Social Interaction Intensity and Investor Behavior

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Abstract

We document a causal effect of social interactions on investor behavior using the number of local soccer games as a measure of social interaction intensity. Social transmission is identifiable in buy but not sell trades. Social Interaction Intensity (SII) increases the sensitivity of buying to past buys, particularly in riskier stocks. This sensitivity is an increasing and convex function of past returns, with higher SII further amplifying the effect. Social interactions cause an extremity shift wherein existing shareholders increase their positions, especially within demographically homogeneous communities. Higher social interaction intensity increases the sensitivity of individual investors' trading volume and portfolio riskiness to past trades. At the market level, SII increases the sensitivity of stock trading volume and retail ownership percentage to past buys.

Keywords: Social Finance, Behavioral Finance, Retail Investor, Portfolio Choice, Peer Effects

JEL classification: D14, G11, G12, G40, G41, G50, G51

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1 Introduction

The growing field of social finance studies how social transmission of ideas affects financial behavior and outcomes. For example, there is evidence that social interactions affect stock market participation and real estate investment (see the reviews of Kuchler and Stroebel 2021 and Hwang 2023). In this paper, we investigate the effects of social interactions on a rich set of investor behaviors using a novel setting that addresses causal identification issues that are present in much of the past literature. Specifically, we use soccer games (or related variables) as a proxy for shifts in the intensity of social interaction to identify social transmission of investing behavior in Israel.

Soccer is the most popular spectator sport in Israel, a country with a population of 9.5 million and an area of 8,000 square miles (both comparable to New Jersey). Despite its small size, Israel has 40 professional soccer stadiums spread across the country, with 22 adult men's leagues managed by the Israel Football Association. The attendance in just one of the four national leagues averaged 56,000 in-person viewers per weekend during the 2022-2023 season. This league's season spanned 36 weekends, over which 2 million tickets were sold. The dominance of soccer as the national sport is also reflected in sports gambling revenue. More than 70% of revenue in sports betting in Israel is from soccer, with the remaining split across all other sports.[1]

Soccer games are social events in which thousands of spectators assemble in a stadium for hours, typically in groups, to observe and chat. Extensive evidence indicates that people become sports fans in large part to satisfy their need for social connection, which Baumeister (2012) describes as "one of the most powerful, universal, and influential human drives."[2] There is strong evidence that attendance at sporting events indeed causes social transmission

[1]For comparison, sports betting in the US is more evenly distributed, with 32.4% of revenue coming from basketball gambling, 26.3% from football, 16% from baseball, and 25.3% from all other sports (Miller 2024).

[2]On the social motivations of sports fans, see Melnick 1993; Wann 2006; and the literature review in Wann and James 2018.

of an important attribute across individuals—viral infection.[3] This suggests that attendance may promote other forms of social transmission as well.

Based on this evidence and the elemental fact that when people meet and spend time together in groups they have wide-ranging conversations, there is every reason to expect that social contact at soccer games promotes transmission of ideas, experiences, and plans. We therefore hypothesize that soccer matches will spread information about investment opportunities and performance. Furthermore, we hypothesize that such effects will increase with attendance at, frequency of, and duration of soccer matches.

In analogy to the study of the spread of disease, several papers have used epidemiological models to study the spread of investment ideas or behavior across investors (Shiller and Pound 1989; Shive 2010; Shiller 2017; Hirshleifer 2020; Huang et al. 2021a). In such models, infections spread more rapidly when the meeting rate between individuals is higher. To test for such effects, we use the number of soccer games played by local soccer teams in each municipality as our primary proxy for social interaction intensity.

For several reasons, soccer matches provide an especially useful setting for studying the effects of social interactions on investment behavior. First, the occurrence of games gives a proxy for time variation in the intensity of social interaction. This means of identification differs from most past studies, which often instead focus on time invariant network linkages and intensity of linkages.

Second, the timing of games is determined in advance at the beginning of the soccer season. This ensures that game-induced shifts in social interaction intensity are not related to recent shifts in investor behavior or stock performance. In addition, the number or outcome of soccer games has little influence on the fundamentals of local publicly traded

[3]Spectator attendance at sporting events has been widely documented to increase the transmission of airborne viruses. See Leeka et al. (2010), Stoecker et al. (2016), Olczak et al. (2020), Carlin et al. (2021), Fischer (2022), Ahammer et al. (2023), Cardazzi et al. (2023).

firms.[4] If the occurrence of soccer games increases investors' level of social interaction and is otherwise unrelated to variations in the stock market or investor behavior, then any observed correlation between investment behavior and the number of soccer games can be attributed solely to the effect of social interactions. This context allows us to test for the effect of social interaction on investment behavior as if investors were randomly assigned different levels of SII. Importantly, our setting allows us to detect heterogeneous effects of SII on investment behavior. As discussed in Section 3.2, the statistical independence of the SII measure ensures the consistent estimation of these effects, even if the variable capturing heterogeneity is subject to omitted variable bias.

Third, the large variations in the number of games, both over time and across municipalities, provide the statistical power needed to explore the effects of social interaction on a richer set of outcome variables than have been considered in past studies. Most such studies focus on a single outcome variable, such as stock market participation. In contrast, we test for contagion in the decision to buy a stock, to buy a given stock for the first time, to participate in the stock market for the first time, to buy additional shares of a stock already owned, and in the holding period of a stock. Furthermore, we test for social interaction effects on portfolio level variables such as volatility and trading volume, and stock level variables such as return, volatility, and skewness. We are also able to test for predicted modulating effects of various community characteristics.

We use stock trading data from a large bank in Israel covering 131,003 accounts from 2005 to 2014. In our basic tests, we focus on the choice to buy a stock as our outcome variable. We hypothesize that investors who recently bought a stock are more likely to be

[4] A soccer game may have transient effects on the use of public transport, restaurant and hotel demand, and demand for other local amenities. However, such effects are likely to be anticipated by the markets and have a trivial effect relative to the fundamental value of even a local publicly traded firm. Edmans et al. (2007) find that aggregate country stock returns are lower when a country's team is eliminated from the Soccer World Cup. However, their study uses international games and shows that the effect only lasts for a single day. Our analysis, presented in Table A1, shows no correlation between various measures of soccer game counts or outcomes and key performance metrics of local firms.

thinking about it and to discuss it with their peers.[5] We therefore test whether investors are more likely to purchase a given stock when exposed to a higher number of investors who have recently bought that stock. Consistent with epidemiological models, we capture this exposure as the interaction of two variables. The first is the number of local investors who bought the stock in the preceding month. The second variable is the count of soccer games played by local teams, which is our main proxy for what we call *social interaction intensity* (SII).

As a descriptive matter, we find that investors are more likely to buy a stock bought by many investors in their municipality during the previous month. This could be because of social transmission, but could also be because an unobserved factor is promoting stock buying in both months.

To test whether social interactions causally influence investor behavior, we estimate how the sensitivity of new purchases to old purchases varies with the number of soccer games played by local teams. We find that this sensitivity is increasing with the number of local team soccer games. This evidence shows that stock buying is contagious, and that greater SII promotes the transmission of investment ideas among investors.

In contrast, SII does not affect the sensitivity of investors' sells to past sells by local peers. Intuitively, buys are likely to reflect investing ideas, which may be socially transmitted, whereas sell transactions may reflect idiosyncratic personal liquidity needs.[6] Furthermore, most retail investors do not sell short, limiting the ability of investors to use selling as a means of exploiting investing ideas.

We find that people are more likely to directly invest in stocks for the first time following months with high market returns, and that this sensitivity increases with SSI. So social interactions also help overcome frictions in initiating direct stock trading. Furthermore,

[5]See, for example, the evidence of Ben-David and Hirshleifer (2012) that the probability of buying or selling a stock is decreasing in the time since that stock was purchased.

[6]Studies of insider trading provide evidence that sells often reflect liquidity needs. Such studies have consistently found a much weaker ability of sell trades than buy trades to predict returns (e.g., Lakonishok and Lee 2015; Ali and Hirshleifer 2017.

greater SSI increases the sensitivity of investors making purchases of stocks they never owned before to the number of past buys of those stocks by their peers. This shows that social interactions expose investors to new investment ideas.

We confirm that these findings are robust to several alternative soccer-based measures of social interaction intensity.

We further test several implications of the model of social transmission of trading strategies of Han, Hirshleifer, and Walden (2022) (HHW). In the model, senders are more likely to share their investment choices if these yielded higher returns (self-enhancing transmission bias). Receivers do not fully adjust for this selection bias in the return reports that they receive, believe that past performance is indicative of future performance, and are more attentive to more extreme return reports. The model predicts that the probability of successful transmission of investment ideas is increasing and convex in past returns. The model further predicts that both the sensitivity of transmission to past returns and the convexity of this relationship increase with the intensity of social interaction, as proxied here by SII.

Consistent with these implications, we find here that investors are more likely to buy a stock that their peers previously bought if it had a higher return, and that this likelihood is convex in the stock's past returns. A higher SII further increases investors' sensitivity to the stock's past returns and the convexity of this relationship.

A third implication of the HHW model is that social transmission attracts investors to stocks with high volatility and skewness. Consistent with this implication, we find that the effect of SII on the sensitivity of current buys to past buys is stronger for riskier stocks—those with higher volatility and skewness. In the HHW model, attraction to such stocks derives from bias in the social transmission of investment ideas, even when investors do not have any preference for the volatility or skewness characteristics.[7]

[7] A complementary social explanation starts from the premise that investors have a preference for lottery-like stocks (Mitton and Vorkink 2007; Barberis and Huang 2008; Kumar 2009; Boyer et al. 2010). If (as a departure from existing models of skewness preference) people who buy lottery stocks talk about them, if hearing about a stock calls investor attention to it, and if this attention reminds investors of the stock's skewness, then social interactions can help transmit the behavior of buying lottery stocks.

We then investigate the population characteristics that influence social transmission. We find that social transmission effects are stronger in communities with high socioeconomic status (using several proxies), likely because wealthy individuals are more likely to engage in stock investing and have casual conversations about it.

Homophily describes the propensity of people to form social connections with others they consider similar to themselves (McPherson et al. 2001.) Owing to homophily and ingroup bias (the tendency to trust and think more highly of one's own group than of other groups), people are likely to have more extensive social interactions and to form stronger personal connections in demographically homogeneous communities. There is extensive evidence that people have greater trust for those who are similar to themselves in various dimensions.[8] We therefore hypothesize that greater demographic homogeneity will result in stronger social transmission of investment ideas. Consistent with this hypothesis, we find that social transmission of stock buying is stronger in municipalities with greater homogeneity in age, wealth, income, and religious affiliation.

Homophily in social networks reduces the diversity of opinions. When people associate with others with similar views, local views can be reinforced, resulting in polarization of opinions (Ertug et al. 2022, Cookson et al. 2023). If investors who already hold a stock are more likely to discuss the stock with other holders, then such an echo chamber effect could promote further buying. Consistent with this, we find that investors who already hold a stock tend to increase their position and hold it for a longer period following months with high SII. We call this the *extremity shift* in investing. It suggests that investors who own a stock perceive the information received from others as confirmatory, or else that the very act of discussing the stock that one holds reinforces investor faith in the stock. Indeed, for some individuals the purpose of a conversation may be to socially validate an existing decision.

Moreover, consistent with echo chambers as a source of extremity shift, we find that the

[8] Research documents higher levels of trust in societies that are more homogeneous in race, ethnicity, language, religion, income, and wealth (Alesina and La Ferrara 2000; Glaeser et al. 2000; Alesina and La Ferrara 2002; Leigh 2006; Putnam 2007).

sensitivity of such additional stock buying to SII is greater in homogeneous municipalities. This suggests that in the context of stock trading, more homogeneous communities tend to socially reinforce existing ideas and behaviors.

We also perform descriptive tests about other possible modulators of the strength of social transmission. We find evidence suggestive that more positive mood or high confidence may contribute to social transmission of buying, using as proxies the past local team win rate and past investor portfolio returns.

If social interactions affect stock trading, they will affect investors' overall portfolios. To test this, we need a measure that captures past buys of any stocks rather than focusing on purchases of a single one. We use the fraction of stocks in each municipality and month with a high number of buys in the previous month as a measure of past buys across all stocks. We find that measures of the risk of investors' portfolios increase with the lagged fraction of high-buy stocks, and that these sensitivities increase in SII. This evidence is consistent with the stock-level evidence described above that SII amplifies especially transmission of the purchase of riskier stocks. This raises the question of whether investors are adequately compensated for their riskier portfolios. Estimates of the effect of SII on investors' portfolio returns are insignificant, likely owing to low power to identify return predictability. Lastly, we test the effect of SII on stock- rather than individual-level outcomes. We replace our municipality level measure of SII with a national level measure defined as the sum of the number of soccer games in all municipalities, weighted by their respective population sizes. We also aggregate our measure of past stock buys across all municipalities.

We find that a stock's trading volume increases with the total number of past buys of that stock, and this sensitivity increases with SII. This result indicates that investors are more active in the stock market during high SII months. Similarly, a stock's fraction of retail ownership increases with the number of past buys, and this sensitivity increases with SII. This effect is driven by the common propensity of investors to buy, but not sell, stocks with high levels of past buys during high SII months.

We also test whether SII helps predict individual stock returns. We do not find such an effect, which is unsurprising, as we find that there is very limited statistical power in the sample to identify such return predictability effects.

We are not the first to test for the effects social interactions on the stock market. Pioneering studies have provided evidence of correlated behavior within social groups (Shiller and Pound 1989; Kelly and Gràda 2000; Duflo and Saez 2002; Duflo and Saez 2003; Kaustia and Knüpfer 2012), and links between investing behavior and sociability measures such as church attendance (Hong et al. 2004), the proportion of buyers and sellers of a stock (Shive 2010), and social capital (Ivković and Weisbenner 2007 or Cannon et al. 2024)). In several cases the authors provide plausible arguments for why these effects likely derive from social interactions.

However, causal effects of social interactions (peer effects) are challenging to identify sharply owing to non-random community assignments and potential confounding factors. The first key contribution of this paper is to identify a causal relationship between social interactions and investor behavior.

Only a few existing papers have sought to identify social interaction in stock trading using exogenous instruments. Brown et al. (2008) provide causal evidence that social interactions affect investors' decision to own stocks (they study direct stock ownership, i.e., not through a mutual fund). Their instrument is stock ownership in the birth states of an investor's nonnative neighbors—those born in different states. They find that this exposure to neighboring stockholders is a positive predictor of investors' decisions to invest in stocks.

Our paper provides a very different kind of evidence that social interactions promote direct stock market participation, based on time variations in the intensity of social interactions. It goes further by examining causal effects of social interaction on a rich set of individual trading and stock market outcomes.

Huang et al. (2021a) estimate communication rates among retail investors using stock-financed M&A. They find increased trading activity (the number or value of trades) in stocks that are in the acquirer's industry both by recipients of acquirer stock and their neighbors. The effect on neighbors is consistent with word-of-mouth communication. Their paper studies social transmission at the industry level using 316 equity financed M&A events. It focuses on a specific investor sub-population—those who actively traded in the year before and after the M&A event and had no holdings in the acquirer industry prior to the transaction. Our paper differs in studying the transmission of investment ideas about individual stocks across the entire population of investors and stocks. Also, our paper again differs in examining effects on a rich set of trading and stock market outcomes.

Hvide and Östberg (2015) find that when employees move to a new workplace, the correlation of their trades with their new coworkers increases over time while the correlation with their old coworkers decreases. However, the move to a new workplace is not random; it is plausibly associated with changes in the employee's preferences or socioeconomic status. Furthermore, even without social interactions, an observed correlation could be driven by exposure to common local information sources (Feng and Seasholes 2004; Engelberg and Parsons 2011) or by familiarity bias (Massa and Simonov 2006; Cao et al. 2011).

To sum up, our tests reveal a rich set of social transmission effects not found or explored in previous studies:

- We find that social interaction promotes the purchase of stocks that an investor has never owned before, consistent with contagion of new investment ideas.
- We provide the first evidence that social interactions induce an extremity shift in stockholding.
- We document that social interaction increases investor trading activity as measured by volume and number of stocks traded. This suggests that casual conversations in general are about the stock market often enough to attract attention to stocks rather than distracting from them.
- We provide the first empirical test of the prediction of the HHW model that the probability of successful transmission of the purchase of a stock is an increasing and

convex function of past returns, with higher social interaction intensity strengthening this relationship.[9]

- We document that social transmission is stronger for high-volatility and high-skewness stocks.
- We provide new tests of the role of socioeconomic factors in social transmission. Consistent with the evidence in Huang et al. 2021a and with research on group homogeneity and social trust and on homophily, we find stronger transmission between investors with similar demographic backgrounds. We go further to show the effect of high socioeconomic status, and that the extremity shift caused by social interactions is stronger in more homogeneous communities.

2 Data

We obtain investment data from a large bank in Israel, covering 131,003 accounts from January 2005 to July 2014. The data includes all stock trades aggregated at the monthly level.[10] The dataset includes annual updates on investors' salaries and the total value of holdings across all accounts within the bank. Additionally, it contains the residential addresses of these investors, as recorded in July 2014.

We collected data on men's professional soccer matches in Israel from 2005 to 2022 from the Israel Football Association's website. The data includes details about each soccer match, including the participating teams and their rankings, match score, and match location. We obtain stock market data on Israeli stocks from the Tel Aviv Stock Exchange website and data on the financial performance and headquarters locations of all publicly listed Israeli firms from Wharton Research Data Services. Lastly, we obtain municipality-level demographic

[9] Kaustia and Knüpfer 2012 document a correlation between past investor returns in a community and new participation in the stock market by other members of that community in the domain of positive but not negative returns.

[10] Our data covers only direct stock trades (i.e., excluding mutual fund trades) conducted through the bank providing the data. This data is comparable with previous studies, which have also used focused samples (Ivković and Weisbenner 2007; Shive 2010; Kaustia and Knüpfer 2012; Hvide and Östberg 2015; Huang et al. 2021a).

information from the Israel Central Bureau of Statistics website, including education, wealth, and religious diversity.

Table 1 provides key summary statistics of our sample. Investors trade an average of 0.66 unique stocks per month, and their stock portfolios exhibit an average monthly return of only 10 basis points. The average holding period for a stock in our sample is 14.5 months, with a median of 8 months. The average annual salary of the investors is 109K ILS (approximately 27K USD), surpassing the national average of 92K ILS in 2008. The average balance across all accounts these investors hold at the bank is 3.8 million ILS. Our sample spans 137 unique municipalities, averaging 1,148 investors per municipality. The average number of soccer games played by local soccer teams is 5.5 games per month.

3 Empirical Specification

We describe the basic specification in Subsection 3.1. We then discuss why this specification is well-identified in Subsection 3.2

3.1 The Basic Specification

Our basic empirical specification is:

$$\begin{aligned} Buy_{i,s,t} = {} & \beta_1 \text{Municipality Buy}_{m,s,t-1} + \beta_2 \text{Games Count}_{m,t} \\ & + \beta_3 (\text{Municipality Buy}_{m,s,t-1} \times \text{Games Count}_{m,t}) + \beta_4 \text{Controls} \\ & + \xi_i + \omega_s + \theta_t + \epsilon_{i,s,t}, \end{aligned} \tag{1}$$

where $Buy_{i,s,t}$ indicates if investor i purchased stock s during month t. *Municipality* $Buy_{m,s,t-1}$ is the log of one plus the number of investors in municipality m who purchased stock s in the preceding month $(t-1)$, which serves as a proxy for the number of potential senders of the social transmission. Investors who recently bought a stock are more likely to be thinking about it and discuss it with their peers. *Games* $Count_{m,t}$ is the log of one plus the number of soccer games played by local teams in municipality m during month t, serving as a proxy for the intensity of social interactions.[11] β_4 is the coefficient vector for the controls. We control for investor and stock level variables, including lagged values of stock return, volatility, beta, and lagged values of investor salary and portfolio return. Our regressions include varying combinations of investor, year-month, and stock fixed effects, with the most stringent specification including both investor-year-month and stock-year-month fixed effects.[12]

The marginal effect of *Municipality Buy* in our specification is given by $\beta_1 + \beta_3 \times$ *Games Count*. For any constant level of *Games Count*, this marginal effect captures the influence of general (non-soccer-related) social interactions on investors' decision to buy a stock. The marginal effect also captures the direct effect of factors influencing investors' demand for a stock during months t and $t-1$ (affecting the variables *Buy* and *Municipality Buy*). Although this effect is not the primary focus of our investigation, we expect it to be positive for any level of *Games Count*.

Our focus is on the effects of SII. In our empirical model, the probability of an investor buying a stock depends on the multiplicative interaction between the number of investors in their municipality who bought the stock in the preceding month and the intensity of social interactions with these investors.

Our first prediction is that holding constant the number of potential transmitters, a higher level of SII increases the likelihood of an investor buying a stock. In our model, this prediction implies that the marginal effect of *Games Count*, given by $\beta_2 + \beta_3 \times$ *Municipality Buy*, will be positive for any level of *Municipality Buy*. Our second prediction is that the effect of SII on social transmission is stronger for a larger number of potential transmitters, implying

[11] In Section 4.1.5, we explore alternative measures of SII that capture variations in local fan game attendance, including the percentage of high-stakes games (e.g., final series, derbies), the percentage of home games, and average distances from municipalities to game venues.

[12] Following the ongoing debate about the suitability of linear fixed effects models for binary response variables, we confirm the robustness of our findings using a municipality-month-stock panel. In this specification, we use *Municipality Buy* at time t as the dependent variable. This specification uses a continuous variable as the dependent variable instead of an indicator variable but does not allow for investor-level control variables.

that $\beta_3 > 0$.

The interaction term, $Municipality\ Buy \times Games\ Count$, is partly analogous to terms in epidemiological models, such as the well-known SIR model, wherein the growth in new infections is proportional to the product of the number of infected individuals and the number of uninfected individuals. This is because a new infection requires a meeting between members of these two groups. However, our investment context differs in that an investor who is already "infected" with past ownership or recent purchase of the stock can become further infected via social interaction with others, implying a further purchase of the stock. So the spread of buying is not limited to the previously "uninfected." For example, when two enthusiasts for a stock meet, they may decide to buy some more. Furthermore, when an enthusiast for a stock explains its virtues to an uninitiated friend, the investor's own attention is drawn back to the arguments for the stock, so the investor may buy some more. Our specification allows for such possibilities.

3.2 Identification

Our identification relies on two assumptions that allow us to detect the causal effect of social interactions as if municipalities were randomly assigned different levels of Social Interaction Intensity (SII).

The first is that our proxy for SII is relevant—that soccer matches involving local teams cause higher levels of social interaction among local investors. We justify this assumption in the Introduction. Based on this assumption, we construct several soccer-based proxies for the level of social interaction intensity. Our primary measure is the number of soccer matches played by local teams. Additional measures capture variations in local fan attendance, including the percentage of high-stakes games (e.g., finals, derbies), the percentage of home games, and average distances from municipalities to game venues.

Our second identification assumption is the exclusion restriction—that there is no direct relationship between the occurrence or outcomes of soccer games and stock performance or investor behavior. In other words, the only avenue of causality is via soccer games increasing the intensity of social interaction. According to this assumption, the increase in SII during months with a high number of soccer games is driven only by the occurrence of the games and not by shifts in investor preferences, information, or market events.

This assumption is justified by the fact that soccer games are scheduled in advance at the beginning of each season. In addition, our analysis presented in Table A1 shows no correlation between the number or outcomes of soccer games and key performance metrics of local firms, supporting our assumption that soccer games do not directly influence firm performance.

If the occurrence of soccer games indeed raises the level of SII and is unrelated to fluctuations in the stock market or investor behavior, then any observed correlation between investment behavior and the number of soccer games can be attributed solely to the effect of social interactions. This context allows us to analyze the effect of social interaction on investment behavior as if municipalities were randomly assigned different levels of SII. Next, we consider the ability of our empirical setting to detect heterogeneous effects of social interactions on investment behavior across different levels of *Municipality Buy*.

Many factors that can influence investor behavior are missing from our model and could bias the estimated parameters. Any variable that influences investor behavior is independent of *Games Count* according to our identification assumption. However, an omitted variable that is correlated with *Municipality Buy* can bias the estimated coefficient β_1, as well as β_2 and β_3 owing to the inclusion of the interaction variable between *Municipality Buy* and *Games Count* in the model.

Nevertheless, omitted variable bias is of limited concern for our estimated coefficients of interest, β_2 and β_3, for several reasons. First, our regressions include investor-month and stock-month fixed effects, which control for any omitted variable that is constant within these dimensions. By including these fixed effects, the set of potential omitted variables that could influence β_2 and β_3 is restricted to those that vary at the municipality-stock level. Second, an omitted variable with a linear relationship to *Municipality Buy* would only bias the estimation of β_1; it would not affect coefficients of interest β_2 or β_3 (See proof in Appendix B). This further narrows the set of relevant omitted variables to those with a nonlinear relationship to *Municipality Buy*. Third, Nizalova and Murtazashvili (2016) and Bun and Harrison (2019) analyze empirical models with interaction terms between an endogenous source of heterogeneity and a treatment variable. As applied to our setting, their find is that if *Municipality Buy* and the omitted variable are jointly independent of *Games Count*, then β_2 and β_3 remain consistent. Additionally, their simulation results indicate that the bias in these coefficients is negligible, even in small samples ($N = 100$). Given our large sample size, any bias in the estimated β_2 and β_3 is expected to be inconsequential.[13]

4 Results

In this section, we first perform our basic tests of whether social interactions affect investor behavior in Subsection 4.1. Next, in Subsection 4.2, we examine hypotheses about how different stock characteristics influence the strength of social transmission. In Subsection 4.3 we test how population characteristics affect social transmission. Finally, in Subsections 4.4 and 4.5, we test for the effects of social interactions on investment portfolios and on market-level outcomes such as trading volume for individual stocks.

4.1 Social Interactions and Investor Behavior

We first test the effect of SII on the transmission of stock buying or selling behavior. We then turn to the influence of social interactions on investors' decisions to initiate stock trading or to buy stocks they had not previously owned. Next, we analyze the effect of SII on the trading of a stock by the existing holders of that stock, to see whether social interactions promote greater moderation or greater extremity. Finally, we confirm the robustness of our

[13]Other empirical studies that use tests motivated by these statistical properties of interaction terms include Annan and Schlenker 2015, Fruehwirth et al. 2019, Huang et al. 2021b, and Bartram et al. 2022.

findings to the use of alternative SII measures.

4.1.1 Buy and Sell Trades

We now describe tests of how social interaction intensity affects the transmission of stock buying behavior. Table 2 summarizes how SII affects stock purchases both directly, and affects the sensitivity of investor stock purchases to recent purchases of the stock by their peers.

The marginal effect of Games Count (our social interaction intensity proxy) on an investor's propensity to buy a stock is 32% at the mean level of all variables and increases with the number of recent buyers of the stock. This is summarized at the bottom of the table. The effect is highly significant. Columns 2-4 indicate that the marginal effect of Games Count remain relatively stable when including control variables and different combinations of fixed effects. This evidence is consistent with the hypothesis that higher intensity of social interaction promotes discussion of stocks, and that such social transmission of investing ideas encourages investors to buy.

These results are illustrated in Figure 1. We estimate the residuals from a regression of *Buy* on investor-year-month and stock-year-month fixed effects, capturing the investors' propensity to purchase a stock net of these fixed effects. The figure presents a contour plot of these residuals as a function of *Games Count* and *Lagged Municipality Buy*. The plot confirms that, for a given number of past stock buyers, a higher level of SII corresponds to increased social transmission. Further, the SII effect is stronger when the number of past stock buyers is larger, as indicated by the steeper decrease of the contour lines at the top of the figure.

We repeat the analysis using a municipality-stock-month panel with contemporaneous Municipality Buy as the dependent variable. The results, which are presented in Table A2, are similar.

We next describe tests of how social interaction intensity affects the transmission of stock selling behavior. Table A3 summarizes how SII affects the sensitivity of investor stock sells to recent sales of the stock by their peers. We find that investors are more likely to sell a stock that was sold by many of their peers in the previous months. However, SII has no economically or statistically significant effect on this relationship.

A possible explanation for this lack of effect is that investors avoid short-selling stocks owing to high costs or personal discomfort. If so, hearing adverse comments about a stock is likely to fall upon infertile ground unless the listener happens to already own the stock. This would greatly restrict social transmission effects.

To evaluate this possibility, we test the effect of SII on the transmission of sell trades among investors using only stocks they already hold in their portfolios. Even in this subsample, we find no effect. This suggests that the lack of an effect is not due solely to short sale avoidance or constraints.

Another possibility is that investors do not discuss their sell trades with others. This may be because investors discussing their investment ideas, but are not inclined to discuss a sell trade that is motivated by liquidity needs. Selling stocks to finance consumption or educational expenditure is common, whereas the choice to buy an individual stock is typically based on a specific investment idea. Similarly, a receiver of an investment message who is planning on selling for liquidity reasons is unlikely to be influenced by the investing ideas of the sender.

4.1.2 Investors' First Trades in a Stock or in Any Stock

We next test the influence of social interactions on investors' decisions to initiate stock trading or to buy stocks they had not previously owned. In Table 3, Panel A, the dependent variable is an indicator for whether an investor purchased a stock they had not previously owned. The positive coefficient on the interaction variable suggests that as a consequence of social interactions, investors learn about new investment opportunities that they might not have considered before.

A limitation of this test is that we might wrongfully classify a stock purchase as an investment in a new stock in cases where the investor already owned the stock before the start of our sample. To mitigate this concern, we conduct a robustness test in which we only use the trades of new stocks in our sample, which took place at least three years after the investor's first observed trading activity. This test ensures that investors did not invest in these stocks for at least three years, though it is still possible that they purchased them before the start of our sample. The results are similar to the full sample results.

We further test how SII intensity affects an individual's decision to participate in the market for individual stocks for the first time. The results are in Panel B. Column 1 presents an investor-month panel test, using an indicator of first-time stock purchase as the dependent variable. Motivated by the model of HHW and the empirical tests of Kaustia and Knüpfer (2012), we use the lagged market return as a proxy for the number of potential advocates for investing in stocks. When the market return has been high, current investors will share information about their investment successes with others.

We find that individuals are more likely to initiate participation in the market for individual stocks after a higher stock market return. Furthermore, consistent with this being a social interaction effect, the sensitivity of initiation to the market return is increasing with SII.

Columns 2 and 3 extend this analysis to a municipality-month panel. In Column 2, we use the number of new traders as the dependent variable, and in Column 3, we examine the growth rate in the number of stock traders. The findings across these columns are consistent: greater SII increases the sensitivity of investors commencing stock trading to past market returns.

A caveat is that some investors were already trading stocks before our sample period. As a robustness test, we classify new traders as investors who started trading stocks during the second half of the sample period after 2009 and obtain similar results. This robustness test ensures that investors we classify as new traders did not trade stocks in the previous five years. However, it is still possible that they traded stocks with a different account or before the start of our sample period.

Importantly, these tests are about stock market entry via direct stock ownership, not participation in the stock market via mutual funds.[14] Our findings provide new causal evidence based on shifts in the intensity of social interaction that social transmission promotes direct investing in individual stocks.

4.1.3 Existing Shareholders' Behavior

There is evidence suggesting that recent purchasers of a stock are especially attentive to that stock. This suggests that such investors are likely to become propagators of social signals, advocating for the purchase of these stocks in subsequent social interactions with their peers. Our previous tests examined this possibility.

A further possibility is that social interactions affect the trading behavior of the recent purchasers, perhaps by reinforcing their preexisting optimism about the stocks that they hold. We describe our tests for this possibility in Table 4. In Panel A, we find that investors who bought a stock in the previous month are more likely to add to their position in high SII months. Panel B shows that these investors tend to hold their stocks for a longer period following high SII months. This evidence suggests that existing shareholders not only disseminate the social signal but are reinforced in their optimism about a stock by interactions with others. This could be because making the case for a stock to others reinforces optimism. Alternatively, it may be that peers are providing affirmation. In any case, the evidence suggests that existing shareholders become more optimistic about the prospects of stocks they hold in high SII months.

[14] Previous tests of stock market entry via direct stock ownership include Hong et al. (2004), Brown et al. (2008), and Kaustia and Knüpfer (2012).

4.1.4 Trading Volume

Trading individual stocks adds idiosyncratic risk relative to indexing, and is therefore a form of active investing. Motivated by the model of HHW, we test whether social interaction promotes greater trading activity.[15] Table 5 describes tests in which we regress different measures of trading activity on Games Count, our proxy for SII. The results indicate that the number of unique stocks traded and the trading volume increase with SII.

Another possible interpretation of this increase in trading activity is that trading is a recreational activity (Shiller, 1992). Spending time with friends may enhance the recreational value of discussing and then trading stocks.

4.1.5 Alternative Measures of Social Interaction Intensity

We test the robustness of our results using different measures of social interaction intensity, which capture variations in game attendance by local fans. The first measure is the percentage of important games (e.g., final series, derbies, matches determining league ranking) out of all games played by local teams in a given month.[16] The second measure is the percentage of home games out of all games played by local teams in a given month. The third measure is the monthly average distance from the municipality to the game venues. We use both the average distance for all games and away games only.

The results are presented in Table 6. Using any of the SII measures, the results consistently indicate that a higher level of SII increases the likelihood of successful social transmission of investment ideas.

[15] In HHW, social interactions induce churning wherein investors who meet others who follow different strategies stochastically switch between the "active" or "passive" strategy. There are several possible interpretations of "active," such as high volatility, high skewness, and trading in individual stocks versus not. In all such cases, if greater social interaction induces churning, it will increase trading in individual stocks. For evidence that social interaction generates churning in a different context (conditional upon public news announcements), see Hirshleifer et al. (2024).

[16] We define a game as important if (a) the game will determine if a team is ranked first, (b) the game will determine if a team is ranked last and will drop to a lower league, (c) the game is a derby (match between two local teams), or (d) the game is part of the finals series in one of the national soccer leagues in Israel.

4.2 Stock Characteristics

To evaluate theories of bias in social transmission of investing strategies, we examine what types of stock investments are more prone to be spread by social interactions. We extend our empirical specification in Equation 1 to include a triple interaction term combining Lagged Municipality Buy, Games Count, and a specific stock characteristic. The results are presented in Table 7.

In column 1, we test the importance of a stock's historical performance on the effectiveness of social transmission. The social transmission effect increases with the stock's recent performance, measured as the previous month's return. In other words, SII increases the sensitivity of stock buying to stock buying by peers more for stocks that have recently experienced high returns.

In column 2, we find that social transmission is stronger for high-volatility stocks, measured as the daily standard deviation of returns over the previous month. In other words, SII increases the sensitivity of stock buying to stock buying by peers more for stocks that are more volatile. To address the possibility that high return variability estimated over a single month might capture a transient effect of short-term abnormal returns rather than a stock characteristic, we repeat this test in column 3, measuring stock volatility as the return standard deviation over the twelve months from $t-13$ to $t-2$, and find similar results.

These findings are intriguing given the volatility and beta anomalies—the finding that high volatility stocks (bearing in mind that beta is a contributor to volatility) earn abnormally low future returns. Our evidence that social interactions promote the buying of volatile stocks suggests that social interactions may be a source of overpricing of such stocks.

Similarly, in columns 4 and 5, we find that social transmission is stronger for high-skewness stocks. In other words, SII increases the sensitivity of stock buying to stock buying by peers more for stocks that have high skewness. Finally, in column 6, we find that social transmission is stronger for stocks with a high trading volume growth rate over recent months. In other words, SII increases the sensitivity of stock buying to stock buying by peers more for stocks that have had a higher recent growth in trading volume.

These findings are intriguing given the lottery stock anomaly—the finding that high skewness stocks earn abnormally low future returns. Our evidence that social interactions promote the purchase of high skewness stocks suggests that social interactions may also contribute to the overpricing of lottery stocks.

These results are consistent with the predictions of HHW. Senders of social transmission display a self-enhancing transmission bias, preferring to share their successful stock picks with their peers and avoiding discussion of failures. This bias implies that the number of senders advocating for a given stock increases with the stock's past return, volatility, and skewness, leading to a higher effectiveness of social transmission.

Receivers in the HHW model also display systematic biases. Consistent with the use of the representativeness heuristic, they do not fully discount the biased sample of returns reported by senders, and naively believing that past performance is indicative of future performance. Receivers are also more attentive to extreme returns reported by senders due to their salience. The combined effect of these biases provides the following predictions about the dependence of social transmission on a stock's past returns. First, the effectiveness of social transmission is increasing and convex in the stock's past returns. Second, the sensitivity of transmission to past returns and the convexity of this relationship both increase with SII.

We test these predictions in Table 8. We divide our sample into six subsamples based on stock return terciles in the previous month and the number of games of local soccer teams in a given month relative to that municipality's median number of monthly games. We report the regression coefficients for each of the subsamples in a regression of Buy on Lagged Municipality Buy. Consistent with the results in Table 7, we find that the effect of social interactions increases with the stock's past returns in both the High and Low Game Count subsamples. The increase in the effect size of past returns is convex, as shown by the larger difference in the coefficients between the High-Med returns relative to the Med-Low returns. Finally, the convexity of the effect is larger for the High Game Count subsample than for the

Low Game Count subsample, indicating that greater social interaction intensity increases convexity.

4.3 Population Characteristics

We next examine which population traits influence social transmission of investment behavior. Especially, we consider the effects of homophily, the tendency of individuals to be socially linked with individuals who are similar to themselves; ingroup bias, the tendency of people to think more highly of an have greater trust for their own group than other groups; and what we call extremity shift, the tendency of individuals in like-minded groups to move to greater extremes, as described in the literature on group polarization and on echo chambers.

Differences in age, religion, and education (correlated with income and wealth) are among the leading traits that divide personal environments and social networks (McPherson et al. 2001). Investors in demographically homogeneous environments are likely to have social interactions with more of their peers (owing to homophily) and form stronger interpersonal connections. This implies greater social influence and persuasion. Alternatively, if there is greater trust in homogeneous populations (e.g., Putnam 2007), again homogeneity may amplify social influence . If so, we expect to see greater social transmission of investing behaviors in more homogenous populations.[17]

We describe these tests in Table 9. Panel A indicates that transmission is stronger in municipalities with higher levels of wealth, salary, education, and trading frequency. These population characteristics are all positively correlated and broadly measure socioeconomic status. Individuals in wealthier municipalities are more likely to have investment accounts

[17]Using a conceptually distinct definition of homophily, HHW predicts that homophily will decrease the rate of social transmission. However, in their paper, homophily is defined and modeled as similarity in investors' selected investment strategies before their social interaction. The intuition is very direct, that communication of a binary investment strategy (Active or Passive) will not convert another investor to that strategy in a group of investors who are already using the same strategy. In our setting, homophily refers to similarity in sociodemographic variables. Investors in homogeneous municipalities have a tendency to share similar investment strategies only to a limited extent; they are unlikely to already be invested in exactly the same stocks prior to meeting.

and engage in casual conversations about stocks.

In Panel B, we test how heterogeneity of traits in the population influences the social transmission of investments. We use four municipality-level heterogeneity measures. The first is a religious heterogeneity index provided by the Israel Central Bureau of Statistics. The other three are the standard deviations of age, salary, and wealth distribution. We find that social transmission is stronger in more homogeneous municipalities across all the heterogeneity measures.

Extending the Table 3 tests, we examine whether greater population homogeneity amplifies the SII effects on investors' decision to initiate stock trading or to purchase stocks they did not previously own. These results are presented in Table A4. Consistent with homophily effects, we find that SII increases the sensitivity of investor's first trades (in a specific stock or any stock) to past buys, and this sensitivity increases with any of the demographic homogeneity measures.

In general, homophily in social networks reduces the diversity of opinions. People tend to associate with others who hold similar views, creating an echo chamber that can lead to an extremity shift, i.e., a tendency for sets of individuals who are initially inclined in a certain direction to move further in that direction. This can cause different sets of individuals to move to opposite extremes in their opinions or behaviors, i.e., polarization.

Extending our analysis in Table 4, we test whether greater population homogeneity amplifies the SII effects on existing shareholders' behavior. These results are presented in Table A5. We find that SII increases the sensitivity to past buys of existing shareholders' propensity to add more stocks to their position and to hold their stocks longer (see the coefficient on the interaction term Lagged Municipality Buy × Games Count). Furthermore, we find that greater homogeneity using any of the demographic homogeneity measures increases this effect of SII (see the coefficient on the triple interaction term Lagged Municipality Buy × Games Count × Population Characteristic). This finding is consistent with homophily promoting an extremity shift, wherein initially optimistic views of existing shareholders in a stock become amplified.[18]

In Table 10, we test whether other possible modulators of social transmission, such as investor emotions or confidence, affect investing behavior. In the spirit of Edmans et al. (2007), in column 1, we use the percentage of team wins as a proxy for investor mood. In column 2, we use the average portfolio return in the previous month among all existing shareholders of a stock in a given municipality. High portfolio returns among existing shareholders, who are likely to be the senders of the social signal, may contribute to a feeling of positive mood or confidence in their investment skills. Similarly, in column 3, we use the effect of the average portfolio return in the previous month among all investors in the municipality who were not holding the stock in their portfolio at the beginning of the month.

We find that the effects of SII are stronger when local teams have a high win rate or when investors (existing shareholders or non-shareholders) had high portfolio returns in the previous month. These results suggest that a positive mood or high self-confidence among both senders and potential receivers enhances the effectiveness of social transmission. Alternatively, a higher win rate may directly influence social interaction through increased attendance at games and more frequent post-game celebrations rather than through an improvement in mood or self-confidence.

4.4 Effects of Social Interaction on Investment Portfolios

We next test how social interactions affect investors' overall portfolios. We analyze an investor-month panel and continue to use Games Count as our measure of SII. We construct a portfolio level version of the Lagged Municipality Buy variable, our proxy for the number of potential senders. For each stock-month, we calculate the normalized value of the number of buyers in the municipality using the preceding 12 months. We define Lagged Percent High Buy as the percentage of stocks in a given municipality-month with a positive normalized

[18] Such an extremity shift can be viewed as generating portfolio polarization, in the sense that deviations from passive indexing become more extreme in divergent directions. For example, an investor who holds stock i and not stock j buys more of stock i, whereas an investor who holds stock j and not stock i buys more of stock j. This causes their holdings to diverge even further, in opposite directions, from passive indexing.

value.[19] The analysis is presented in Table 11. Our main interest is in the coefficient on the interaction term between Lagged Percent High Buy and Games Count.

Columns 1 and 2 indicate that social interactions also increase portfolio riskiness, measured as portfolio beta or return volatility. This is consistent with our previous results that social transmission of recent buying behavior by peers is stronger for riskier stocks, because over time such purchases should increase the share of riskier stocks in investor portfolios.

We also performed tests of whether social interactions affect portfolio performance at one-month and three-month horizons. Results are insignificant, likely owing to low power in our sample to identify return predictability.

4.5 Effects of Social Interaction on Market-Level Outcomes for Individual Stocks

In this section, we test how social interaction intensity affects market-level outcomes such as prices and trading activity for individual stocks. We analyze a stock-month panel and adjust our variables to fit a market-level analysis for each stock. Instead of using the community-level Games Count variable as our measure of SII, we define National Social Interaction as the sum of the number of games in all municipalities, weighted by the respective population sizes of these municipalities. We define Lagged National Buy as the log of one plus the total number of investors who purchased a given stock in the previous month. Our main interest is the coefficient of the interaction term between these two variables.

The analysis is presented in Table 12. Column 1 indicates that social interaction intensity increases stock trading volume. This result is consistent with our previous analysis in Table 5, which shows that SII increases investor-level trading volume.

In columns 2 and 3, we perform this test for subsamples of stocks in the bottom or top market value terciles. The effect of SII on trading volume is stronger for low market value stocks and is only marginally significant for high market value stocks ($t = 1.89$). The

[19] Our results are robust to using the monthly average normalized values of stock buys in each municipality.

difference in effect size is likely driven by the larger proportion of foreign investors who invest in high market value stocks. Such investors are not influenced by the local social interactions driven by soccer matches in Israel. Additionally, there is a larger proportion of domestic institutional investors in high market value stocks. Such investors may be less prone to social transmission biases than retail investors.

We next explore whether SII promotes retail ownership in stocks. Our sample includes all the retail investors of one of the largest banks in Israel. We define the retail ownership percentage in a stock as the ratio of the market value of stock holdings by all investors in our sample to the total market value of that stock. Our sample comprises only a subset of retail investors and therefore in the aggregate understates total retail ownership. If investors in our sample are a constant proportion of the retail investor population across stocks and time, then our estimated effects provide lower bounds for social interaction effect on retail ownership. In column 4, we find that a stock's fraction of retail ownership increases with the number of buys of that stock in the previous month, and that this relationship is stronger for higher levels of SII. As with the SII effect on trading volume, columns 5 and 6 indicate that the social interaction effect is stronger in low market value stocks.

We also tested whether SII affects stock returns. We examined up to three lead months to capture any delayed effects, and various subsamples, including high and low market value stocks. Additionally, we tested if a municipality's lagged number of buyers predict local stock returns. All results are insignificant. However, we also find that the return tests have minimal statistical power. The standard error of the key test coefficient is very large, implying a wide confidence interval compatible with large positive or negative return predictability.

4.6 The Role of Investor Mood

An alternative possible interpretation of some of our findings derives from the possibility that the occurrence of a soccer game improves investor mood. If so, a greater number of soccer games in a location would be associated with more optimistic investor mood. This is plausible since soccer is a recreational activity.[20]

One possibility is that soccer is associated with positive mood, but that the effect of mood is mainly to amplify social interaction effects. Research in psychology establishes a causal link between mood and sociability (Fredrickson 1998, 2001; Forgas 2002; Waugh and Fredrickson 2006; Whelan and Zelenski 2012; Forgas 2022). The positive mood induced by attending a soccer game may enhance social interactions among fans, thereby increasing the transmission of investment ideas. This interpretation is consistent with the suggestive evidence in Section 4.3 that social transmission is stronger conditional on the local team having a greater number of past wins, which may proxy for better mood in the community.

Another possibility is that soccer games improve mood, and that the mood directly influences investor behavior rather than operating via social interaction. For example, better mood may promote optimism and risk taking (see the review of mood effects in Hirshleifer 2015). Even so, mood effects do not provide a credible explanation for our findings.

First, mood-induced optimism might explain why investors would buy stocks in general, but does not immediately explain why investors selectively buy stocks that were recently purchased by others in their municipality. This point is not fatal for a mood-based mechanism, if we add the further assumption that investors have limited attention and focus only on a subset of salient stocks at any given time. If so, *Games Count* could be an indicator of optimistic investor mood, and *Lagged Municipality Buy* can capture investor attention, and thereby mood-induced optimism, being directed to a specific set of stocks. This would explain the positive coefficient on the interaction term between these variables

However, existing evidence on mood, sports, and the stock market opposes this interpretation. Edmans et al. (2007) study the effects of national soccer, cricket, rugby, and basketball game outcomes on aggregate stock market returns. They find that stock market returns are on average negative on days following a sports defeat, and lower than the mean

[20]A similar possibility is relevant for previous research on social interaction and investment behavior. Discussions of investments among retail investors typically occur in positive mood settings examined in prior research, such as church gatherings, socializing with neighbors, or socializing in the workplace (see literature review in Section 1).

return across days with no game. This indicates that any potential positive mood effect on the days after sports games deriving from sheer game occurrence is outweighed by the negative mood effect of experiencing a defeat.[21]

More crucially, for our purposes, they find no difference in stock returns on days following a win versus days with no game. This implies that any mood boost from the sheer occurrence of the game, even when combined with the good news of a victory, does not materially affect investor behavior. If game occurrence together with a victory does not make investors more optimistic about investing prospects, then conditioning only upon game occurrence (and not victory) surely does not make investors more optimistic. This evidence therefore opposes the idea that occurrence-driven optimism is a key source of investor buying.[22]

Furthermore, direct mood effects do not explain why the effects of game occurrences on buying is stronger in demographically homogeneous municipalities. In contrast, this is an immediate implication of the social interaction mechanism, based on extensive evidence that social interactions are stronger in more homogeneous communities (we review evidence of this in Section 4.3).

A more intricate way in which mood could play into trading involves sequences of victories by the local soccer team. Such sequences could boost fans' mood in future games. Victories also can generate additional game occurrences in leagues where the number of games depends on team performance. However, this possibility is present in only two out of the 22 leagues in our sample which are structured as single-elimination tournaments.[23] These leagues constitute only a small fraction of our sample of game occurrences due to single-elimination format and generate only a small fraction of the variation in number of

[21] Transient mood effects that do not persist beyond game day are unlikely to explain our findings as less than seven percent of the games in our sample take place on a weekday before the market closes.

[22] Indeed, the evidence of Edmans et al. that sports game have either negative return effects (after defeats) or neutral effects (after victories) suggests that on average sports event occurrences have a negative effect on mood.

[23] In the remaining 20 leagues, the number of games is fixed in advance and does not depend on team performance.

game occurrences.[24] Furthermore, the gap between games is typically longer than a week, making it unlikely that any positive mood effect from a win would persist to the next game (as compared with the one-day mood effect of game outcomes documented by Edmans et al. 2007). Finally, the finding of Edmans et al. that mood affects returns only after defeats, not victories, opposes the idea that sequences of victories are driving our results.

5 Conclusion

We test for the causal effect of social interactions on investor behavior and market outcomes using the number of soccer games in Israel as a measure of social interaction intensity. Social interactions influence investor stock purchases, particularly in riskier stocks. The probability of social transmission of stock-buying behavior is an increasing and convex function of past returns, with higher social interaction intensity strengthening this relationship. Increased intensity of social interactions cause existing shareholders to increase their existing stock positions and to hold stocks longer. This is especially the case in demographically homogeneous municipalities, which is consistent with an extremity shift effect, as considered in theories of echo chambers and polarization. Social interactions also increase trading volume, and portfolio risk. At the stock level, increased SII causes higher trading volume and increased retail ownership percentage. These findings highlight that biases in the social transmission of investing ideas have systematic effects on investor behavior and market outcomes. Looking forward, the use of variations in social interaction intensity for empirical testing suggests new directions for future research, such as identifying the effect of social interaction intensity on financial decisions such as credit card and retirement account selection, mortgage refinancing, and insurance choice.

[24] The variation in the number of games across municipalities and months is driven primarily by differences in the number of soccer teams in each municipality, the leagues in which these teams compete, and variations in league schedules.

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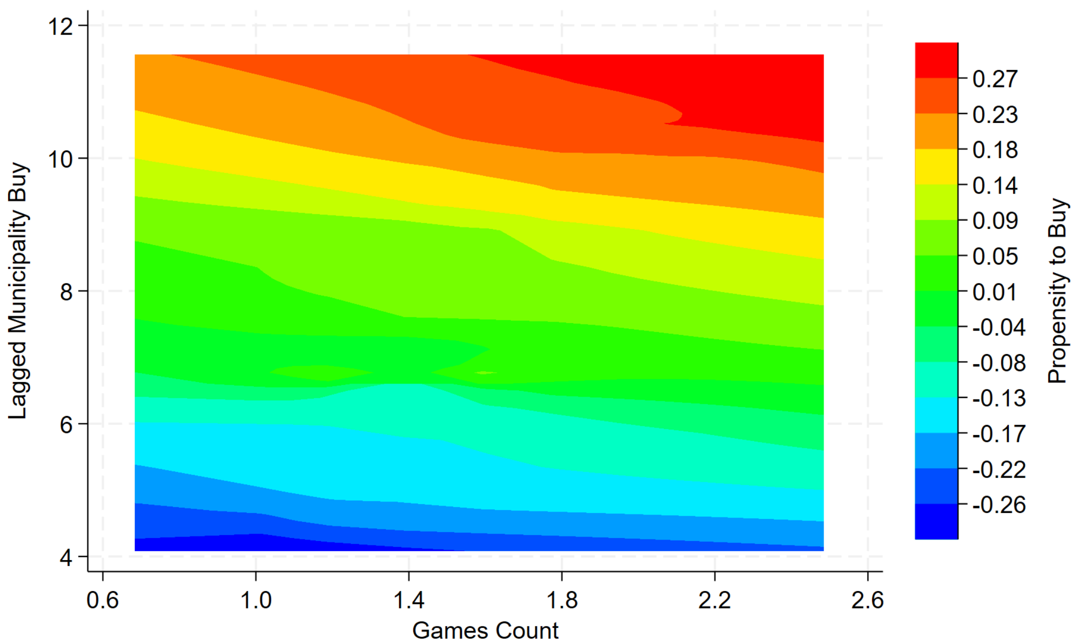
Figure 1. Social Interaction Intensity and Investor Stock Buys



The figure displays the average residuals from a regression of *Buy* on investor-year-month and stock-year-month fixed effects, grouped into 10 x 10 bins of *Games Count* and *Lagged Municipality Buy*.

Table 1. Summary Statistics

Panel A: Investors

	observations	mean	std. dev.	p10	p50	p90
Unique Stocks Traded	131,003	0.66	0.58	0.00	0.34	1.31
Unique Stocks Bought	131,003	0.26	0.37	0.00	0.22	0.78
Unique Stocks Sold	131,003	0.24	0.33	0.00	0.14	0.56
Portfolio Return	131,003	0.00	0.15	-0.14	-0.01	0.08
Portfolio Return Std. Dev.	131,003	0.03	0.03	0.01	0.02	0.08
Portfolio Beta	131,003	1.06	1.34	-1.30	1.07	4.77
Holding Period	131,003	14.54	16.19	1.00	8.00	48.00
Salary	131,003	109,284	120,576	7,320	85,548	234,264
Wealth	131,003	3,850,138	3,119,871	32,154	700,307	8,302,325

Panel B: Municipalities

	observations	mean	std. dev.	p10	p50	p90
Monthly Game Count	137	5.45	4.73	3	4	10
Number of Investors	137	1,148	1,084	93	752	3,152

Panel A provides investor-level summary statistics. The number of unique stocks traded and portfolio statistics are monthly averages. Holding Period is the average duration in months an investor holds a stock. Salary is annual ILS (about 0.25 USD) and does not include investment income. Wealth is the average end-of-month value of all holdings with the bank (including non-investment accounts). Panel B provides summary statistics at the municipality level. Game Count is the monthly average number of games played by local soccer teams. Number of Investors is the number of unique investors who reside in each municipality.

Table 2. Social Interaction Intensity and Investor Stock Buys

	Buy (1)	Buy (2)	Buy (3)	Buy (4)
Lagged Municipality Buy × Games Count	0.025***	0.032***	0.038***	0.027***
	(3.32)	(3.33)	(3.67)	(3.54)
Lagged Municipality Buy	2.058***	0.777**	0.633	0.721***
	(5.76)	(2.57)	(1.23)	(3.62)
Games Count	-0.142***	-0.157***	-0.163***	
	(-2.47)	(-3.13)	(-3.22)	
Stock Return		0.049***	0.050***	
		(4.12)	(4.49)	
Stock Return Volatility		0.075***	0.069***	
		(4.57)	(7.30)	
Stock Beta		-0.018***	-0.013***	
		(-3.82)	(-2.83)	
Portfolio Return		0.023		
		(0.70)		
Salary		0.001		
		(1.60)		
Investor FE	Yes	Yes		
Year-Month FE	Yes	Yes		
Stock FE	Yes	Yes	Yes	
Investor × Year-Month FE			Yes	Yes
Stock × Year-Month FE				Yes
N	243,389,731	243,389,731	219,675,909	210,044,736
adj R^2	0.096	0.095	0.353	0.296
Games Count marginal effect	0.32	0.31	0.31	0.31
marginal effect Z Value	[6.45]	[5.56]	[4.38]	[4.17]

Buy is an indicator for whether an investor i purchased stock s during month t. Lagged Municipality Buy is the log of one plus number of investors in the municipality that purchased stock s during month $t-1$. Games Count is the log of one plus the monthly number of games played by soccer teams based in the municipality. Stock Return is the lagged one month stock return. Stock Return Volatility is the standard deviation of stock return calculated over 12 months ending at month $t-1$. Stock Beta is the one year beta calculated using daily data over 12 months ending at month $t-1$ using the TA-125 index as the market portfolio and the three-month Israeli government bond yield as the risk free rate. Portfolio Return is the investor's portfolio return over the 12 months ending at month $t-1$. Salary is the most recent annual salary of the investor. Reported t-statistics in parentheses are heteroskedasticity-robust and clustered at the investor level. The symbols ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Games Count marginal effect is calculated at the mean levels of all variables.

Table 3. Social Interaction Intensity and Investor First Trades

Panel A: New Stock Buys

	New Stock Buy (1)	New Stock Buy (2)	New Stock Buy (3)
Lagged Municipality Buy × Games Count	0.058***	0.059***	0.052***
	(4.150)	(2.949)	(3.444)
Lagged Municipality Buy	0.212**	0.207**	0.224**
	(2.139)	(2.157)	(2.29)
Games Count	-0.335***	-0.341**	
	(-3.953)	(-2.325)	
Controls	Yes	Yes	
Investor FE	Yes		
Year-Month FE	Yes		
Stock FE	Yes	Yes	
Investor × Year-Month FE		Yes	Yes
Stock × Year-Month FE			Yes
N	243,389,731	219,675,909	210,044,736
adj R^2	0.175	0.382	0.331
Games Count marginal effect	0.738	0.732	0.734
marginal effect Z Value	[3.55]	[3.49]	[3.31]

Panel B: First Stock Purchase

Dependent Variable	First Trade	Municipality First Trade Count	Number of Traders Growth Rate
Panel	Investor-Month (1)	Municipality-Month (2)	Municipality-Month (3)
Lagged Market Return × Games Count	0.030***	0.015***	0.009***
	(3.729)	(2.852)	(2.931)
Games Count	-0.052**	-0.041***	-0.026***
	(-2.134)	(-2.992)	(-3.497)
Investor FE	Yes		
Municipality FE		Yes	Yes
Year-Month FE	Yes	Yes	Yes
N	10,959,711	12,878	12,878
adj R^2	0.141	0.26	0.298
Games Count marginal effect	0.073	0.038	0.039
marginal effect Z Value	[3.04]	[2.98]	[2.86]

In Panel A, New Stock Buy is an indicator for whether an investor i purchased stock s during month t and did not own stock s before. Lagged Municipality Buy is the log of one plus number of investors in the municipality that purchased stock s during month $t-1$. Games Count is the log of one plus the monthly number of games played by soccer teams based in the municipality. Control variables are defined in Table 2 and include stock return, stock return volatility, stock beta, investor portfolio return, and investor salary. In Panel B, the dependent variable in Column 1 is an indicator for whether an investor purchased any stock for the first time. In Column 2, the dependent variable is the log of one plus the number of investors that purchased any stock for the first time in a given municipality-month. In Column 3, the dependent variable is the growth rate in the number of stock traders in a given municipality-month. Lagged Market Return is the monthly return of the TA-125 index in month $t-1$. Reported t-statistics in parentheses are heteroskedasticity-robust and clustered at the investor level in all investor level regressions and at the municipality level in columns 2 and 3 of Panel B. The symbols ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Games Count marginal effect is calculated at the mean levels of all variables.

Table 4. Social Interaction Intensity and Existing Shareholder Behavior

Panel A: Purchase of Additional Stocks by Existing Shareholders

	Net Buy (1)	Net Buy (2)	Net Buy (3)
Lagged Municipality Buy × Games Count	0.009***	0.011***	0.008***
	(3.64)	(4.18)	(4.54)
Lagged Municipality Buy	0.238***	0.233***	0.246***
	(2.67)	(3.22)	(3.01)
Games Count	-0.409***	-0.416***	
	(-2.71)	(-3.64)	
Controls	Yes	Yes	
Investor FE	Yes		
Year-Month FE	Yes		
Stock FE	Yes	Yes	
Investor × Year-Month FE		Yes	Yes
Stock × Year-Month FE			Yes
N	174,278,866	150,467,088	146,170,732
$adj\ R^2$	0.074	0.332	0.273

Panel B: Holding Period of Existing Shareholders

	Holding Period (1)	Holding Period (2)	Holding Period (3)
Lagged Municipality Buy × Games Count	0.572***	0.613***	0.589***
	(3.14)	(3.76)	(2.90)
Lagged Municipality Buy	3.637	4.295	4.189
	(0.93)	(0.47)	(1.16)
Games Count	4.913***	4.018***	
	(3.25)	(4.18)	
Controls	Yes	Yes	
Investor FE	Yes		
Year-Month FE	Yes		
Stock FE	Yes	Yes	
Investor × Year-Month FE		Yes	Yes
Stock × Year-Month FE			Yes
N	32,160,611	28,838,463	27,589,448
$adj\ R^2$	0.586	0.711	0.742

In Panel A, the sample includes only investors that purchased a given stock in month $t-1$ or before. Net Buy is an indicator for whether an investor i purchased additional shares of stock s during month t. Lagged Municipality Buy is the log of one plus number of investors in the municipality that purchased stock s during month $t-1$. Games Count is the log of one plus the monthly number of games played by soccer teams based in the municipality. In Panel B, the sample includes only investors that purchased a given stock in month $t-1$. The dependent variable is the number of months an investor kept the stock in their portfolio before selling it in part or in full for the first time. Control variables are defined in Table 2 and include stock return, stock return volatility, stock beta, investor portfolio return, and investor salary. Panel A includes both contemporaneous and lagged stock returns as control variables. Reported t-statistics in parentheses are heteroskedasticity-robust and clustered at the investor level. The symbols ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 5. Social Interaction Intensity and Investor Trading Volume

	Stock Buys Count (1)	Stock Sells Count (2)	Stock Trades Count (3)	Stock Buys Value (4)	Stock Sells Value (5)	Stock Trades Value (6)
Games Count	0.032***	0.014*	0.034***	0.054***	0.016**	0.049***
	(2.540)	(1.911)	(2.739)	(2.659)	(2.113)	(3.127)
Portfolio Return	0.061**	0.039	0.056**	0.117**	0.242***	0.092
	(2.183)	(1.382)	(2.084)	(2.077)	(2.834)	(1.470)
Salary	0.001	-0.001	-0.000	-0.003**	-0.002	-0.002
	(0.830)	(-1.257)	(-0.206)	(-2.258)	(-0.761)	(-0.928)
Investor FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
N	10,959,711	10,959,711	10,959,711	10,959,711	10,959,711	10,959,711
adj R^2	0.385	0.377	0.412	0.448	0.443	0.463

The dependent variables in columns 1-3 are the log of one plus the number of unique stock transactions (buy, sell, or total) in month t. The dependent variables in columns 4-6 are the log of one plus the value of stock transactions (buy, sell, or total) in month t. Game Count is the log of one plus the monthly number of games of soccer teams based in the municipality. Portfolio Return is the investor's portfolio return over the 12 months ending at month $t-1$. Salary is the most recent annual salary of the investor. Reported t-statistics in parentheses are heteroskedasticity-robust and clustered at the investor level. The symbols ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 6. Alternative Measures of Social Interaction Intensity

Panel A: Game Location and Importance

Dependent Variable	Buy	Buy	Buy	Buy	Buy	Buy
Interaction Variable Games Share	Important Games Share (1)	Important Games Share (2)	Important Games Share (3)	Home Games Share (4)	Home Games Share (5)	Home Games Share (6)
Lagged Municipality Buy × Interac.	0.038***	0.046***	0.033***	0.035***	0.042***	0.031***
	(3.29)	(3.28)	(3.22)	(2.81)	(2.49)	(2.72)
Lagged Municipality Buy	0.738***	0.759***	0.771***	0.598***	0.653***	0.547***
	(2.85)	(2.58)	(2.80)	(2.92)	(2.73)	(3.11)
Interaction Variable	-0.051	-0.042		-0.022**	-0.023**	
	(-0.77)	(-0.51)		(-2.23)	(-2.09)	
Controls	Yes	Yes		Yes	Yes	
Investor FE	Yes			Yes		
Year-Month FE	Yes			Yes		
Stock FE	Yes	Yes		Yes	Yes	
Investor × Year-Month FE		Yes	Yes		Yes	Yes
Stock × Year-Month FE			Yes			Yes
N	243,389,731	219,675,909	210,044,736	243,389,731	219,675,909	210,044,736
adj R^2	0.096	0.352	0.292	0.094	0.355	0.289

Panel B: Distance of Games

Dependent Variable	Buy	Buy	Buy	Buy	Buy	Buy
Interaction Variable	Distance of Games (1)	Distance of Games (2)	Distance of Games (3)	Distance of Away Games (4)	Distance of Away Games (5)	Distance of Away Games (6)
Lagged Municipality Buy × Interac.	-0.012***	-0.015***	-0.017***	-0.005***	-0.007***	-0.011***
	(-2.88)	(-2.81)	(-3.12)	(-2.73)	(-2.83)	(-3.01)
Lagged Municipality Buy	0.843***	0.811***	0.782***	0.835***	0.777***	0.688***
	(3.21)	(2.83)	(2.68)	(3.13)	(2.83)	(2.52)
Interaction Variable	0.004	0.005		0.001	0.001	
	(0.35)	(0.95)		(0.61)	(0.27)	
Controls	Yes	Yes		Yes	Yes	
Investor FE	Yes			Yes		
Year-Month FE	Yes			Yes		
Stock FE	Yes	Yes		Yes	Yes	
Investor × Year-Month FE		Yes	Yes		Yes	Yes
Stock × Year-Month FE			Yes			Yes
N	243,389,731	219,675,909	210,044,736	243,389,731	219,675,909	210,044,736
adj R^2	0.267	0.279	0.299	0.268	0.278	0.301

Buy is an indicator for whether an investor i purchased stock s during month t. Lagged Municipality Buy is the log of one plus number of investors in the municipality that purchased stock s during month $t-1$. Games Count is the log of one plus the monthly number of games played by soccer teams based in the municipality. In Panel A, the interaction variable in Columns 1-3 is the share of important games out of all the games played by local soccer teams in month t. A game is classified as important if (a) the game will determine if a team is ranked first (b) the game will determine if a team is ranked last (and will drop to a lower league) (c) the game is a derby (match between two local teams) (d) The game is part of the final games series in one of the national soccer leagues in Israel. The interaction variable in Columns 4-6 is the share of home games out of all the games played by local soccer teams in month t. In Panel B, the interaction variable in columns 1-3 is the log one plus the average distance between the game stadium and the municipality in month t. The interaction variable in columns 4-6 is the log one plus the average distance in away games between the game stadium and the municipality in month t. Control variables are defined in Table 2 and include stock return, stock return volatility, stock beta, investor portfolio return, and investor salary. Reported t-statistics in parentheses are heteroskedasticity-robust and clustered at the investor level. The symbols ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 7. Social Interaction Intensity, Investor Stock Buys, and Stock Characteristics

Dependent Variable	Buy	Buy	Buy	Buy	Buy	Buy
Stock Characteristic	Ret at t-1	Ret Std. at t-1	Ret Std. t-13 to t-2	Ret Skew at t-1	Ret Skew t-13 to t-2	Change in Volume
	(1)	(2)	(3)	(4)	(5)	(6)
Lagged Municipality Buy × Games Count × Char.	0.013***	0.023***	0.025***	0.029***	0.022**	0.008***
	(3.12)	(2.86)	(3.26)	(3.02)	(1.97)	(3.61)
Lagged Municipality Buy × Games Count	0.021***	0.015***	0.017***	0.020***	0.017***	0.013***
	(3.54)	(3.33)	(3.57)	(4.17)	(3.86)	(3.22)
Lagged Municipality Buy	0.486**	0.514***	0.568***	0.611**	0.527**	0.429*
	(2.24)	(3.27)	(3.63)	(1.98)	(2.03)	(1.78)
Investor × Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Stock × Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
N	210,044,736	210,044,736	210,044,736	210,044,736	210,044,736	210,044,736
adj R^2	0.301	0.297	0.297	0.298	0.298	0.251

Buy is an indicator for whether an investor i purchased stock s during month t. Lagged Municipality Buy is the log of one plus number of investors in the municipality that purchased stock s during month $t-1$. Games Count is the log of one plus the monthly number of games played by soccer teams based in the municipality. Change in Volume is the stock total trading volume in month $t-1$ over the average monthly trading volume in months $t-4$ to $t-2$. Reported t-statistics in parentheses are heteroskedasticity-robust and clustered at the investor level. The symbols ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 8. Social Interaction Intensity and Convexity of Stock Returns

	Return at $t-1$		
Games Count	Low	Med	High
Low	0.713**	0.724**	0.739***
	(1.99)	(2.06)	(2.84)
High	0.791**	0.803***	0.832***
	(2.13)	(3.18)	(4.75)

Each coefficient represents a single regression of Buy on Lagged Municipality Buy for different subsamples. Buy is an indicator for whether investor i purchased stock s during month t. Lagged Municipality Buy is the log of one plus number of investors in the municipality that purchased stock s during month $t-1$. High and Low subsamples of Games Count include months in which the number of soccer games played by local teams is above or below the municipality's median number of games. All regressions include the control variables stock return, volatility, stock beta, investor portfolio return, and investor salary defined in Table 2. All regressions include investor, year-month, and stock fixed effects. Reported t-statistics in parentheses are heteroskedasticity-robust and clustered at the investor level. The symbols ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 9. Social Interaction Intensity, Investor Stock Buys, and Population Characteristics

Panel A: Population Level Characteristics

Dependent Variable	Buy	Buy	Buy	Buy
Population Characteristic	Wealth	Salary	Education	Number of Trades
	(1)	(2)	(3)	(4)
Lagged Municipality Buy × Games Count × Char.	0.009***	0.010***	0.008***	0.017***
	(3.05)	(2.99)	(3.00)	(3.58)
Lagged Municipality Buy × Games Count	0.019***	0.019**	0.019***	0.021***
	(3.10)	(2.27)	(3.24)	(2.60)
Lagged Municipality Buy	0.433**	0.468***	0.408**	0.536***
	(2.16)	(3.21)	(2.23)	(2.97)
Investor × Year-Month FE	Yes	Yes	Yes	Yes
Stock × Year-Month FE	Yes	Yes	Yes	Yes
N	210,044,736	210,044,736	210,044,736	210,044,736
adj R^2	0.294	0.296	0.301	0.302

Panel B: Population Heterogeneity

Dependent Variable	Buy	Buy	Buy	Buy
Population Characteristic	Age Std. Dev.	Religious Heterogeneity	Salary Std. Dev.	Wealth Std. Dev.
	(1)	(2)	(3)	(4)
Lagged Municipality Buy × Games Count × Char.	-0.009**	-0.012***	-0.027***	-0.014**
	(-2.88)	(-2.64)	(-3.59)	(-2.32)
Lagged Municipality Buy × Games Count	0.033***	0.038***	0.030***	0.031***
	(2.92)	(2.61)	(3.66)	(3.84)
Lagged Municipality Buy	0.395**	0.417*	0.493***	0.457**
	(2.04)	(1.81)	(2.42)	(2.26)
Investor × Year-Month FE	Yes	Yes	Yes	Yes
Stock × Year-Month FE	Yes	Yes	Yes	Yes
N	210,044,736	210,044,736	210,044,736	210,044,736
adj R^2	0.301	0.301	0.302	0.297

Buy is an indicator for whether an investor i purchased stock s during month t. Lagged Municipality Buy is the log of one plus number of investors in the municipality that purchased stock s during month $t-1$. Games Count is the log of one plus the monthly number of games played by soccer teams based in the municipality. In Panel A, Wealth is the average end of month value of all holdings with the bank (including non-investment accounts). Salary is annual ILS (about 0.25 USD) and does not include investment income. Education is the share of high school graduates in the municipality obtained from the 2008 Census of the Israel Central Bureau of Statistics. Number of Trades is the number of trades of the investor over the preceding 12 months. In panel B, Age Standard Deviation is calculated for each municipality using the 2014 Census of the Israel Central Bureau of Statistics. Religious Heterogeneity for each municipality is measured using a 1 to 12 scale where a higher number reflects a higher degree of heterogeneity. The measure is obtained from the 2013 Census of the Israel Central Bureau of Statistics. Salary and Wealth standard deviations are calculated at the municipality level. Reported t-statistics in parentheses are heteroskedasticity-robust and clustered at the investor level. The symbols ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 10. Social Interaction Intensity, Investor Stock Buys, and Investor Affect

Dependent Variable	Buy	Buy	Buy
Population Characteristic	Game Wins Share	Current Shareholders Portfolio Return	Non-current Shareholders Portfolio Return
	(1)	(2)	(3)
Lagged Municipality Buy × Games Count × Char.	0.012**	0.015**	0.011***
	(2.25)	(2.16)	(3.18)
Lagged Municipality Buy × Games Count	0.018***	0.018***	0.014***
	(2.89)	(2.91)	(3.01)
Lagged Municipality Buy	0.492***	0.522***	0.427**
	(2.67)	(2.48)	(2.17)
Investor × Year-Month FE	Yes	Yes	Yes
Stock × Year-Month FE	Yes	Yes	Yes
N	210,044,736	210,044,736	210,044,736
$adj\ R^2$	0.296	0.299	0.304

Buy is an indicator for whether an investor i purchased stock s during month t. Lagged Municipality Buy is the log of one plus number of investors in the municipality that purchased stock s during month $t-1$. Games Count is the log of one plus the monthly number of games played by soccer teams based in the municipality. Game Wins Share is calculated for each municipality month as the number of game wins over the total number of games played by local soccer teams. Current Shareholders Portfolio Return is the average return in month $t-1$ of investors that purchased a given stock in month $t-1$ or before. Non-current Shareholders Portfolio Return is the average return in month $t-1$ of investors that did not hold the stock at the beginning of month t. Reported t-statistics in parentheses are heteroskedasticity-robust and clustered at the investor level. The symbols ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 11. Social Interaction Intensity and Portfolio Outcomes

Dependent Variable	Portfolio Beta	Portfolio Return Std. Dev.
	(1)	(2)
Lagged Percent High Buy x Games Count	0.018***	0.002***
	(3.44)	(2.97)
Lagged Percent High Buy	0.064	0.017**
	(1.22)	(1.99)
Games Count	-0.021	-0.086
	(-0.50)	(-1.16)
Controls	Yes	Yes
Investor FE	Yes	Yes
Year-Month FE	Yes	Yes
N	10,959,711	10,959,711
adj R^2	0.317	0.516

Portfolio Beta and Portfolio Return Standard Deviation are estimated over one month using daily data. Games Count is the log of one plus the monthly number of games played by soccer teams based in the municipality. For each stock-month, we calculate the normalized value of the number of buyers in the municipality using the preceding 12 months. *Lagged Percent High Buy* is the lagged percent of stocks in a given municipality-month with a positive normalized value. Control variables are defined in Table 2 and include investor portfolio return, and investor salary. Reported t-statistics in parentheses are heteroskedasticity-robust and clustered at the investor level. The symbols ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 12. Social Interaction Intensity and Stock Market Outcomes

Dependent Variable	Volume	Volume	Volume	% Retail Ownership	% Retail Ownership	% Retail Ownership
Sample	All Stocks	Low MV Stocks	High MV Stocks	All Stocks	Low MV Stocks	High MV Stocks
	(1)	(2)	(3)	(4)	(5)	(6)
National Social Interaction × Lagged National Buy	0.031***	0.045***	0.014*	0.002***	0.004**	0.001***
	(3.13)	(3.29)	(1.89)	(3.00)	(2.19)	(2.75)
Lagged National Buy	0.576***	0.624***	0.510***	0.014***	0.017***	0.010***
	(3.47)	(3.13)	(2.72)	(2.84)	(3.41)	(3.48)
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
N	799,846	265,718	267,483	799,846	265,718	267,483
$adj\ R^2$	0.813	0.708	0.663	0.639	0.618	0.554

The dependent variable in columns 1-3 is the log of one plus monthly trading volume. The dependent variable in columns 4-6 is the market value of the stock holdings of all investors in our sample over the total market value of the stock. Low/High MV stocks are the top and bottom terciles of the stocks market value in month t-1. National Social Interaction is the sum of number of soccer games in all municipalities weighted by the population size. Lagged National Buy is the log of one plus number of investors that purchased the stock during month t-1. Reported t-statistics in parentheses are heteroskedasticity-robust and clustered at the stock level. The symbols ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Appendices
For Online Publication

A Additional Tables

Table A1. Soccer Games and Firm Performance

	Sales	ROA
	(1)	(2)
Games Count	-0.023	-0.229
	(-0.86)	(-0.91)
Home Games Count	-0.026	-1.168
	(-1.08)	(-0.99)
Important Games Count	-0.002	0.883
	(-0.08)	(1.13)
Wins Count	0.015	0.099
	(0.73)	(0.52)
Team Rank	-0.003	-0.001
	(-0.45)	(-1.17)

Each coefficient represents the slope of a univariate regression. The dependent variable in Column 1 is the log of one plus the company's quarterly sales. The dependent variable in Column 2 is ROA, defined as the operating income before depreciation scaled by total assets. The sample includes all public firms listed on the Tel Aviv Stock Exchange from 2007-Q1 to 2021-Q4. All explanatory variables are in logs and aggregated at the municipality-quarter level. Games Count, Home Game Count, Important Game Count, and Wins Count refer to the number of games played by soccer teams based in the municipality of a company's headquarters. Important Games criteria are defined in Table 6. Team Rank is the quarterly best ranking of the leading soccer team in the municipality. All regressions include year-quarter and firm fixed effects. Reported t-statistics in parentheses are heteroskedasticity-robust and clustered at the firm level. The symbols ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table A2. Social Interaction Intensity and Investor Stock Buys: Municipality Level Analysis

	Municipality Buy (1)	Municipality Buy (2)	Municipality Buy (3)	Municipality Buy (4)
Lagged Municipality Buy × Games Count	0.813***	0.794***	0.829***	0.792***
	(3.88)	(3.76)	(3.01)	(3.10)
Lagged Municipality Buy	2.907***	2.923***	2.682***	2.894***
	(3.92)	(3.98)	(3.72)	(3.67)
Games Count	3.355***	3.017***	3.254***	
	(3.89)	(3.55)	(3.21)	
Controls		Yes	Yes	
Municipality FE	Yes	Yes		
Year-Month FE	Yes	Yes		
Stock FE	Yes	Yes	Yes	
Municipality × Year-Month FE			Yes	Yes
Stock × Year-Month FE				Yes
N	1,165,733	1,165,733	1,063,819	1,022,501
adj R^2	0.541	0.544	0.573	0.569
Games Count marginal effect	1.14	1.11	1.09	1.10
marginal effect Z Value	[5.14]	[5.03]	[4.77]	[4.58]

Municipality Buy is the log of one plus number of investors in the municipality that purchased stock s during month t. Games Count is the log of one plus the monthly number of games played by soccer teams based in the municipality. Control variables are defined in Table 2 and include stock return, stock return volatility, and stock beta. Reported t-statistics in parentheses are heteroskedasticity-robust and clustered at the municipality level. The symbols ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Games Count marginal effect is calculated at the mean levels of all variables.

Table A3. Social Interaction Intensity and Investor Stock Sells

Panel A: Full Sample

	Sell (1)	Sell (2)	Sell (3)	Sell (4)
Lagged Municipality Sell × Games Count	-0.005	-0.009	-0.008	-0.003
	(-0.72)	(-0.88)	(-0.97)	(-0.57)
Lagged Municipality Sell	0.040***	0.039***	0.039***	0.041***
	(4.19)	(4.62)	(5.03)	(4.39)
Games Count	-0.083***	-0.082***	-0.093***	
	(-3.34)	(-2.92)	(-3.72)	
Controls		Yes	Yes	
Investor FE	Yes	Yes		
Year-Month FE	Yes	Yes		
Stock FE	Yes	Yes	Yes	
Investor × Year-Month FE			Yes	Yes
Stock × Year-Month FE				Yes
N	243,389,731	243,389,731	219,675,909	210,044,736
adj R^2	0.049	0.05	0.109	0.084
Games Count marginal effect	-0.157	-0.151	-0.148	-0.149
marginal effect Z Value	[-3.81]	[-3.64]	[-3.52]	[-3.58]

Panel B: Existing Shareholders Only

	Sell (1)	Sell (2)	Sell (3)	Sell (4)
Lagged Municipality Sell × Games Count	0.009	0.011	0.012	0.010
	(1.19)	(1.08)	(1.04)	(0.99)
Lagged Municipality Sell	0.198***	0.155***	0.146***	0.150**
	(2.84)	(2.53)	(3.14)	(2.24)
Games Count	-0.092**	-0.090***	-0.098***	
	(-2.08)	(-3.19)	(-3.66)	
Controls		Yes	Yes	
Investor FE	Yes	Yes		
Year-Month FE	Yes	Yes		
Stock FE	Yes	Yes	Yes	
Investor × Year-Month FE			Yes	Yes
Stock × Year-Month FE				Yes
N	11,319,618	11,319,618	10,324,284	9,907,493
adj R^2	0.061	0.061	0.127	0.083
Games Count marginal effect	-0.172	-0.168	-0.164	-0.164
marginal effect Z Value	[-2.23]	[-2.71]	[-2.48]	[-2.41]

Sell is an indicator for whether an investor i sold stock s during month t. Lagged Municipality Sell is the log of one plus number of investors in the municipality that sold stock s during month t-1. Games Count is the log of one plus the monthly number of games played by soccer teams based in the municipality. Control variables are defined in Table 2 and include stock return, stock return volatility, stock beta, investor portfolio return, and investor salary. Panel A includes the full sample, and Panel B includes only investors holding stock s in their portfolio at the beginning of month t. Reported t-statistics in parentheses are heteroskedasticity-robust and clustered at the investor level. The symbols ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Games Count marginal effect is calculated at the mean levels of all variables.

Table A4. Social Interaction Intensity, Investor First Trades, and Population Heterogeneity

Panel A: New Stock Buys

Dependent Variable	New Stock Buy	New Stock Buy	New Stock Buy	New Stock Buy
Population Characteristic	Age Std. Dev. (1)	Religious Heterogeneity (2)	Salary Std. Dev. (3)	Wealth Std. Dev. (4)
Lagged Municipality Buy × Games Count × Char.	-0.011	-0.014**	-0.027***	-0.021***
	(-1.42)	(-2.16)	(-2.93)	(-2.47)
Lagged Municipality Buy × Games Count	0.055***	0.059***	0.054***	0.054***
	(3.47)	(3.12)	(4.02)	(3.83)
Lagged Municipality Buy	0.188***	0.201**	0.312***	0.283***
	(2.49)	(2.16)	(3.27)	(3.62)
Investor × Year-Month FE	Yes	Yes	Yes	Yes
Stock × Year-Month FE	Yes	Yes	Yes	Yes
N	210,044,736	210,044,736	210,044,736	210,044,736
$adj\ R^2$	0.331	0.331	0.331	0.331

Panel B: First Stock Purchase

Dependent Variable	First Trade	First Trade	First Trade	First Trade
Population Characteristic	Age Std. Dev. (1)	Religious Heterogeneity (2)	Salary Std. Dev. (3)	Wealth Std. Dev. (4)
Lagged Market Return × Games Count × Char.	-0.000	-0.003**	-0.008***	-0.006***
	(-1.23)	(-1.79)	(-2.91)	(-2.62)
Lagged Market Return × Games Count	0.030***	0.031*	0.033***	0.032***
	(3.11)	(1.84)	(2.64)	(2.83)
Investor FE	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes
N	10,959,711	10,959,711	10,959,711	10,959,711
$adj\ R^2$	0.141	0.141	0.142	0.142

In Panel A, Buy New Stock is an indicator for whether an investor i purchased stock s during month t and did not own stock s before. Lagged Municipality Buy is the log of one plus number of investors in the municipality that purchased stock s during month $t-1$. Games Count is the log of one plus the monthly number of games played by soccer teams based in the municipality. Population characteristics are defined in Table 9. In Panel B, the dependent variable is an indicator for whether an inversor purchased any stock for the first time. Lagged Market Return is the monthly return of the TA-125 index in month $t-1$. Reported t-statistics in parentheses are heteroskedasticity-robust and clustered at the investor level. The symbols ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table A5. Social Interaction Intensity, Existing Shareholder Behavior, and Population Heterogeneity

Panel A: Purchase of Additional Stocks by Existing Shareholders

Dependent Variable	Net Buy	Net Buy	Net Buy	Net Buy
Population Characteristic	Age Std. Dev. (1)	Religious Heterogeneity (2)	Salary Std. Dev. (3)	Wealth Std. Dev. (4)
Lagged Municipality Buy × Games Count × Char.	-0.0006*	-0.0006*	-0.0009***	-0.0007***
	(-1.72)	(-1.84)	(-3.06)	(-2.53)
Lagged Municipality Buy × Games Count	0.009***	0.009***	0.009***	0.009***
	(3.83)	(4.66)	(3.97)	(3.21)
Lagged Municipality Buy	0.421***	0.247***	0.253***	0.248***
	(3.14)	(3.56)	(3.17)	(3.05)
Investor × Year-Month FE	Yes	Yes	Yes	Yes
Stock × Year-Month FE	Yes	Yes	Yes	Yes
N	146,170,732	146,170,732	146,170,732	146,170,732
adj R^2	0.273	0.273	0.274	0.274

Panel B: Holding Period of Existing Shareholders

Dependent Variable	Holding Period	Holding Period	Holding Period	Holding Period
Population Characteristic	Age Std. Dev. (1)	Religious Heterogeneity (2)	Salary Std. Dev. (3)	Wealth Std. Dev. (4)
Lagged Municipality Buy × Games Count × Char.	-0.003	-0.044*	-0.162**	-0.129***
	(-1.16)	(-1.88)	(-2.13)	(-2.67)
Lagged Municipality Buy × Games Count	0.592***	0.609***	0.682***	0.653***
	(2.83)	(3.84)	(3.91)	(4.07)
Lagged Municipality Buy	4.211	4.172	3.943	4.007
	(0.66)	(1.08)	(1.34)	(1.59)
Investor × Year-Month FE	Yes	Yes	Yes	Yes
Stock × Year-Month FE	Yes	Yes	Yes	Yes
N	27,589,448	27,589,448	27,589,448	27,589,448
adj R^2	0.743	0.744	0.745	0.745

In Panel A, the sample includes only investors that purchased a given stock in month $t-1$ or before. Net Buy is an indicator for whether an investor i purchased additional shares of stock s during month t. Lagged Municipality Buy is the log of one plus number of investors in the municipality that purchased stock s during month $t-1$. Games Count is the log of one plus the monthly number of games played by soccer teams based in the municipality. Population characteristics are defined in Table 9. In Panel B, the sample includes only investors that purchased a given stock in month $t-1$. The dependent variable is the number of months an investor kept the stock in their portfolio before selling it in part or in full for the first time. Reported t-statistics in parentheses are heteroskedasticity-robust and clustered at the investor level. The symbols ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

B Omitted Variable Bias in OLS with an Interaction Term

Consider the following model:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_1 X_2 + \beta_4 Z + \epsilon \quad (1)$$
$$Z = a + bX_1 + u, \quad (2)$$

where $X_2 \perp\!\!\!\perp X_1$, and $X_2 \perp\!\!\!\perp Z$. Substituting (2) into (1) gives

$$\begin{aligned} Y &= \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_1 X_2 + \beta_4(a + bX_1 + u) + \epsilon \\ &= (\beta_0 + \beta_4 a) + (\beta_1 + \beta_4 b)X_1 + \beta_2 X_2 + \beta_3 X_1 X_2 + (\epsilon + \beta_4 u). \end{aligned} \quad (3)$$

It follows that if a researcher who does not observe Z estimates the model

$$Y = \beta_0^* + \beta_1^* X_1 + \beta_2^* X_2 + \beta_3^* X_1 X_2 + \epsilon^*, \quad (4)$$

then the estimated parameters are

$$\begin{aligned} \beta_0^* &= \beta_0 + \beta_4 a \\ \beta_1^* &= \beta_1 + \beta_4 b \\ \beta_2^* &= \beta_2 \\ \beta_3^* &= \beta_3. \end{aligned} \quad (5)$$

So when the omitted variable Z is independent of X_2 and has a linear relationship with X_1, then β_2^* and β_3^* are unbiased.