Friends with Benefits: Social Capital and Household Financial Behavior

Brad Cannon[†] David Hirshleifer[‡] Joshua Thornton[§]

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Using friendship data from Facebook, we study the effects of three aspects of social capital on individual investment and saving behavior. We find that social capital is strongly associated with stock market participation and propensity to save. Furthermore, the most important measure of social capital in explaining these outcomes is Economic Connectedness, measured as the fraction of one's social network with high socioeconomic status. One standard-deviation greater Economic Connectedness is associated with 2.9% greater stock market participation and 5.0% greater propensity to save. Compared to Network Clustering or Volunteering Rate, Economic Connectedness explains more than 6 times the variation in stock market participation and more than 4 times the variation in propensity to save.

[†]Binghamton University, bcannon@binghamton.edu
[‡]University of Southern California
[§]Baylor University, joshua_thornton@baylor.edu

1 Introduction

Over the past three decades, social capital — the quality of an individual's social network — has emerged as an important determinant of various political and economic outcomes Durante et al. (2023). In this paper, we apply Facebook friendship data to study the relationship between social capital and household financial behavior. In particular, we focus on household stock market participation and propensity to save.

While providing important insight, past research about social capital has been constrained by the absence of comprehensive data on the structure of social networks. In consequence, previous studies have overcome data limitations by studying the relationship between a particular manifestation of social capital and an outcome of interest. In the household finance literature, social capital has been shown to influence stock market participation through social capital proxies ranging from average credit scores to civic engagement (Guiso, Sapienza, and Zingales (2004), Bricker and Li (2017)).

In contrast, by applying extensive social network data from Facebook in combination with data on stock market participation and savings behavior from the IRS, we are able to study the effects of social capital on a representative set of U.S. households based on recorded social network data. Additionally, drawing upon the research of Chetty et al. (2022), the data allow us to differentiate between three types of social capital and help disentangle which aspects are most important for household financial decisions. We find that one of these measures, *Economic Connectedness* (EC) — defined as the fraction of an individual's friend group with high socioeconomic status (SES) — is particularly important in explaining stock market participation and savings behavior.

Social capital, at its fundamental level, is a measure of the value in one's social network. When viewed as an investment in one's social network with expected returns, social capital is similar to other neo-capital theories such as human capital or cultural capital (Lin (1999)). Similar to a portfolio of financial assets, there are numerous ways to invest in one's network, which is evident from the variety of definitions offered for social capital in a large and interdisplinary body of work (Fulkerson and Thompson (2008)). Generally, however, definitions of social capital fall into two broad categories: social networks (e.g., friendships between different types of people or presence of cliques) and societal norms (e.g., civic engagement or trust in institutions). In this paper, we view social capital as a multidimensional concept, consistent with papers such as Durante et al. (2023) and Guiso and Sodini (2013), and examine variables that reflect both views of social capital.

The three measures of social capital we consider are: (1) Economic Connectedness, (2) Network Clustering, and (3) Volunteering Rate.[1] While each measure is contained within social capital more broadly, each has a precise meaning and role. Economic Connectedness measures the fraction of one's social network who have high socioeconomic status. As such, this measure focuses on the type of people in one's social network. Especially among low-SES households, Economic Connectedness can be thought of as a type of "bridging capital" because it measures the connectedness between individuals from different socioeconomic backgrounds. Network Clustering, on the other hand, captures the likelihood that two friends of a focal individual are friends with each other. Network Clustering can therefore be thought of as a type of "bonding capital" because it measures the cohesiveness of one's social network. Lastly, Volunteering Rate measures local rates of volunteering. Instead of focusing on one's social network, this measure is more closely related to civic engagement.

As motivating evidence, as shown in Figures 1 and 2, we find that Economic Connectedness is the aspect of social capital with the strongest relationship to stock market participation and propensity to save. Controlling for relevant county characteristics, a one-decile increase in Economic Connectedness is associated with an increase of nearly 4% for stock market participation and over 5% for propensity to save.[2] Furthermore, compared to Network Clustering or Volunteering Rate, Economic Connectedness explains more than 6 times the variation in stock market participation and more than 4 times the variation in propensity

[1] These measures were provided by Chetty et al. (2022).

[2] The slope of the best-fit line for EC in Figure 1 is 0.039. The slope for the best-fit line for EC in Figure 2 is 0.052.

to save. These results are true for both high-SES and low-SES individuals.

An important implication of classic models (Merton (1969), Sharpe (1964)) is that all investors, regardless of wealth or risk preferences, should invest in the market portfolio. In reality, a substantial fraction of households do not own stock. Over the last three decades, a large literature has tried to explain this "participation puzzle."[3] One of the leading explanations is based on fixed participation costs (Vissing-Jorgensen (2002)). Examples of participation costs include administrative costs for account setup and information acquisition costs. Such "set-up costs" (Hirshleifer (1988)) could also be psychic costs of gaining comfort with relevant procedures. In either case, individuals will only invest if the benefit from stock market participation outweighs the fixed cost of participation.

This is more likely to occur if an individual has a greater amount of wealth available to invest in the market. So the fixed cost framework is consistent with the observed positive correlations between stock market participation and wealth (Vissing-Jorgensen (2002)), cognitive skills (Grinblatt, Keloharju, and Linnainmaa (2011), van Rooij, Lusardi, and Alessie (2011)), and risk tolerance (Vissing-Jorgensen and Attanasio (2003)).[4] A distinctive feature of our study is that we use social network data to study the effects of three aspects of social capital on stock market participation and savings behavior.

Our finding that high socioeconomic friends encourage stock market participation and saving is broadly consistent with the fixed cost explanation discussed above. High-SES individuals are more likely to participate in the stock market because the benefit of a given risk premium is amplified by an investment of greater scale, making it more likely that the risk-adjusted benefit from investment can clear the hurdle of the fixed participation cost. This suggests that individuals with higher Economic Connectedness (i.e. those with more high-SES friends) will tend to have more friends who participate in the stock market. In

[3] For a review, see Guiso and Sodini (2013)

[4] Additionally, many empirical papers have documented other variables that are associated with stock market participation. For example, stock market participation is correlated with peer stock market participation (Brown et al. (2008)), peer stock market performance (Kaustia and Knüpfer (2012)), political beliefs (Kaustia and Torstila (2011)), and trust in institutions (Giannetti and Wang (2016)).

turn, having more participating friends may encourage participation.

There are several reasons why participating in the stock market may be contagious. First, it can lower information acquisition costs (i.e. friends might discuss investment opportunities or cost-mitigation strategies, Hong, Kubik, and Stein (2004)). Second, it can increase familiarity with and psychological comfort of stock investing (Cao, Wang, and Zhang (2005), Cao et al. (2009)). Third, it can increase the social utility from investing if friends enjoy discussing investments with each other. Each of these channels should lead to a positive relationship between Economic Connectedness and stock market participation, regardless of socioeconomic status.

A similar argument can be made for savings behavior. Wealth and savings are positively correlated. Therefore, individuals with higher Economic Connectedness will have a higher fraction of friends that save. If savings is socially contagious, either by increasing social utility or by increasing financial literacy, we expect to see a positive relationship between Economic Connectedness and savings behavior, regardless of socioeconomic status.

Our empirical strategy takes a four-pronged approach. First, we apply extensive U.S. data from Facebook to get a representative picture of household friendship networks, and a representative sample from the IRS to understand financial behavior. Second, we incorporate data from the American Community Survey to control for well-known drivers of stock market participation and savings behavior. Third, we test for reverse causality using childhood Economic Connectedness. Because childhood friendships are created before people typically start making their own financial decisions, such friendships are not influenced by stock market participation or savings behavior. Fourth, we use changes in the income of non-local friends as a plausibly exogenous shock to Economic Connectedness.

Our results provide evidence of a substantial and statistically significant relationship between social capital and household financial behavior. One standard-deviation greater Economic Connectedness is associated with 2.9% greater stock market participation and 5.0% greater propensity to save. Furthermore, compared to network cohesiveness or civic engagement, Economic Connectedness is the most important aspect of social capital in explaining both stock market participation and propensity to save.

This is seen graphically in Figures 1 and 2. However, the dominance of Economic Connectedness is even more striking in regression tests. The adjusted R^2 results from Tables 3 and 4 indicate that, compared to Network Clustering or Volunteering Rate, Economic Connectedness explains more than 6 times the variation in stock market participation and more than 4 times the variation in propensity to save.

These effects could derive from omitted variables that are not fully captured by our controls. However, we find broadly similar results when we use childhood EC as our independent variable. Therefore, these results are unlikely to be driven by reverse causality.

Additionally, we use a quasi-experimental approach to determine whether or not the observed relationships are causal. We find that a greater increase in the income of non-local friends leads to a greater increase in stock market participation and a greater increase in propensity to save. This evidence supports a causal interpretation of our main results.

Lastly, in order to determine if our results are driven by one specific part of the income distribution, we split our sample into two subsamples: individuals with below-median income and individuals with above-median income. Our results hold across both subsamples. This is important because it shows that high-SES individuals are not the exclusive drivers of our results. Furthermore, we find suggestive evidence in favor of a step-by-step savings process in which individuals save first, invest second, and bolster both account third.

This paper contributes to four streams of literature. First, it extends the literature on social capital by showing that social capital is positively associated with stock market participation and savings behavior in the U.S. As such, we contribute to the growing field of social finance (Hirshleifer (2020)). Furthermore, we adopt a multidimensional view of social capital and show that Economic Connectedness is the most important social capital proxy in explaining household financial behavior.

Second, we contribute to the household finance literature on stock market participation.

We show that a proxy for social capital, Economic Connectedness, is important in explaining stock market participation. This relationship holds even after controlling for well-known drivers of stock market participation such as education, wealth, financial literacy, and race. We also show that total county-level stock market investment increases with EC. This suggests that both the intensive margin and the extensive margin of stock market participation are positively associated with social capital.

Third, we contribute to the literature on household savings behavior by showing that Economic Connectedness is positively associated with propensity to save. This relationship is highly significant even after controlling for well-known determinants of savings behavior. Additionally, we find that total county-level interest income increases with EC. This evidence suggests that both the intensive margin and the extensive margin of savings behavior are also positively associated with social capital.

Fourth, we extend the literature on cycles of poverty and lifetime wealth accumulation. All of the results mentioned previously are true for low-SES as well as high-SES individuals. This suggests that neither end of the SES distribution is exlusively driving our results. Furthermore, our subsample analysis provides suggestive evidence in favor of a step-by-step savings process in which households contribute to savings accounts first, investment accounts second, and bolster both accounts third. Taken together, our results suggest that encouraging friendships across socioeconomic classes could improve lifetime wealth accumulation and help break cycles of poverty for individuals with low socioeconomic status.

2 Data Description

While social capital has been a theme of household finance papers since, at least, Guiso, Sapienza, and Zingales (2004), different papers use various proxies for social capital, including cheating on school tests and turnout in elections. To facilitate research in this area, Chetty et al. (2022) outline three distinct measures of social capital – Economic Connectedness, Network Clustering, and Volunteering Rate – and develop geographic measures for each component of social capital using extensive data on friendships from Facebook. We provide a brief description of these measures; see Chetty et al. (2022) for more details. In order to disentangle which components of social capital influence stock market participation and propensity to save, we obtain these county-level measures of social capital from `www.socialcapital.org`.

Economic Connectedness measures the fraction of individuals' friends who have above-median income. Specifically, the primary definition is "two times the share of high-SES friends among low-SES individuals, averaged over all low-SES individuals in the county". Both high-SES and low-SES are based on the median national income level. As this measure considers friendships from the perspective of below-median income individuals, this measure only applies to the low-SES subset of households in each county. In our analysis, we also account for the analogous effect for high-income individuals by using the Economic Connectedness measure provided by Chetty et al. (2022) for high-SES individuals. This measure is calculated as two times the share of high-SES friends among *high*-SES individuals.[5]

Network Clustering can be thought of as the tightness of the average circle of friends in a county. More precisely, it is measured as the "average fraction of an individual's friend pairs who are also friends with each other."

Lastly, Volunteering Rate quantifies the average involvement of members in the community. It is defined as the percentage of Facebook users who are members of a group which is predicted to be about 'volunteering' or 'activism' based on group title and other group characteristics. Our analysis centers around these three measures and their impact on stock market participation and savings behavior.

We obtain tax return information from the the IRS's Statistics of Income (SOI) database. The SOI breaks down tax returns for each tax season by geographic regions and adjusted gross income. As our measures of social capital are constructed using county-level data from

[5]In reverse causality tests, we use a similar methodology to combine two childhood Economic Connectedness measures; one for high-SES individuals and one for low-SES individuals.

2018, the SOI data we collect is from Tax Year 2018 and contains information about the cross section of counties from that year. Furthermore, because Economic Connectedness is uniquely measured for low-SES and high-SES individuals in each county, we use the SOI data that is broken out by AGI categories.

There are 8 AGI categories ranging from "Under $1" to "$200,000 or more". We exclude the "Under $1" group from our sample as it likely contains individuals with artificially low income that are not representative of low-SES individuals. We also exclude the $50,000 to $75,000 range, as the median income from 2018 falls within this category (the U.S. median household income was $63,179 in 2018, according the U.S. Census Bureau). This leaves us with three low-SES observations and three high-SES observations for each county in 2018.

Using these AGI groupings, we assign the low-SES Economic Connectedness value for each county to the AGI groups below the median national income and the high-SES Economic Connectedness value for that county to households above the median national income. For our main analysis, we create one observation per county. We do this by summing the IRS values for each AGI grouping within a county. For our county-level Economic Connectedness measure, we take the weighted average of Economic Connectedness per county where the weights are determined by the number of tax returns in each AGI group. AGI groups below the mean national income are assigned the standard Economic Connectedness measure, and AGI groups above the mean are assigned the analagous high-SES measure.

Using the SOI data, we create several variables related to investment and savings behavior. Though there is not a record to indicate if a household participates in the stock market, tax returns contain several pieces of information that are a consequence of stock market participation. For our first variable of interest, we use the receipt of dividend income as a proxy for each household's participation in the stock market (Brown et al., 2008). It takes a positive value if the household receives dividends from stocks or taxable equity mutual funds. For each county, we compute the fraction of tax forms that received dividend income. While there are certainly households holding stocks that do not have dividend income, this can be thought of as a lower bound of the fraction of households participating in the stock market.

We also measure the propensity to save at the county level. Analogous to our stock market participation proxy, we use the fraction of households receiving interest income as a proxy for propensity to save. We also view this as a lower bound for propensity to save, as there are likely households who save in non-interest bearing accounts or who do not receive enough interest income to be reported on tax forms. Though participation measures are useful to gauge the extensive margin of investments or savings (i.e. the decision to participate), they do not measure how much of one's income is being allocated to the stock market or to a savings account. To proxy for this intensive margin, we compute total dividend income and total interest income, in natural logarithms, for each county.

Several variables other than social capital have been shown to help explain cross-sectional variation in stock market participation and savings behavior. To control for these, we collect demographic information for each county in 2018 from the American Community Survey. Specifically, we construct the natural logarithms of median income, total population, and population per square mile. Furthermore, we include percent male, percent Black, percent Asian, percent Pacific Islander, percent Hispanic, median age, and percent with a high school education as control variables in our analysis. Additionally, we use data from Stoddard and Urban (2020) to create a dummy variable for each state that has a state-mandated financial education requirement for high-school graduation. We interact this state dummy with the high-school graduation percentage to proxy for the financial literacy of a county.

Table 1 reports county-level summary statistics for each of our variables of interest. The first two variables, *P(Div)* and *P(Int)* are dependent variables in our regressions and capture the probability that a tax return has dividend income or interest income, respectively. Given that the average value of *P(Div)* is 0.162 and *P(Int)* 0.303, our estimates seem comparable to other estimates of participation rates, especially because our estimates represent lower bounds.

Economic Connectedness is the first aspect of social capital that we study. It measures the fraction of an individual's friend group with high SES. Because this value is slightly below one, we can infer that the average person in the average county has slightly more low-SES friends than high-SES friends. However, as the standard deviation is 0.199, there is a fair amount of variation across counties. *Network Clustering* is the second aspect of social capital that we study. It captures the fraction of an individual's friend group that are in turn friends with each other. *Volunteering Rate* is the third aspect of social capital that we study. It captures the fraction of individuals in a county who are members of 'volunteering' or 'activism' groups, as defined by Chetty et al. (2022).[6] The variables *Population Density, Population, Median Income, Percent Male, Percent Black, Percent Asian, Percent Islanders, Percent Hispanic* and *Median Age* are county-level control variables that come from the American Community Survey. *Financial literacy* is a dummy variable that equals one if a state had financial literacy high school graduation requirement in 2018. *High School* also comes from the American Community Survey and measures the fraction of a county that has graduated high school.

Table 2 reports correlations for each of our variables of interest. As can be seen from this table, Economic Connectedness is strongly associated with *P(Div)* and *P(Int)*. This is partially due to the power of this explanatory variable and partially due to our construction of *EC*, which depends on the number of tax returns in each IRS AGI bucket for a given county. This makes Economic Connectedness directly related to the county's income distribution. As such, in our regressions, we include control variables such as median income and education.

[6] It is worth noting that unlike *Economic Connectedness*, *Network Clustering* and *Volunteering Rate* have much lower averages and standard deviations. In regressions, this likely leads to higher nominal coefficient estimates, relative to *Economic Connectedness*. In our results, we try to keep this distinction clear and provide a comparable interpretation of economic significance among these social capital variables.

3 Methodology

Consistent with our multidimensional view of social capital, we follow suit with Chetty et al. (2022) and study three distinct aspects of social capital in each of our tests. First, we study Economic Connectedness, or the fraction of one's friend group that has high socioeconomic status. Economic Connectedness takes full advantage of the Facebook data because it combines network information with individual characteristics (i.e. socioeconomic status).

Second, we study Network Clustering, or the probability that two friends of a focal individual are in turn friends with each other. To further elucidate the differences between Economic Connectedness and Network Clustering, consider the data structure of these two variables. While Economic Connectedness combines network data with individual characteristics, Network Clustering relies solely on data about the social network.

Third, we use Facebook data to proxy for the rate of volunteering in each county. We include this Volunteering Rate in our regressions to study civic engagement. Previous papers, such as Guiso, Sapienza, and Zingales (2004), have used similar measures of civic engagement to study the effect of social capital on economic outcomes. However, this facet of social capital is not only conceptually distinct from Economic Connectedness and Network Clustering, but it also captures very different data than these other two measures. In particular, civic engagement does not rely on an individual's social network at all.

We include each of these aspects of social capital jointly in our county-level regressions. we control for known drivers of stock market participation and savings behavior such as gender, income, race, education, financial literacy, population, and population density. Standard errors throughout our analysis are adjusted for heteroskedasticity.

Despite the use of controls, it is still possible that a relationship between stock market participation (or savings behavior) and Economic Connectedness could be driven by other mechanisms. For example, it is entirely plausible that individuals who invest are more likely to have friends with high SES. Perhaps, they meet these friends at investment clubs or seminars. In this case, it is the act of investing (or saving) that is leading to increased Economic Connectedness. We address such causality concerns in two ways. First, to specifically address reverse causality, we use the measure of childhood Economic Connectedness from Chetty et al. (2022). This measure utilizes parent-child linkages to study Economic Connectedness based on childhood friendships. Because childhood friendships are made before individuals typically start filing taxes, these childhood friendships cannot be directly influenced by an individual's stock market participation or savings behavior. Second, to address causality concerns more broadly, we analyze the change in a county's stock market participation and propensity to save in response to the change in income of non-local friends. Using this quasi-experimental approach allows us to navigate concerns dealing with self-selection to counties.

4 Results

4.1 Probability of Stock Market Participation

Our first set of tests analyzes the relationship between social capital and stock market participation. Our use of dividend income from tax returns as a proxy for stock market participation does not capture all investing activity. However, since only someone who participates can receive a dividend, it provides a lower bound on the rate of stock market participation.

Table 3 reports results for eight regressions of county-level stock market participation on our three measures of social capital. Each of the odd-numbered columns report results with no controls, while the even-numbered columns include controls for population, population density, median income, race, age, gender, education, and financial literacy. The first six specifications focus on an individual measure of social capital (i.e. EC, Network Clustering, or Volunteering Rate). The last two specifications include all three measures of social capital. In all specifications, we estimate standard errors adjusted for heteroskedasticity.

The results from the first row of columns (1), (2), (7) and (8) show that Economic Connectedness is positively associated with the probability of dividend income. Regardless of the specification, this relationship is highly significant and suggests that having high-SES friends can lead to increased participation in the stock market.

The standard deviation of Economic Connectedness is 0.199. Therefore, even with full controls (column (8)), a one standard-deviation increase in Economic Connectedness is associated with a 2.9% increase ($0.147 * 0.199$) in stock market participation. Economically, the magnitude of this relationship is quite large, a 18% increase relative to the mean (0.029/0.162).

The effects are weaker for the other two measures of social capital. While Network Network Clustering shows a positive relationship, it has a much smaller standard deviation of 0.02. Therefore, a one standard-deviation increase in Network Clustering is associated with a 1.2% increase in stock market participation. Furthermore, the point estimate on Network Clustering only becomes positive once control variables are included. Absent controls, it has a significantly negative relation with stock market participation. Volunteering Rate, on the other hand, shows no relationship with stock market participation once controls are included.

Another way to assess the relative importance of these three measures in explaining stock market participation is to compare adjusted R^2 values. In column (1), we see that Economic Connectedness is able to explain over 56% of the variation in stock market participation. This is more than 11 times the variation explained by Network Clustering (5.0%), and it is more than 6 times the variation explained by Volunteering Rate (8.7%). As such, our results indicate that Economic Connectedness is the most important aspect of social capital in explaining stock market participation.

4.2 Propensity to Save

Next, we run a similar series of tests to study the relationship between social capital and savings behavior. Our proxy for propensity to save is the fraction of all tax returns in a county that report interest income. Again, this measure provides a lower bound on average county savings behavior.

Table 4 reports results for eight regressions of county-level propensity to save on our three measures of social capital. Each of the odd-numbered columns report results with no controls, while the even-numbered columns include controls for population, population density, median income, race, age, gender, education, and financial literacy. The first six specifications focus on an individual measure of social capital (i.e. EC, Network Clustering, or Volunteering Rate). The last two specifications include all three measures of social capital.

The savings results are remarkably similar to the stock market participation results and suggest that Economic Connectedness is the most important aspect of social capital in explaining propensity to save. The results from the first row of columns (1), (2), (7), and (8) show a positive relationship between Economic Connectedness and propensity to save. This relationship is highly significant across all specifications and provides evidence that having high-SES friends is associated with increased savings rates.

The economic magnitude of this relationship is large. Considering the specification with full controls (column (8)), a one standard-deviation increase in Economic Connectedness is associated with a 5.0% increase ($0.251 * 0.199$) in propensity to save. This represents an increase of more than 16% relative to the mean (0.050/0.303).

The other two measures of social capital are also less important in explaining propensity to save. In fact, they show a very similar pattern to the stock market participation results from Table 3. While Network Clustering has a positive and statistically significant relationship with propensity to save, the economic magnitude of the relationship is much smaller than it is for Economic Connectedness. A one standard-deviation increase in Network Clustering is associated with a 1.1% increase in propensity to save. After including controls, Volunteering Rate has no relationship with propensity to save.

Another way to compare the relative importance of these three measures of social capital is to compare the adjusted R^2 values. Looking at the bottom row of columns (1), (3), and (5) of Table 3, Economic Connectedness explains nearly 54% of the variation in propensity to save, while Network Clustering explains 2% of the variation and Volunteering Rate explains roughly 13% of it. Therefore, Economic Connectedness appears to be the most important aspect of social capital for explaining propensity to save.

4.3 Causality Tests

While our findings indicate that Economic Connectedness is especially important for stock market participation and propensity to save, our results thus far rely on control variables as a means of identification. This can be problematic as participating in the stock market is influenced by many factors, some of which are likely correlated with Economic Connectedness. To better identify the causal effect of Economic Connectedness on stock market participation and propensity to save we conduct two sets of tests. Our first tests rely on Childhood friendship data and specifically address reverse causality. Our second set of tests use cross-county social networking data and focus on changes in income to non-local friends to address causality concerns more broadly.

4.3.1 Reverse Causality

Reverse causality is a highly relevant concern in evaluating these findings since it is plausible that stock market participation or savings behavior might influence an individual's social network. For example, perhaps individuals who invest in the stock market join investment clubs or attend investing seminars. Because stock market participation increases with wealth, these individuals would be more likely to have high-SES friends. If such an explanation is true, we would see a positive relationship between Economic Connectedness and stock market participation, but it would be driven by stock market participation not by Economic Connectedness.

In order to address reverse causality, we run a series of tests with childhood Economic Connectedness as the independent variable. These tests are nearly identical to the method Chetty et al. (2022) use to address reverse causality. Results from our reverse causality tests are presented in Table 5.The first three columns present results in which $P(Div)$ is the dependent variable. The final three columns present results in which $P(Int)$ is the independent variable. Columns (2), (3), (5), and (6) include controls, and columns (3) and (6) include all three measures of social capital as independent variables.

The first three columns show a positive and statistically significant relationship between childhood Economic Connectedness and stock market participation. The last three columns show a positive and statistically significant relationship between childhood Economic Connectedness and savings behavior. Taken together, these results show the same basic pattern as the results from Tables 3 and 4. Therefore, reverse causality is not likely to be the main driver of our findings.

4.3.2 Non-local Income Shocks

We next address causality concerns more broadly by analyzing changes in stock market participation and propensity to save following income shocks to non-local friends. While our reverse causality tests provide evidence toward a causal role for Economic Connectedness, it is possible that Economic Connectedness still does not have a causal effect. For instance, people who tend to participate in the stock market may simply be attracted to living in regions with high Economic Connectedness. As a result, we could observe high stock market participation rates in regions with high Economic Connectedness for reasons unrelated to social interactions. This is critical because policy aimed to improve Economic Connectedness would not have its intended effect if our findings are a consequence of selection rather than social interactions. To provide evidence that Economic Connectedness has a causal effect on stock market participation and propensity to save, we implement a quasi-experimental approach using cross-county friendship data. Specifically, we test whether the change in income of non-local friends is related to the the change in stock market participation of a given county. Our identifying assumption is that the change in income of non-local friends impacts the stock market participation or savings of a given county only through friendship linkages.

To conduct this analysis, we collect data measuring the social connectedness of county pairs, $SCI_{i,j}$ (Bailey et al., 2018). This data records the relative probability that any two individuals from two given counties are friends on Facebook. For our purposes, we use this data to approximate, for a given county i, the average change in income of its non-local Facebook friends. Specifically, for county i, we first multiply each social connectedness measure $SCI_{i,j}$ by the population in county j. As the population of county i is still implicitly in the denominator of this value, it is an approximation of the number of Facebook friends in county j for the average person in county i. We then use these friendship values to weight the change in income of all non-local counties from 2016 to 2017. We exclude counties within 250 miles of county i, as well as county i itself, in our computation to detach our measure from potential local economic shocks. Finally, we multiply the weighted average by one minus the fraction of local friends in a given county. This accounts for the fact that some counties may have a greater fraction of local friends than other counties. Concisely, our measure of change in non-local income for each county is:

$$\Delta NonlocalIncome_i = \left(1 - \frac{SCI_{i,i} * Pop_i}{\sum_{k=1}^{N} SCI_{i,k} * Pop_k}\right) * \frac{\sum_{j=1}^{N} SCI_{i,j} * Pop_j * \Delta Income_j}{\sum_{j=1}^{N} SCI_{i,j} * Pop_j} \quad (1)$$

where $j \neq i$ and county j is not within 250 miles of county i.

We use this measure to test whether stock market participation and savings are related to the change in non-local friends' income. We do this by regressing the change in a county's stock market participation or propensity to save on $\Delta NonlocalIncome$. We measure changes in stock market participation and propensity to save from 2017 to 2018 and include all control variables considered in earlier regressions.

In Table 6, we provide evidence that Economic Connectedness has a causal impact on stock market participation and savings. More precisely, we show that the change in income of non-local friends has a positive and significant relation with changes in stock market participation and propensity to save. In terms of economic magnitude, one standard-deviation greater change in non-local income leads to 0.00049 greater change in stock market participation and 0.00068 greater change in propensity to save. While these numbers appear small, the variables of interest in our regressions represent county-level changes, which are sticky by nature. With this is mind, a one standard deviation change in non-local income leads to an increase in stock market participation of 66.74% and 5% for propensity to save, relative to their mean changes.

As these findings come from non-local friends, they are immune to effects coming directly from local economic conditions. Furthermore, because these linkages are friendship-based, they highlight the social aspect of Economic Connectedness. Lastly, as the explanatory variable focuses on the change in wealth to a "fixed" group of friends, the findings indicate that the *income*, not just the type, of one's friends matters in explaining stock market participation and savings.

4.4 Total Dividend Income and Interest Income

We next explore how Economic Connectedness is related to total dividend income and total interest income. While our earlier tables provide evidence that Economic Connectedness helps explain variation in stock market participation and propensity to save, these measures focus on extensive margins. In other words, counties where individuals have more wealthy friends tend to have more stock market participation and higher rates of saving.

There has been much research on the decision to save, but the intensive margins of saving and investing is also very important. On the one hand, counties with greater Economic Connectedness may save (invest) more of their income than areas with less Economic Connectedness. If this is the case, then we should observe more total savings and more total investing in areas with greater Economic Connectedness. From a policy perspective, this interpretation would imply that improving Economic Connectedness would induce more saving and investing among households, likely through a reduction of consumption, and should lead to greater future wealth.

On the other hand, areas with greater Economic Connectedness may not save more, but instead spread their savings out more between the stock market and interest-bearing accounts. In this case, diversification might be playing a role, and we would not necessarily expect to see more total savings or total investing in areas with greater Economic Connectedness. In this case, Economic Connectedness also wouldn't necessarily have lead to more future wealth, though we could still observe greater stock market participation and propensity to save. From a policy perspective, this interpretation would imply that improving Economic Connectedness would not induce more savings among households but would instead increase diversification among those already saving. If policymakers want to increase saving, investing, and future wealth, then it is important to differentiate between these two channels.

To test whether total dividend income and interest income are related to Economic Connectedness, we estimate similar regressions to those in Tables 3 and 4, but we replace our dependent variables with the natural logarithms of county-level total dividend income and total interest income. The results are reported in Table 7. In column (1), we see a strong positive relation between Economic Connectedness and total dividend income. The coefficient on Economic Connectedness is 2.790 (t = 16.43). Given that the standard deviation of Economic Connectedness is 0.199, a one standard deviation increase in Economic Connectedness is associated with a 0.56% increase in total dividends (2.790 * 0.199). This effect on total dividend income is consistent with Economic Connectedness being related to more investing rather than diversification. Control variables are added in columns (2) and (3), and the effect from Economic Connectedness remains robust. As with our extensive margin results, Network Clustering and Volunteering Rate also show positive point estimates, with Network Clustering being statistically significant though economically less important.

Moving to interest income, Economic Connectedness is also positively related to total interest income in columns (4) through (6). After including all controls and social capital measures, the coefficient on Economic Connectedness is 1.567 (t = 13.11) in column (6).

In comparison, the coefficients on the other social capital measures are indistinguishable from zero. Overall, Table 7 provides evidence that Economic Connectedness is positively associated with the intensive margin of investing behavior and saving behavior. This implies that the higher participation rates are the result of households increasing saving and investing rather than diversifying across multiple investment opportunities.

4.5 Low SES vs. High SES

We next study whether the influence of household social capital on financial decisions depends on the household's SES. As policy is typically directed at improving the financial well-being of lower-income individuals, it is important that our results are not driven exclusively by high-SES households. In Table 8, we repeat our earlier analysis but create two observations per county; one for low-SES individuals and one for high-SES individuals. We construct our sample, as before, by summing IRS variables for each county. This time, however, we construct separate county-level variables for below-median AGI groups and above-median AGI groups. As the Economic Connectedness measures we obtain from Chetty et al. (2022) provide values for high-SES and low-SES individuals for each county, we simply use the counties' standard EC values for the below-median sample and the analagous high-SES Economic Connectedness values for the above-median sample.[7]

In column (1) we see that among low-SES households, all three social capital measures are positively and significantly related to stock market participation. For Economic Connectedness, the coefficient of 0.06 ($t = 8.12$) indicates that a one standard deviation increase in Economic Connectedness is associated with a 1.1% increase in the probability of stock market participation (0.060*0.177). This corresponds to an 11.4% increase, relative to the mean participation rate (0.114/0.093) among low-SES households. Interestingly, Network Clustering has a similar economic magnitude, though its precision is weaker (0.495, $t = 4.06$).

[7]For reference, we report summary statistics for low and high SES groups in Appendix Table A1. We also report correlations between variables of interest for the low-SES group in Appendix Table A2 and for the high-SES group in Appendix Table A3.

A one standard deviation increase in Network Clustering is associated with a 1.0% increase in stock market participation. Though statistically significant, the economic magnitude of Volunteering Rate is quite small (0.070, $t = 2.67$).

Moving to column (2), we see that Economic Connectedness (0.335, $t = 24.38$) and Network Clustering (0.891, $t = 7.29$) are positively related to stock market participation among high-SES households while Volunteering Rate is not (-0.022, $t = -0.53$). Though these large coefficient magnitudes make it seem as if social capital measures matter more for the stock market participation of high-SES individuals, there are two important things to consider. First, consistent with the fixed cost framework of Vissing-Jorgensen (2002), the mean stock market participation rate of low-SES households (0.093) is far lower than for high-SES households (0.321). Considering these mean participation rates, Economic Connectedness has a similar percentage impact on low-SES and high-SES households. Second, stock market participation is likely not the first step along the savings path for individuals. Because roughly 80% of low-SES households do not have interest income, the likely first step for most is to save in an interest-bearing account. For high-SES households, where almost 55% already have interest income, transitioning to the stock market is a natural next step.

Consistent with this step-by-step savings process, we see that for the propensity to save among low-SES households, the coefficient on Economic Connectedness in column (3) is more than twice as large as the corresponding coefficient in column (1). The coefficient of 0.161 ($t = 16.01$) indicates that when Economic Connectedness is one standard deviation higher, the probability of receiving interest income is 2.8% higher. Compared to the mean rate of 19.5%, this corresponds to a 14.6% increase. Similar to column (1), Network Clustering appears with a positive and significant coefficient, though the magnitude is slightly reduced. Volunteering Rate, on the other hand, is indistinguishable from zero. For the high-SES group in column (4), we see that Economic Connectedness and Network Clustering have a positive relationship with the probability of interest income.

In the final four columns of Table 8, we consider the intensive margins of investing and saving for both high-SES and low-SES groups. Regardless of socioeconomic status, Economic Connectedness is positively related to total dividends and total interest income. The relationship is statistically significant in all columns except column (5), which falls just below the significance threshold. The relation between the intensive margins and Economic Connectedness is especially pronounced among the high-SES group. When total dividends is the dependent variable, the coefficient on Economic Connectedness is 2.405 ($t = 18.73$). When total interest is the dependent variable, the coefficient is 2.613 ($t = 22.40$). In comparison, the coefficients for the low-SES group are 0.173 ($t = 1.74$) and 0.747 ($t = 7.24$), respectively. This large gap in the intensive margin is consistent with the step-by-step savings process described earlier. After deciding to open a savings account, the next natural step would be to start investing in the stock market. After a household has opened both a savings account and an investment account, then we might expect an increase in the intensive margins. Overall, Table 8 suggests that Economic Connectedness is most related to extensive margin decisions for low-SES households – whether to invest (save) or not – and most related to intensive margin decisions for high-SES households – how much to invest (save). This substantiates the interpretation that Economic Connectedness can help households progress through a natural saving process.

4.6 Robustness Tests

In all of our tests, we have used the probability of receiving dividend income as a proxy for stock market participation. While we view this as a reasonable lower bound for stock market participation, there are other IRS data that are informative about stock market participation. One such variable is capital gain income. In the Appendix, we replicate our analysis of stock market participation using capital gain income as our dependent variable. Each of the results is consistent with our main analysis and interpretation. In fact, the similarity of the coefficients for Economic Connectedness is striking. This is evident is comparing Table 3, where the probability of receiving dividend income is the dependent variable, to Appendix

Table A4, where the probability of receiving capital gain income is the dependent variable. With no controls, the coefficient of Economic Connectedness is 0.250 (t = 60.21) in Table 3, while its corresponding estimate is 0.237 (t = 67.01) in Table A4. With the full set of controls and social capital measures, the coefficient of Economic Connectedness is 0.147 (t = 15.46) in Table 3, and its corresponding estimate is 0.181 (t = 19.77) in Table A4. The largest difference in the capital gain analysis is that while Network Clustering appears to matter for some specifications of dividend income, it is almost never significantly positive for capital gains.

In addition to our capital gain analysis, we have considered other combinations of control variables for county-level demographic information. Additionally, we have estimated all of our regressions using each AGI bucket as a separate observation for each county and clustering our standard errors at the county level. Regardless of our regression model, we always find a positive relationship between Economic Connectedness and household financial behavior.

5 Conclusion

Despite high historical returns to investing in the stock market, many households do not own stocks. As participating in the stock market is crucial to developing wealth over the life-cycle, understanding how to promote participation is important for improving financial well-being, especially for those less inclined to participate.

Social capital is a promising candidate for policy interventions to promote market participation and saving. Loosely speaking, social capital is the strength of one's social network. It has been shown to influence myriad economic and political outcomes. From the perspective of individual investment and savings decisions, social capital can potentially reduce any fixed costs, whether pecuniary or psychic. By interacting with a variety of members in a community, one is more likely to cross paths with individuals that can provide information and reduce the discomfort associated with stock market participation and with planning saving for retirement. In this paper, we apply friendship data from Facebook and financial data from the IRS to study whether and how social capital influences individual investment and savings behavior.

Using county-level data from the social networks of 27.2 million Facebook users and financial information from IRS tax returns, we consider three aspects of social capital: Economic Connectedness, Network Clustering, and Volunteering Rate. Our evidence indicates that Economic Connectedness is especially important for household financial decisions. A one standard deviation increase in Economic Connectedness is associated with a 2.9% increase in stock market participation and a 5.0% increase in the propensity to save. Relative to their mean values, this represents an 18% increase in stock market participation and a 16% increase in savings. Furthermore, while Network Clustering and Volunteering Rate explain, at most, 8.7% of variation in stock market participation, Economic Connectedness explains 56.3%. Similarly, Network Clustering and Volunteering Rate explain, at most, 13.1% of variation in propensity to save, while Economic Connectedness explains 53.6%. Lastly, using changes in income of non-local friends as exogenous shocks to Economic Connectedness, we provide evidence in favor of a causal interpretation of these results.

We also examine how Economic Connectedness relates to the intensive margin of financial decision-making– how much people invest or save. Similar to our extensive margin results, we find that Economic Connectedness is positively related to both total dividend income and total interest income. Because Economic Connectedness is positively associated with the extensive and intensive margins of both saving and investing, we conclude that having wealthy friends increases saving and investing behavior jointly, rather than increasing diversification by reallocating savings funds to riskier assets.

A major policy issue is how to help low-SES households invest and save for the future. If our results were exlusively driven by high-SES individuals, we would not be able to offer policy suggestions. Therefore, we provide a subsample analysis about the effects of economic connnectedness separately for low-SES and high-SES households. In our analysis of low-SES households, we provide evidence that while each measure of social capital is positively associated with both stock market participation and savings, Economic Connectedness is especially important. Among the high-SES group, we also find that Economic Connectedness is the most important aspect of social capital. Interestingly, Economic Connectedness is especially important along the intensive margin for the high-SES group and along the extensive margin for the low-SES group. This difference is consistent with a step-by-step savings process in which individuals save first and invest second. Our evidence suggests that having wealthy friends not only helps households to begin saving, but also influences financial decisions even after getting over the initial hurdle of deciding to save.

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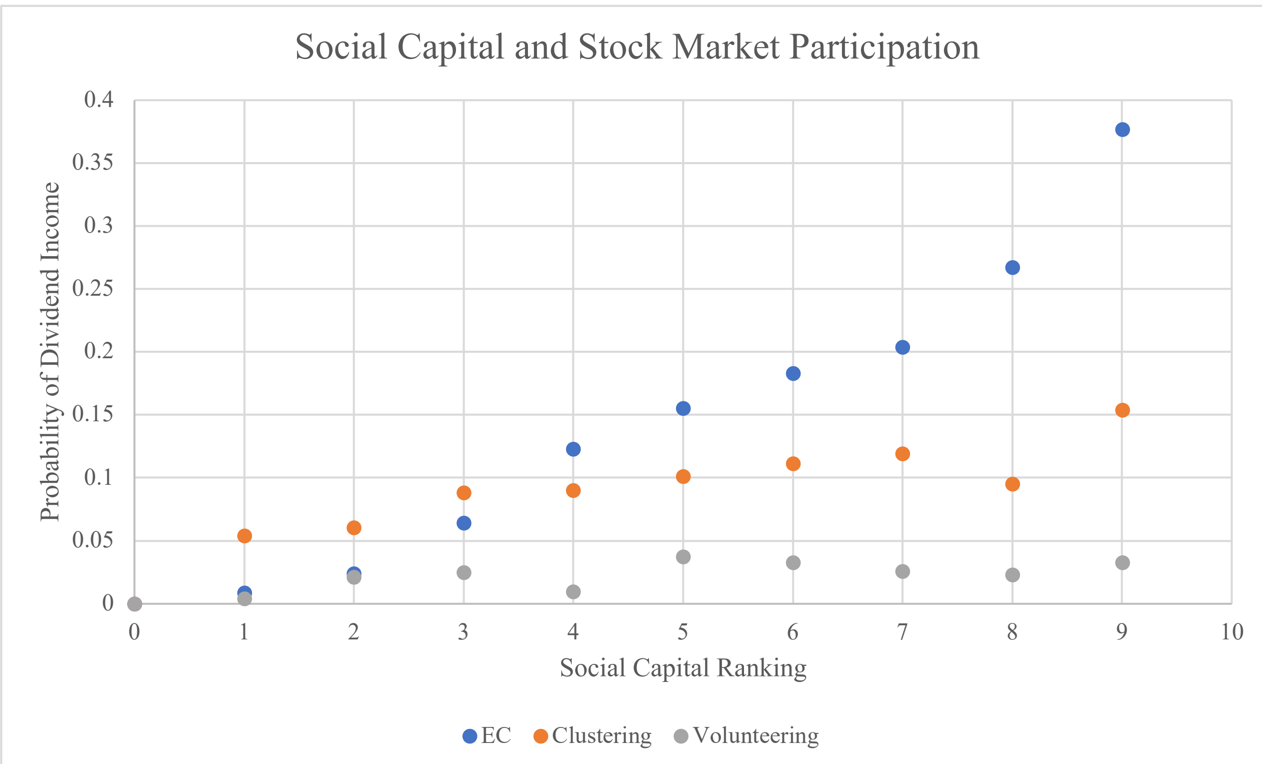

Figure 1: **Social Capital and Stock Market Participation.** This figure reports coefficients from a regression of county-level stock market participation on three facets of social capital: Economic Connectedness (EC), Network Clustering, and Volunteering Rate. We capture stock market participation with dividend income. Each measure of social capital is divided into twenty groups. We include a total of 27 indicator variables, 9 for each of the three aspects of social capital. We also include controls for population, population density, median income, race, age, gender, education, financial literacy, and AGI group.

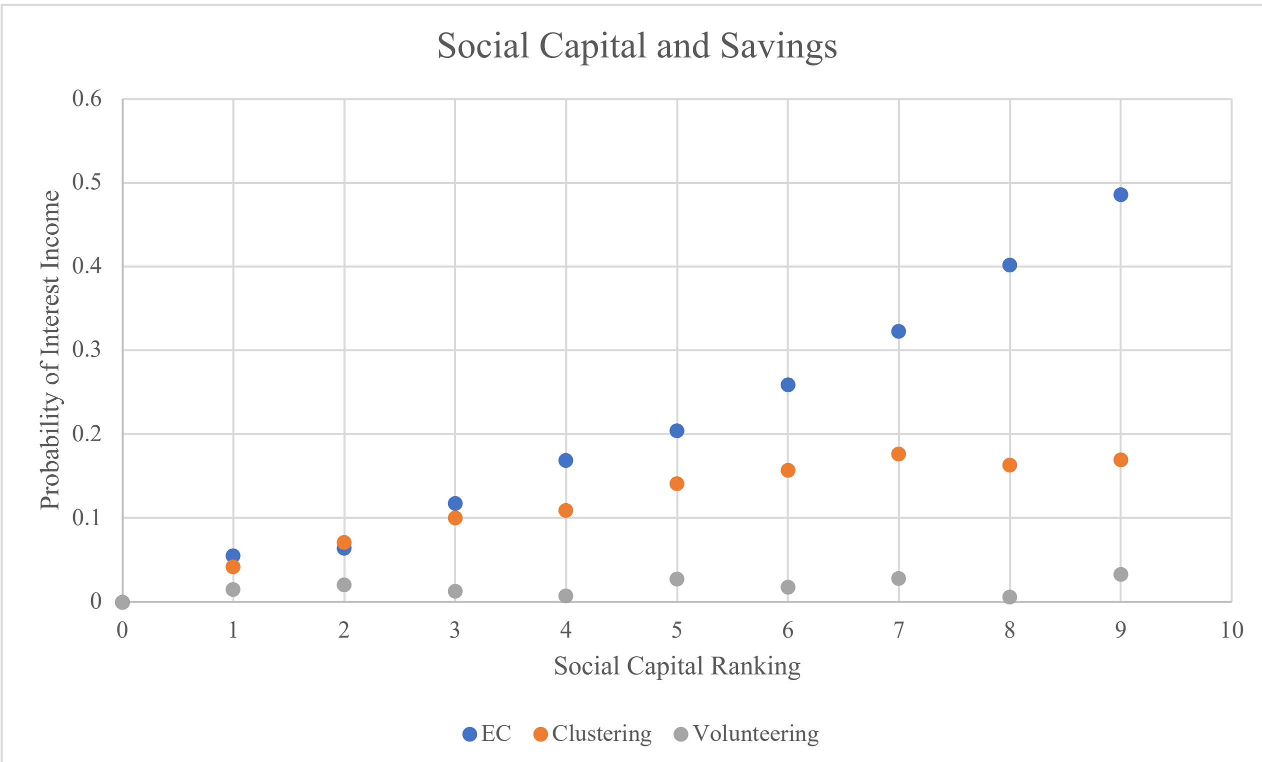

Figure 2: **Social Capital and Savings.** This figure reports coefficients from a regression of county-level savings behavior on three facets of social capital: Economic Connectedness (EC), Network Clustering, and Volunteering Rate. We capture savings behavior with interest income. Each measure of social capital is divided into twenty groups. We include a total of 27 indicator variables, 9 for each of the three aspects of social capital. We also include controls for population, population density, median income, race, age, gender, education, financial literacy, and AGI group.

Table 1: **Summary Statistics.** This table reports county-level summary statistics. *P(Div)* is the probability that a tax return has dividend income. *P(Int)* is the probability that a tax returns has interest income. *Economic Connectedness* is the first aspect of social capital that we study. It measures the fraction of an individual's friend group with high SES. *Network Clustering* is the second aspect of social capital that we study. It captures the fraction of an individual's friend group that are friends with each other. *Volunteering Rate* is the third aspect of social capital that we study. It captures the fraction of individuals in a county who are members of 'volunteering' or 'activism' groups. The variables *Population Density, Population, Median Income, Percent Male, Percent Black, Percent Asian, Percent Islanders, Percent Hispanic, and Median Age* are county-level control variables. *Financial literacy* is a dummy variable that equals one if a state had financial literacy high school graduation requirement in 2018. *High School* measures the fraction of a county that has graduated high school.

	Obs	Mean	Std	p25	p50	p75
P(Div)	3088	0.162	0.068	0.111	0.158	0.205
P(Int)	3088	0.303	0.088	0.239	0.294	0.363
Economic Connectedness	3017	0.940	0.199	0.803	0.936	1.079
Network Clustering	3088	0.116	0.020	0.103	0.115	0.127
Volunteering Rate	3088	0.078	0.035	0.055	0.073	0.094
Ln(Population Density)	3087	3.820	1.708	2.868	3.831	4.768
Ln(Population)	3088	10.315	1.444	9.343	10.179	11.143
Ln(Median Income)	3087	10.819	0.249	10.658	10.818	10.961
Percent Male	3088	0.501	0.023	0.489	0.496	0.506
Percent Black	3088	0.090	0.144	0.007	0.023	0.102
Percent Asian	3088	0.014	0.028	0.003	0.006	0.013
Percent Islanders	3088	0.001	0.004	0.000	0.000	0.001
Percent Hispanic	3088	0.092	0.137	0.021	0.041	0.095
Median Age	3088	41.243	5.337	38.000	41.200	44.400
Financial Literacy	3088	0.577	0.494	0.000	1.000	1.000
Percent HS or Higher	3088	0.866	0.062	0.829	0.879	0.912

Table 2: **Correlation Matrix.** This table reports correlations for each of our variables of interest. *P(Div)* is the probability that a tax return has dividend income. *P(Int)* is the probability that a tax returns has interest income. *Economic Connectedness* is the first aspect of social capital that we study. It measures the fraction of an individual's friend group with high SES. *Network Clustering* is the second aspect of social capital that we study. It captures the fraction of an individual's friend group that are friends with each other. *Volunteering Rate* is the third aspect of social capital that we study. It captures the fraction of individuals in a county who are members of 'volunteering' or 'activism' groups. *Population Density, Population, Median Income, Percent Male, and Median Age* are county-level control variables. *Financial literacy* is a dummy variable that equals one if a state had financial literacy high school graduation requirement in 2018. *High School* measures the fraction of a county that has graduated high school.

	P(Div)	P(Int)	EC	Clust	Vol	Den	Pop	Inc	Male	Age	FinLit	HS
P(Div)	1.00											
P(Int)	0.75	1.00										
Economic Connectedness	0.75	0.73	1.00									
Network Clustering	-0.22	-0.14	-0.37	1.00								
Volunteering Rate	0.30	0.36	0.35	-0.04	1.00							
Ln(Population Density)	0.02	-0.16	0.03	-0.50	-0.22	1.00						
Ln(Population)	0.07	-0.15	0.06	-0.58	-0.19	0.88	1.00					
Ln(Median Income)	0.63	0.48	0.78	-0.55	0.15	0.32	0.38	1.00				
Percent Male	-0.03	-0.01	0.04	0.10	0.08	-0.32	-0.26	-0.00	1.00			
Median Age	0.27	0.42	0.08	0.19	0.22	-0.30	-0.37	-0.11	-0.04	1.00		
Financial Literacy	-0.07	-0.00	-0.10	-0.06	-0.03	-0.09	-0.12	-0.08	0.01	-0.04	1.00	
Percent HS or Higher	0.68	0.65	0.73	-0.35	0.37	0.09	0.14	0.60	-0.12	0.19	-0.10	1.00

Table 3: **Probability of Stock Market Participation.** This table reports results for regressions of county-level stock market participation on three facets of social capital: Economic Connectedness (EC), Network Clustering, and Volunteering Rate. We capture county-level stock market participation using the probability of dividend income. Columns (1) and (2) report results for Economic Connectedness. Columns (3) and (4) report results for Network Clustering. Columns (5) and (6) report results for Volunteering Rate. In columns (7) and (8), we include all three aspects of social capital in the regressions. In columns (2), (4), (6), and (8) we include controls for population, population density, median income, race, age, gender, education, and financial literacy.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	P(Div)	P(Div)	P(Div)	P(Div)	P(Div)	P(Div)	P(Div)	P(Div)
Economic Connectedness	0.250***	0.143***					0.253***	0.147***
	(60.21)	(14.56)					(45.86)	(15.46)
Network Clustering			-0.746***	0.483***			0.186 *	0.614***
			(-8.25)	(4.34)			(2.46)	(5.31)
Volunteering Rate					0.576***	0.032	0.073*	0.024
					(14.93)	(1.08)	(2.57)	(0.84)
Controls		YES		YES		YES		YES
Observations	3017	3015	3088	3086	3088	3086	3017	3015
Adj. R^2	0.563	0.676	0.050	0.626	0.087	0.617	0.567	0.690

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4: **Probability of Interest Income.** This table reports results for regressions of county-level interest income on three facets of social capital: Economic Connectedness (EC), Network Clustering, and Volunteering Rate. Columns (1) and (2) report results for Economic Connectedness. Columns (3) and (4) report results for Network Clustering. Columns (5) and (6) report results for Volunteering Rate. In columns (7) and (8), we include all three aspects of social capital in the regressions. In columns (2), (4), (6), and (8) we include controls for population, population density, median income, race, age, gender, education, and financial literacy.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	P(Int)	P(Int)	P(Int)	P(Int)	P(Int)	P(Int)	P(Int)	P(Int)
Economic Connectedness	0.322***	0.247***					0.331***	0.251***
	(61.74)	(19.10)					(50.77)	(19.69)
Network Clustering			-0.614***	0.411***			0.661***	0.561***
			(-6.99)	(3.57)			(6.88)	(5.28)
Volunteering Rate					0.919***	0.045	0.265***	0.016
					(17.67)	(1.18)	(6.81)	(0.45)
Controls		YES		YES		YES		YES
Observations	3017	3015	3088	3086	3088	3086	3017	3015
Adj. R^2	0.536	0.690	0.020	0.630	0.131	0.627	0.568	0.697

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 5: **Childhood Economic Connectedness.** This table reports results for regressions of the probability of dividend income (columns (1) - (3)) or the probability of interest income (columns (4) - (6)) on childhood EC. We include childhood EC instead of our standard measure of EC to address concerns related to reverse causality. In columns (1) and (2) and columns (4) and (5), we only include the focal aspect of social capital in our regressions, namely Childhood EC. In columns (3) and (6), we include all three aspects of social capital in our regressions. In columns (2), (3), (5), and (6) we include controls for population, population density, median income, race, age, gender, education, and financial literacy.

	(1) P(Div)	(2) P(Div)	(3) P(Div)	(4) P(Int)	(5) P(Int)	(6) P(Int)
Child EC	0.161^{***}	0.053^{***}	0.057^{***}	0.158^{***}	0.091^{***}	0.094^{***}
	(36.43)	(6.78)	(7.77)	(28.81)	(9.89)	(10.37)
Network Clustering			0.770^{***}			0.659^{***}
			(5.44)			(4.73)
Volunteering Rate			0.040			-0.006
			(1.28)			(-0.15)
Controls		YES	YES		YES	YES
Observations	2728	2727	2727	2728	2727	2727
Adj. R^2	0.347	0.660	0.681	0.201	0.643	0.652

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 6: **Nonlocal Income Shocks.** This table reports results for regressions of the change in stock market participation (columns (1) and (2)) or the change in propensity to save (columns (3) and (4)) on the change in income of nonlocal friends. The dependent variables capture changes from 2017 to 2018. The independent variable measures the change in the income of nonlocal friends from 2016 to 2017. Friends are classified as nonlocal if they live more than 250 miles from the focal county. In columns (2) and (4), we include controls for population, median income, race, age, gender, education, and financial literacy.

	(1)	(2)	(3)	(4)
	Δ P(Div)	Δ P(Div)	Δ P(Int)	Δ P(Int)
Δ Nonlocal Income	0.075***	0.058*	0.192***	0.081*
	(2.88)	(1.74)	(5.89)	(1.82)
Controls		YES		YES
Observations	3141	3140	3141	3140
Adj. R^2	0.002	0.002	0.014	0.100

t statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 7: **Totals.** This tables reports results for regressions of the total county-level dividend income (columns (1) - (3)) or the total county-level interest income (columns (4) - (6)) on aspects of social capital. In columns (1) and (2) and columns (4) and (5), we only include the focal aspect of social capital in our regressions, namely Economic Connectedness. In columns (3) and (6), we include all three aspects of social capital in our regressions. In columns (2), (3), (5), and (6) we include controls for population, population density, median income, race, age, gender, education, and financial literacy.

	(1)	(2)	(3)	(4)	(5)	(6)
	ln(TotD)	ln(TotD)	ln(TotD)	ln(TotI)	ln(TotI)	ln(TotI)
Economic Connectedness	2.790***	1.139***	1.147***	2.467***	1.572***	1.567***
	(16.43)	(8.82)	(8.97)	(16.78)	(13.07)	(13.11)
Network Clustering			2.369**			-1.632
			(2.72)			(-1.44)
Volunteering Rate			0.763*			-0.555
			(2.28)			(-1.77)
Controls		YES	YES		YES	YES
Observations	3017	3015	3015	3017	3015	3015
Adj. R^2	0.086	0.924	0.924	0.087	0.934	0.934

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 8: **Probability of Stock Market Participation: Subsamples.** This table reports results for regressions of various county-level measures of financial behavior on all three aspects of social capital. We split our regressions into two subsamples: below-median SES and above-median SES. Columns (1), (3), (5), and (7) are regressions on the low-SES subsample, and columns (2), (4), (6), and (8) are regressions on the high-SES subsample. The dependent variables are probability of dividend income (columns (1) and (2)), probability of interest income (columns (3) and (4)), total county-level dividend income (columns (5) and (6)), and total county-level interest income (columns (7) and (8)). Columns (1) - (3) report results for the low-SES subsample, and columns (4) - (6) report results for the high-SES subsample. Columns (1), (2), (4), and (5) report results for regressions which only include our focal aspect of social capital, namely Economic Connectedness. In all specifications, we include all three aspects of social capital in our regressions, and we include controls for population, population density, median income, race, age, gender, education, and financial literacy.

	P(Div)		P(Int)		ln(TotD)		ln(TotI)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Low	High	Low	High	Low	High	Low	High
Economic Connectedness	0.060***	0.335***	0.161***	0.366***	0.173	2.405***	0.747***	2.613***
	(8.12)	(24.38)	(16.01)	(20.61)	(1.74)	(18.73)	(7.24)	(22.40)
Network Clustering	0.495***	0.891***	0.426***	0.852***	3.001***	2.784**	-1.081	-1.194
	(4.06)	(7.29)	(4.92)	(5.92)	(3.54)	(3.12)	(-0.85)	(-1.11)
Volunteering Rate	0.070**	-0.022	0.048	-0.048	1.227***	0.392	-0.302	-0.870*
	(2.67)	(-0.53)	(1.56)	(-0.93)	(4.47)	(1.05)	(-1.02)	(-2.53)
Observations	3015	3015	3015	3015	3012	3014	3015	3015
Adjusted R^2	0.588	0.579	0.690	0.424	0.937	0.922	0.936	0.931

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A1: **Summary Statistics: Subsamples.** This table reports county-level summary statistics for two subsamples: below-median SES and above-median SES. We consider only variables that differ between the Low-SES and High-SES subsamples. *P(Div)* is the probability that a tax return has dividend income. *P(Int)* is the probability that a tax returns has interest income. *EC* measures the fraction of an individual's friend group with high SES.

	Low-SES					
	Obs	Mean	Std	p25	p50	p75
P(Div)	3088	0.093	0.049	0.059	0.089	0.120
P(Int)	3088	0.195	0.072	0.143	0.186	0.237
EC	3017	0.814	0.177	0.695	0.807	0.936
	High-SES					
	Obs	Mean	Std	p25	p50	p75
P(Div)	3088	0.321	0.093	0.256	0.320	0.383
P(Int)	3088	0.543	0.099	0.477	0.543	0.612
EC	3017	1.253	0.177	1.135	1.258	1.384

Table A2: **Correlation Matrix: Low SES.** This table reports correlations among the below-median SES subsample for the following variables. *P(Div)* is the probability that a tax return has dividend income. *P(Int)* is the probability that a tax returns has interest income. *Economic Connectedness* is the first aspect of social capital that we study. It measures the fraction of an individual's friend group with high SES. *Network Clustering* is the second aspect of social capital that we study. It captures the fraction of an individual's friend group that are friends with each other. *Volunteering Rate* is the third aspect of social capital that we study. It captures the fraction of individuals in a county who are members of 'volunteering' or 'activism' groups. The variables *Population Density, Population, Median Income, Percent Male, and Median Age* are county-level control variables. *Financial literacy* is a dummy variable that equals one if a state had financial literacy high school graduation requirement in 2018. *High School* measures the fraction of a county that has graduated high school.

	P(Div)	P(Int)	EC	Clust	Vol	Den	Pop	Inc	Male	Age	FinLit	HS
P(Div)	1.00											
P(Int)	0.65	1.00										
Economic Connectedness	0.64	0.64	1.00									
Network Clustering	-0.05	0.03	-0.27	1.00								
Volunteering Rate	0.37	0.41	0.39	-0.04	1.00							
Ln(Population Density)	-0.20	-0.35	-0.10	-0.50	-0.22	1.00						
Ln(Population)	-0.14	-0.36	-0.08	-0.58	-0.19	0.88	1.00					
Ln(Median Income)	0.42	0.25	0.66	-0.55	0.15	0.32	0.38	1.00				
Percent Male	0.05	0.05	0.08	0.10	0.08	-0.32	-0.26	-0.00	1.00			
Median Age	0.35	0.54	0.13	0.19	0.22	-0.30	-0.37	-0.11	-0.04	1.00		
Financial Literacy	-0.11	-0.01	-0.11	-0.06	-0.03	-0.09	-0.12	-0.08	0.01	-0.04	1.00	
Percent HS or Higher	0.59	0.55	0.70	-0.35	0.37	0.09	0.14	0.60	-0.12	0.19	-0.10	1.00

Table A3: **Correlation Matrix: High SES.** This table reports correlations among the above-median SES subsample for the following variables. *P(Div)* is the probability that a tax return has dividend income. *P(Int)* is the probability that a tax returns has interest income. *Economic Connectedness* is the first aspect of social capital that we study. It measures the fraction of an individual's friend group with high SES. *Network Clustering* is the second aspect of social capital that we study. It captures the fraction of an individual's friend group that are friends with each other. *Volunteering Rate* is the third aspect of social capital that we study. It captures the fraction of individuals in a county who are members of 'volunteering' or 'activism' groups. The variables *Population Density, Population, Median Income, Percent Male, and Median Age* are county-level control variables. *Financial literacy* is a dummy variable that equals one if a state had financial literacy high school graduation requirement in 2018. *High School* measures the fraction of a county that has graduated high school.

	P(Div)	P(Int)	EC	Clust	Vol	Den	Pop	Inc	Male	Age	FinLit	HS
P(Div)	1.00											
P(Int)	0.66	1.00										
Economic Connectedness	0.65	0.50	1.00									
Network Clustering	-0.22	-0.07	-0.47	1.00								
Volunteering Rate	0.16	0.17	0.28	-0.04	1.00							
Ln(Population Density)	0.18	-0.03	0.17	-0.50	-0.22	1.00						
Ln(Population)	0.20	-0.02	0.22	-0.58	-0.19	0.88	1.00					
Ln(Median Income)	0.48	0.25	0.77	-0.55	0.15	0.32	0.38	1.00				
Percent Male	-0.13	-0.09	-0.03	0.10	0.08	-0.32	-0.26	-0.00	1.00			
Median Age	0.20	0.30	-0.03	0.19	0.22	-0.30	-0.37	-0.11	-0.04	1.00		
Financial Literacy	-0.00	0.08	-0.05	-0.06	-0.03	-0.09	-0.12	-0.08	0.01	-0.04	1.00	
Percent HS or Higher	0.57	0.44	0.71	-0.35	0.37	0.09	0.14	0.60	-0.12	0.19	-0.10	1.00

Table A4: **Probability of Stock Market Participation: Capital Gain Income.** This table reports results for regressions of county-level stock market participation on three facets of social capital: Economic Connectedness (EC), Network Clustering, and Volunteering Rate. We capture county-level stock market participation using the probability of capital gain income (or losses). Columns (1) and (2) report results for Economic Connectedness. Columns (3) and (4) report results for Network Clustering. Columns (5) and (6) report results for Volunteering Rate. In columns (7) and (8), we include all three aspects of social capital in the regressions. In columns (2), (4), (6), and (8) we include controls for population, population density, median income, race, age, gender, education, and financial literacy.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	P(CG)	P(CG)	P(CG)	P(CG)	P(CG)	P(CG)	P(CG)	P(CG)
Economic Connectedness	0.237***	0.180***					0.235***	0.181***
	(67.01)	(19.70)					(54.94)	(19.77)
Network Clustering			-0.778***	-0.146*			0.099*	-0.008
			(-14.80)	(-2.14)			(2.03)	(-0.13)
Volunteering Rate					0.577***	0.003	0.092***	-0.019
					(15.83)	(0.09)	(3.61)	(-0.80)
Controls		YES		YES		YES		YES
Observations	3017	3015	3088	3086	3088	3086	3017	3015
Adj. R^2	0.600	0.723	0.063	0.637	0.102	0.636	0.603	0.723

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A5: **Childhood EC: Capital Gain.** This table reports results for regressions of the probability of capital gain income on childhood EC. We include childhood EC instead of our standard measure of EC to address concerns related to reverse causality. In columns (1) and (2), we only include the focal aspect of social capital in our regressions, namely Childhood EC. In column (3), we include all three aspects of social capital in our regressions. In columns (2) and (3) we include controls for population, population density, median income, race, age, gender, education, and financial literacy.

	(1) P(CG)	(2) P(CG)	(3) P(CG)
Child EC	0.134***	0.046***	0.046***
	(34.57)	(6.79)	(6.83)
Network Clustering			0.055
			(0.78)
Volunteering Rate			-0.025
			(-1.02)
Controls		YES	YES
Observations	2728	2727	2727
Adj. R^2	0.302	0.675	0.675

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A6: **Total Capital Gain Income.** This table reports results for regressions of the total county-level capital gain income on aspects of social capital. In columns (1) and (2), we only include the focal aspect of social capital in our regressions, namely Economic Connectedness. In column (3), we include all three aspects of social capital in our regressions. In columns (2) and (3) we include controls for population, population density, median income, race, age, gender, education, and financial literacy.

	(1)	(2)	(3)
	ln(TotCG)	ln(TotCG)	ln(TotCG)
Economic Connectedness	3.059***	1.634***	1.606***
	(19.21)	(11.08)	(10.91)
Network Clustering			-4.240***
			(-4.04)
Volunteering Rate			0.052
			(0.14)
Controls		YES	YES
Observations	3016	3014	3014
Adj. R^2	0.111	0.908	0.908

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A7: **Probability of Capital Gain Income: Subsamples.** This table reports results for regressions two aspects of capital gains income on Economic Connectedness. In columns (1) and (2), the dependent variable is probability of capital gains income. In columns (3) and (4), the dependent variable is total county-level capital gains income. We divide our sample into two subsamples: below-median SES (columns (1) and (3)) and above-median SES (columns (2) and (4). In all specifications, we include controls for population, population density, median income, race, age, gender, education, and financial literacy.

	P(CG)		ln(TotCG)	
	(1)	(2)	(3)	(4)
	Low	High	Low	High
Economic Connectedness	0.084***	0.379***	0.839***	2.764***
	(15.31)	(27.59)	(6.76)	(20.90)
Network Clustering	-0.004	0.032	-2.593*	-3.485***
	(-0.09)	(0.36)	(-2.00)	(-3.51)
Volunteering Rate	0.005	-0.045	0.217	-0.142
	(0.31)	(-1.16)	(0.64)	(-0.39)
Observations	3015	3015	3009	3013
Adjusted R^2	0.682	0.599	0.878	0.918

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$