212)	(0.041)
	[1.293]	[1.925]	[1.291]	[1.136]	[1.223]	
$\frac{\overline{Score}}{100}$ × Yrs. ed.		-0.067*				
		(0.034)				
		[0.972]				
SCF observed trusting			0.201**			
			(0.056)			
			[1.223]			
Zip code stock ownership				2.123**		
				(0.387)		
				[1.304]		
I.H.S. real income ($2002)	0.560**	0.561**	0.562**	0.562**	0.633**	0.127**
	(0.053)	(0.053)	(0.053)	(0.053)	(0.060)	(0.015)
I.H.S. real wealth ($2002)	0.092**	0.092**	0.092**	0.091**	0.097**	0.024**
	(0.012)	(0.012)	(0.012)	(0.012)	(0.013)	(0.003)
Head age	-0.041**	-0.040**	-0.039**	-0.040**	-0.046**	-0.007**
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.003)
Head age^2	0.000**	0.000**	0.000**	0.000**	0.001**	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Yrs. ed.	0.188**	0.658**	0.186**	0.188**	0.207**	0.056**
	(0.015)	(0.241)	(0.014)	(0.015)	(0.013)	(0.004)
Married	0.357**	0.358**	0.362**	0.365**	0.348**	0.132**
	(0.112)	(0.112)	(0.112)	(0.113)	(0.115)	(0.033)
Single male	0.176*	0.178*	0.164*	0.183*	0.147**	0.067**
	(0.099)	(0.099)	(0.099)	(0.099)	(0.087)	(0.030)
White	0.534**	0.530**	0.532**	0.524**	0.619**	0.170**
	(0.081)	(0.082)	(0.081)	(0.082)	(0.082)	(0.023)
Willing to take fin. risk	0.592**	0.590**	0.589**	0.594**	0.581**	0.185**
	(0.066)	(0.066)	(0.066)	(0.066)	(0.067)	(0.019)
Controlled for						
Family size dummies	Yes	Yes	Yes	Yes	Yes	Yes
Tract characteristics	Yes	Yes	Yes	Yes	Yes	Yes
County economic conditions	Yes	Yes	Yes	Yes	Yes	Yes
Yearly fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
N	14,122	14,122	14,122	14,113	14,137	14,122

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

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

	Logistic Analysis of Stock Ownership						**Tobit Analysis**
	Tract level				County level		Tract level
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\frac{\overline{Score}}{100}$	0.481***	2.358***	0.307**	0.322***	0.482***	0.139***	0.128***
	(0.093)	(0.360)	(0.135)	(0.101)	(0.169)	(0.032)	(0.040)
	[1.245]	[2.921]	[1.147]	[1.158]	[1.116]	[1.179]	
County grew up $\frac{\overline{Score}}{100}$						0.362***	
						(0.023)	
						[1.599]	
$\frac{\overline{Score}}{100} \times$ years of edu.		-0.135***					
		(0.024)					
Risk tolerance			0.032***				
			(0.011)				
ZIP code stock ownership				1.045***			
				(0.235)			
I.H.S. real income ($2002)	0.612***	0.605***	0.566***	0.612***	0.630***	0.665***	0.186***
	(0.036)	(0.036)	(0.060)	(0.037)	(0.037)	(0.010)	(0.015)
I.H.S. real wealth ($2002)	0.070***	0.071***	0.097***	0.072***	0.063***	0.055***	0.023***
	(0.005)	(0.005)	(0.012)	(0.005)	(0.004)	(0.001)	(0.002)
Head age	-0.005	-0.004	-0.008	-0.004	0.007	-0.004**	0.005*
	(0.006)	(0.006)	(0.014)	(0.006)	(0.007)	(0.002)	(0.003)
Head age^2	0.019***	0.018***	0.020	0.017***	0.008	0.016***	0.002
	(0.006)	(0.006)	(0.014)	(0.006)	(0.007)	(0.002)	(0.003)
Yrs. ed.	0.184***	1.117***	0.130***	0.183***	0.170***	0.186***	0.065***
	(0.009)	(0.171)	(0.013)	(0.009)	(0.009)	(0.003)	(0.004)
Married	0.218***	0.222***	0.306***	0.208***	0.254***	0.328***	0.069***
	(0.057)	(0.057)	(0.096)	(0.057)	(0.058)	(0.018)	(0.025)
Single male	0.082	0.084	0.047	0.083	0.130**	0.152***	0.083***
	(0.059)	(0.059)	(0.096)	(0.060)	(0.062)	(0.019)	(0.026)
White	0.666***	0.657***	0.610***	0.666***	0.766***	0.840***	0.233***
	(0.055)	(0.055)	(0.085)	(0.056)	(0.059)	(0.016)	(0.024)
Controlled for							
Family size dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Tract characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County economic conditions	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Yearly fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	22,731	22,731	7,064	22,396	18,073	10,653	16,587

Table 7: Other Measures of Social Capital and Stock Ownership

Note: Standard errors are presented in parentheses. Data used in estimation of the upper and lower panel are 2004, 2007, and 2010 SCF, pooled together, and a sample constructed using the 1999–2013 PSID, respectively. Control variables are the same as in tables 5 and 6. Credit score averages are calculated using the FRBNY/Equifax CCP data, county voting data are from the *Guardian* newspaper, county blood donation data are estimated using data from the American Red Cross, and FCC complaints data can be accessed at https://www.fcc.gov/consumer-help-center-data. Standard errors are clustered at county level and corrected for multiple imputation (SCF only). *, **, and *** denote 90, 95, and 99 percent statistical significance, respectively.

			SCF		
	(1)	(2)	(3)	(4)	(5)
$\frac{\overline{Score}}{100}$	0.861**				0.607**
	(0.212)				(0.273)
Pct. voting		0.798			0.752
		(0.584)			(0.682)
Pct. donating blood			0.016		0.023
			(0.015)		(0.016)
FCC complaints				-0.351**	-0.161**
				(0.151)	(0.078)
			PSID		
	(1)	(2)	(3)	(4)	(5)
$\frac{\overline{Score}}{100}$	0.481***				0.663***
	(0.169)				(0.225)
Pct. voting		0.142			0.051
		(0.380)			(0.425)
Pct. donating blood			-0.008		-0.004
			(0.009)		(0.0010)
FCC complaints				0.056	0.122
				(0.131)	(0.141)

Table 8: Dynamic Analysis

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

	Entry analysis				Exit analysis			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta \frac{\overline{Score}}{100}$	0.272				0.150			
	(0.252)				(0.270)			
	[1.046]				[1.020]			
$\Delta^{+} \frac{\overline{Score}}{100}$		0.517*	0.885**	0.871**		0.272	-0.214	-0.291
		(0.300)	(0.383)	(0.394)		(0.333)	(0.432)	(0.447)
		[1.064]	[1.111]	[1.110]		[1.029]	[0.978]	[0.970]
$\Delta^{-} \frac{\overline{Score}}{100}$		-0.074	-0.427	-0.407		-0.087	0.877	0.998
		(0.340)	(0.419)	(0.426)		(0.447)	(0.596)	(0.615)
		[0.992]	[0.956]	[0.958]		[0.993]	[1.072]	[1.082]
$\frac{\overline{CS_0}}{100}$	0.457***	0.460***	0.456***	0.458***	-0.374***	-0.370***	-0.369***	-0.355***
	(0.110)	(0.110)	(0.110)	(0.110)	(0.127)	(0.127)	(0.127)	(0.127)
	1.222	[1.224]	[1.222]	[1.222]	[0.885]	[0.885]	[0.886]	[0.890]
Controlled for								
Individual char.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Δ Local char. and econ conditions	No	No	Yes	Yes	No	No	Yes	Yes
Δ Zip code stock ownership	No	No	No	Yes	No	No	No	Yes
Yearly fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	19,880	19,880	19,880	19,880	4,539	4,539	4,539	4,539