An Epidemic Model of Investor Behavior

Sophie Shive*

June 3, 2008

Abstract

I test whether social influence affects individual investors' trading and stock returns. In each of the 20 most active stocks in Finland over nine years, the number of owners in a municipality multiplied by the number of investors who do not own a stock, a measure of the rate of transmission of diseases and rumors through social contact, predicts individual investor trading. I control for known determinants of trade including daily news and show that competing explanations for the relation are unlikely. Socially motivated trades predict stock returns and the effects are not reversed, suggesting that individuals share useful information. Individuals' susceptibility to social influence has declined during the period, but the opportunities for social influence have increased.

---

*Mendoza College of Business, University of Notre Dame, email sshive1@nd.edu Tel. (574) 631-8301. Thanks to Robert Battalio, Sugato Bhattacharyya, Jonathan Carmel, Shane Corwin, Werner De Bondt, Wayne Ferson, David Hirshleifer, Gautam Kaul, Jussi Keppo, George Korniotis, Alok Kumar, Reuven Lehavy, Tim Loughran, Adair Morse, Vikram Nanda, Uday Rajan, Nejat Seyhun, Clemens Sialm, Katherine Spiess, Noah Stoffman, Amit Seru, Kathy Yuan, and especially Paul Schultz and Tyler Shumway for valuable comments. Thanks also to seminar participants at the University of Michigan, the University of Notre Dame, the University of Toronto, the Stockholm School of Economics, and the 2007 Western Finance Association Meetings. All errors are mine.

I. Introduction

Financial models commonly treat investors as independent agents. These agents trade to smooth consumption, rebalance their portfolios, or to exploit private information. In contrast, recent empirical work has found that investors trade far more than these models would predict. Odean (1999) attributes the excessive trading to an incorrectly perceived information advantage. If individuals act independently, these frequent, sub-optimal trades may well wash out without affecting prices, but there is growing evidence that individual actions are related.

Shiller (1989) writes that "Investing in speculative assets is a social activity. Investors spend a substantial part of their leisure time discussing investments, reading about investments, or gossiping about others' successes or failures in investing. It is thus plausible that investors' behavior (and hence prices of speculative assets) would be influenced by social movements." Sorescu and Subrahmanyam (2006) provide evidence that investors focus on the content of analyst recommendations, and do not much consider the skill of the person making them, which suggests that they may also be open to peer influence. In this study, I examine whether social influence can account for a portion of individual trades, and whether these trades can affect returns.

The first contribution of this paper is to introduce a new model of the determinants of trade that includes a measure of trades caused by social influence. The measure of socially-motivated trades is based on the empirical epidemic literature, which has a long, successful history in modelling the infection rate of diseases, email viruses and rumors. An epidemic setup models the rate of new occurrences as proportional to the number of infected agents in a population multiplied by the number of susceptible agents. In this model, the social influence factor is the number of active investors who own the stock, and thus have a generally positive opinion about its prospects, multiplied by the number of active investors who don't own the stock and therefore have either no opinion or a negative one. The factor measures the likelihood that two people of different opinions about the stock will meet and one person will influence the other, and the coefficient on the factor thus measures the sensitivity of individual investor trades to social influence.

Unlike spatial correlation of trades, which is used to measure social influence in extant studies, this measure is not subject to the critique which plagues the empirical literature on social influence. Manski (1993) points out that there can be many alternative causes of spatially correlated behavior, such as news and local characteristics. By using a measure that exists prior to trading on each day, I avoid this endogeneity problem.

The second contribution of this study is to show, in a dataset of virtually all daily trades in Finland from 1995 to 2003, that the social influence factor is a strongly significant predictor of individual investor trades in each of the 20 highest-volume stocks. These stocks make up over 58 percent of the market capitalization of Finnish equities. The significance remains after controlling for municipality-level education and income, recent return, news articles, and recent volume. The result is robust to alternative specifications and control variables, and to tests of alternative explanations including unobserved municipality-level characteristics, tax-loss trading, employee trading, other forms of news besides national newspapers, and local brokers.

The social influence factor is also economically significant. A ten percent increase in the social influence factor is associated with a 20 percent increase in the number of individual investor buys and sells. I also show that individuals' susceptibility to social influence, which is partly explained by municipality-level characteristics, has declined during the sample period, but the factor itself has been generally increasing.

Last, I show that social influence-motivated trading predicts stock returns in an economically significant way. The estimate of social trading is not calculated with price data, yet it explains contemporaneous and future stock returns, independently of past returns and the number of buy and sell transactions.

My work is related to recent theoretical literature that suggests several ways in which investment decisions can spread socially. One well-known example is the informational cascades of Bikhchandani, Hirshleifer, and Welch (1992) and Banerjee (1992), where agents who have imperfect information optimally give some weight to prior agents' decisions.[1] Costly information, or concerns about neighbors' relative wealth, as in Horst and Scheinkman (2006), may also motivate imitation. Finally, Shiller (1995) states that investors may simply be drawn to imitate others. In sum, trades that are caused by social influence may be based on little or no new information about the firm.

[1] Although Avery and Zemsky (1998) show that cascades do not form when prices are endogenous and there is only one dimension of uncertainty, it is plausible to assume that there are several dimensions of uncertainty in financial markets. Their example of two dimensions is 1. the presence of and 2. the effect of a shock.

Several empirical studies examine how social influence affects various aspects of investing. Hong, Kubik, and Stein (2004) and Brown, Ivković, Smith, and Weisbenner (2008) find that the decision to participate in the equity market depends on the decisions of others in the investor's social network. The former study also finds that households who report more participation in social activities are also more likely to participate in the market.

The literature also explores whether social interaction affects portfolio choice. Ivković and Weisbenner (2007) find that investors are more likely to purchase stocks from a particular industry if other investors in their zip code purchase stocks from that industry. Hong, Kubik, and Stein (2005) show that mutual fund managers' holdings are similar to those of other managers in the same city, and suggest that "The evidence can be interpreted in terms of an epidemic model in which investors spread information about stocks to one another via word of mouth." Feng and Seasholes (2004) provide evidence that trades in a particular province in the People's Republic of China are more correlated internally than they are with trades placed in a second province. In Finland, Grinblatt, Keloharju, and Ikäheimo (2007) show that neighbors influence automobile purchase decisions, which suggests that they may influence portfolio decisions as well.

This study is the first to show that social interaction affects not only daily trades, but also returns. Due to the richness of the data, it is the first to be able to control for some crucial determinants of trade such as daily news, and to examine the two components of the effect of social interaction on trading: the opportunities for social influence in the environment and the propensity of traders to be influenced given a level of opportunity. Using the measures presented in this paper, one can calculate the amount of social trading in a stock and predict returns from these trades. This can facilitate the implementation of policies to dampen social contagion and its effect on prices.

The paper proceeds as follows. Section I presents an overview of the data and initial evidence of social influence on individual investors' transactions. Section II presents the empirical model and the intuition behind it. Section III estimates the model, Section IV presents robustness checks, section V looks at alternative explanations of the results section VI examines the determinants and time series of social influence, and the last section concludes.

II. The Model

A. Modelling Social Trades

The objective of this study is to examine to what extent social interaction influences individual trades. To measure social trading, I use a variable inspired by the epidemic literature, which dates back at least to Daniel Bernoulli in his eighteenth century description of of smallpox and was expanded on by Kermack and McKendrick (1927). Today, these models are used to describe diseases like SARS and the spread of rumors. Epidemic models have in common that the rate at which new infections occur is proportional to the number of infected people multiplied by the number of susceptible people in the population. Now a ubiquitous measure of the rate of transmission through social contact, epidemic models are loosely related to the models of product adoption used in marketing and to hazard models.[2]

The intuition behind the model is that people who have strong opinions about a stock are likely to take a position in the stock and share the opinion with others. The model of social interactions is inspired by the workhorse 'SIR' model of epidemiology. The name SIR, or Susceptible-Infective-Recovered/Removed, reflects the three states that individuals in the population can find themselves in. This model considers a population of $S_{i,j,t}$ (susceptible) investors in municipality i who do not own asset j at time t, and $I_{i,j,t}$ (infective) investors who do own the asset. It is more likely that an investor interacts with someone from her own municipality than from another. In epidemiology, the infection (here, buying) rate is proportional to the number of infected investors (stock owners) times the number of susceptible investors (non-owners) of each stock j in each municipality i and day t, $S_{i,j,t} * I_{i,j,t}$. Let us call this proportionality constant $\beta_{j,b,social}$ where b represents buys.

Note that the variable $S \times I$ is multiplicative. This is meant to capture the fact that adding one infected person to a population allows her to potentially meet and infect each susceptible person, so that the infection rate is multiplicative in the sizes of the infected (I) and susceptible (S) groups, and proportional to $S \times I$.

[2]Given the volume of literature about this model, I do not review it here. For a synopsis of older work, see Mollison (1995). More recent work by U.S.-based authors can be found at www.pubmedcentral.nih.gov.

The multiplicative nature of the epidemic model leads to differing behavior among municipalities with the same proportion of infected, if they have different sized populations. The more people there are in the municipality, the more contacts can happen between these people, and the higher the infection rate, because each susceptible person is liable to meet many infected people. In a group of 100, each of ten infected people has the potential to meet the 90 susceptible people, and at each meeting infect each with some probability β, so the expected number of new infections will be 900β, or 9β per person. In a group of 10, one infected person can only potentially meet 9 others and infect them with some probability β, so the expected number of new infections will be only β, or 0.9β per person. β takes into account not only the probability of infection if a meeting occurs, but also the probability that a meeting takes place. Thus, this structure assumes that people living in areas with high populations will converse with more people on a given day than those living in areas with small populations. One could also assume that people have contact with the same number of other people no matter how populated the area in which they reside. This case is discussed in the Robustness section.

Since there will be other municipality-level variables in the model, to avoid collinearity I divide both sides by the total number of investors in the region, and proceed to model daily trades per investor for each stock.

$$\text{Social Buys Per Investor}_{i,j,t} = \beta_{j,b,social} * S_{i,j,t} I_{i,j,t} / Investors_{i,j,t}. \tag{1}$$

$$(2) \qquad \text{Social Sells Per Investor}_{i,j,t} = \beta_{j,s,social} S_{i,j,t} I_{i,j,t} / Investors_{i,j,t}.$$

Henceforth, $S_{i,j,t}I_{i,j,t}/Investors_{i,j,t}$ will be shortened to $SIpi_{i,j,t}$. Furthermore, when a variable is averaged, I remove the corresponding subscript. For example, $S_j * I_j$ is $S_{i,j} * I_{i,j}$ averaged over all i.

B. Controls for Alternative Determinants of Trade

Clearly, the model must incorporate characteristics of financial markets that are not present in typical epidemic models. Many characteristics of populations and markets can affect individuals' buying rate of a particular stock j. This section describes the variables, and details on the empirical construction of these variables appear in the following section.

News tends to cause investors to react together, which could possibly be mistaken for social interaction-based trading if not included in the model. Barber and Odean (2008) show that news about a stock encourages individual investors to trade it. Frieder and Subrahmanyam (2005) find that investors tend to trade stocks with brand names that they recognize, and possibly have seen in news and advertisements. Finnish newspaper circulation is the third highest in the world after Norway and Japan, and 87 percent of the population over age 12 reads the newspaper every day according to Virtual Finland, a website containing statistics about Finland. I expect $News_{j,t}$, a measure of recent news about stock j, to positively influence both buys and sells, due to attention and the process trading that incorporates information into price.

Another potential determinant of trading frequency is the past weeks' return on the stock ($LReturn_{j,t}$), which has been shown by Bange (2000), Griffin, Nardari, and Stulz (2007), and Barber and Odean (2008) to be a predictor of trading behavior. This effect may manifest itself the buying or selling of individual investors. The well-known disposition effect (see Shefrin and Statman (1985), Odean (1998), and Shumway and Wu (2005), for example) predicts that individuals will tend to sell their winning stocks and hold onto their losers, in which case we would expect the sign on lagged returns to be positive for sales.

High volume can also attract attention, and the highest volume stocks are often published in the Finnish newspapers in a special list. $LVolume_{j,t}$ is the previous day's trading volume in the stock and is meant to control for the attention that high volume attracts. Individual trading may also be related to $Income_i$. There is no predicted sign on *Income*, as more investor sophistication might not necessarily lead to additional trades.

Last, I control for the percentage of investors in the municipality who own the stock,($Nholdpi_{i,j,t}$). This is important especially for the model of sells, because short-selling is almost nonexistent in Finland according to Bris, Goetzmann, and Zhu (2004), and thus only owners can sell stock.

C. The Full Model

The social variable and the control variables can be combined into a model of daily investor trades in each municipality i for each stock j at each day t.

$$\begin{aligned}\text{Total Buys Per Investor}_{i,j,t} = {} & \beta_{j,b,Social} * SIpi_{i,j,t}I_{i,j,t} + \beta_{j,b,Owners} * Nholdpi_{i,j,t} \\ & + \beta_{j,b,News} * News_{j,t} + \beta_{j,b,LR} * LReturn_{j,t} + \beta_{j,b,LV} * LVolume_{j,t} \\ & + \beta_{i,b,Income} * Income_i + \beta_{i,b,Popdens} Popdens_i.\end{aligned}$$

$$\begin{aligned}\text{Total Sells Per Investor}_{i,j,t} = {} & \beta_{j,s,Social} SIpi_{i,j,t}I_{i,j,t} + \beta_{j,s,Owners} * Nholdpi_{i,j,t} \\ & + \beta_{j,s,News} * News_{j,t} + \beta_{j,s,LR} * LReturn_{j,t} + \beta_{j,b,LV} * LVolume_{j,t} \\ & + \beta_{i,s,Income} Income_i + \beta_{i,s,Popdens} Popdens_i.\end{aligned}$$

The first hypothesis to test is whether $\beta_{j,b,social}$, the social buying parameter, and $\beta_{j,s,social}$, the social selling parameter, are positive and significant in predicting buys and sells, once we have controlled for the other variables. These coefficients will capture some but not all social interactions, because many social interactions may happen across municipalities, in which case they are not picked up by $SIpi_{i,j,t}$. If there are no trades due to social interaction, there is no reason why these social variables should be significant. Note that since the trades are a per-investor measure, they are unrelated to the population size of a municipality. Since they evolve over time, they are unlikely to be entirely related to stable municipality-level characteristics.

III. Data and Estimation

A. Trading and Security Data

A.1. Overview

This study uses a data set containing all equity trades in Finland from the period 12/1994-1/2004. The data is held by the Finnish Central Securities Depository (FCSD) and includes 97% of the total market capitalization of Finnish stocks. The register reports the trades of all investors, both retail and institutional. The data also includes very detailed individual investor characteristics that are not available elsewhere, including postal code, age, sex, identification number of the investor, and details of the trade. A thorough description of an earlier and shorter version of this dataset can be found in Grinblatt and Keloharju (2000).

The Finnish stock market resembles the U.S. market in many ways. For example, a recent survey by the Finnish Foundation for Share Promotion reveals that the average individual stock equity investor in Finland holds only 3.6 stocks, which is close to the 4 stocks held by the average U.S. individual investor.[3] I focus on individuals because

[3]Source: www.nordicum.com, issue 4/2005, page 12.

they live in only one municipality, unlike institutions which can have branches in several municipalities.

While this data set only records direct share holdings and not indirect holdings through mutual funds, mutual funds were rare in Finland during this time period. According to the Helsinki Exchange's 1997 Mutual Fund Report, there were only 42,139 equity mutual fund accounts open in Finland at the end of 1997. Even if each of these accounts belongs to a separate individual, this is quite small compared to the over one million individual investors in this data set.

Of the 62,946,476 total observations in the data set, 56,261,530 involve exchange-traded stocks and 18,180,860 (32 percent) of these are non-cancelled trades by individuals residing in reported municipalities. I exclude transactions not involving the exchange: inheritances, gifts, swaps, option exercises, marriage settlements, and direct sales like equity offerings. This eliminates less than one percent of individuals' transactions. The resulting sample is the basis for the estimation.

For the empirical analysis, I use transactions in the twenty stocks with the highest number of trades during the period 12/1994-1/2004. Table 1, Panel A lists the stocks and the percent of total individual investor trades that they comprise.

Table 1 Approximately Here

Nokia accounts for almost 17 percent of the trades by individuals in the database. In the period studied, Nokia represented over half of the Finnish market capitalization. In 2000 there were 94,500 Nokia common shareholders and 4,693,000 shares outstanding, but no shareholder owned five percent or more of the stock. In 2001, approximately one quarter of the trades originated in the United States, fifteen percent in Sweden, and less than one percent were traded by foreigners on the Helsinki exchange.

The second most traded stock, Sonera, is a Finnish telecommunications company headquartered in Helsinki. It was quite actively traded during its short public existence from 1999 to 2002 when merged with Telia, and represents seven percent of the individual trades in the database.

The other 18 stocks are technology and telecommunications firms, financial firms, and a paper mill, and each account for between 1 and 3.5 percent of the total number of individual trades. The top twenty stocks used in this study make up 58.3 percent of all trades by individuals. The firms range in average market cap over the period from 153 million euros to 75 billion. Some are located in just one municipality, but one firm has locations in as many as 24, according to the addresses listed on company web sites.

A.2. Illustration: A Map of Finland

Finland covers approximately 11,600 square miles (1 square mile = 2.590 square kilometers approximately) and is subdivided into 3000 zip codes, 444 municipalities, and 20 regions. Figure 1 contains yearly maps of Finland for 1997 to 2001. For visual clarity in the maps, I aggregate the zip codes into 100 sections averaging 116 square miles each. The dark circles represent sections where buy transactions outnumber sell transactions in Nokia stock and the clear circles represent sections where sells outnumber buys. It is apparent that these areas form a geographic pattern, and this pattern evolves over time as would an epidemic. Further, the evolution of the buying patterns coincides with the price rise of 2000. In 2000 and 2001, all zip codes have more individual investor buys than sells. Thus, institutional and foreign investors were net sellers during this period. This suggests that individuals may have been influential, at least for the smaller stocks that are traded mostly in Finland, in determining stock prices, during the "bubble" period. The next section begins to examine this relation in the data.

Figure 1 Approximately Here

B. Variables

B.1. Social Interaction

Table 1, Panel B presents firm-level summary statistics of the variables used in the model. If $SIpi$ is high in a particular group, there is more potential for socially motivated trades. I measure share holdings directly by counting how many people own the stock in each municipality on each day.

To obtain an estimate of the number of investors in each postal code, I sum the number of individuals who have made any trade in any asset over the past year and over the next year. The results are similar if the number of investors is defined as all people who made a trade in the database. The total population of individuals who have made any trade in the database is is 1,211,121. There were approximately 5,100,000 people in Finland during our sample period and 3,400,000 were between the ages of 15 and 64. It appears that many of these did not participate directly in the equity market.

B.2. Control Variables Measuring Other Determinants of Trade

Other variables used in this study are meant to control for potential determinants of individual trade in equities as described in the previous section. Summary statistics of the municipality-level variables appear in Table 2. In this table, but not in the estimation, the 444 municipalities are grouped into 20 regions.

Table 2 Approximately Here

To control for the effects that news about a stock may have on trading, $News_{j,t}$, is the number of news articles published in the Finnish and major European business journals about firm j on days t and $t-1$. The journal articles were gathered from Factiva. The average number of articles per day ranges from 0.3 to 1.1, with a standard deviation ranging from 0.7 to 3 depending on the stock. For a typical stock, there is no news for many days and then a flurry of articles as an event occurs. Note that I did not attempt to classify the news as good or bad, because it is difficult to know investor expectations before the news event occurred. Many events might be interpreted as good news by some investors and bad news by others.

Past weekly return, $LReturn_{j,t}$, is the return on stock j from days $t-8$ to $t-1$, taken from Datastream. $LVolume_{j,t}$ is the previous day's volume for stock j and is meant to control for the stock-level attention that high volume attracts. This variable was garnered from the database of trades.

Municipality-level $Income_i$ is measured by the average income in municipality i from Statistics Finland. The data were gathered in 2000, which is in the middle of the sample period of the Finnish trading data. Since the population's growth rate is less than one half of a percent per year, I assume that it also remains fairly stable in its demographic structure throughout the sample period.

In the Robustness section, I describe other variables that, though they are sometimes statistically significant, do not change the significance of the results and are thus are not included in the model tabulated here. These include lagged buys and sells per investor, additional lags of past volume and returns, other municipality characteristics such as education, and the squared number of owners per investor and population size to rule out any potential dependencies on size.

C. Model Estimation and Results

C.1. Estimation procedure

I estimate the model described in the previous section monthly for each of the 20 stocks in a panel tobit setup with municipality random effects. I use a panel model in order to account for municipality effects, and I use a tobit model because the dependent variables, daily buys and sells per investor, can only assume zero or positive values. Unlike in linear regression, in a tobit model there is a positive probability that the dependent variable is zero and no probability of negative values. A good reference for information about the tobit model is Wooldridge (2002).

In this setup, I use random municipality effects because the maximum likelihood estimator in nonlinear panel data models with fixed effects is known to be biased and inconsistent. This is due to the "incidental parameters problem" when T, the length of the time-series, is fixed (See Neyman and Scott (1948)). The random effects tobit model corrects for cluster effects in the covariance matrix and autocorrelation in the error terms.[4] Controlling for cluster effects automatically controls for heteroskedasticity. Unfortunately, there is no consensus on an appropriate R^2 measure for panel tobit models.

The expected number of trades per investor may change over time due to influences possibly not captured by any of the control variables. Due to the size of the data set, I can alleviate this potential problem by estimating the model monthly with daily data for each stock. The aggregate results appear in Tables 3 and 4.

C.2. Estimation Results

Table 3 presents the estimated parameters for buys and sells alone, without control variables. Median p-values and the percentage of positive values are presented in smaller type below the estimates (means are similar and therefore not presented). I

[4]I thank William Greene at NYU for providing this insight.

bold a median coefficient in the tables and refer to it as 'statistically significant' when at least 90 percent of the coefficients are positive and the median p-value is below .10. The coefficients in the tables are multiplied by 10,000. For example, in Table 3, the coefficient on $SIpi$ for Nokia buys has a median value of .02/10,000, and 100 percent of the 108 (Table, Panel A) monthly estimations have positive coefficients. Further, the median p-value for these estimations was 0.00. Mean p-values are similar and not displayed. In Table 3, without any control variables, the coefficients are statistically significant at the ten percent level for each stock.

Table 3 Approximately Here

Table 4, Panels A and B present the estimated parameters with the control variables included in the model. The social parameters are positive in at least 96 percent of months and the median p-value is below .10 in 19 out of 20 cases for both buys and sells. Nokia and Sonera, the most frequently traded stocks, have smaller coefficients, suggesting that social effects are weaker for the most liquid stocks.

Table 4 Approximately Here

$Nholdpi$, the percentage of investors who own the stock, has a positive median coefficient in 14 cases out of 20, and significantly positive for 6 stocks. For sells, the median coefficient is positive in 17 out of 20 cases, and statistically significant in 8 cases. This reflects the fact that only stock owners can sell the stock, and the higher the percentage of owners in a municipality, the more sales per person there are likely to be.

The median monthly coefficient on $News$ is positive in 19 out of 20 cases for buys, and 18 out of 20 cases for sells, although the sign changes many times on a month-to-month basis. The combination of low median p-values and ambiguous (though usually positive) sign of the relation suggests that both buys and sells are generally related to the amount of recent news about the firm, but that some news dampens the desire to buy, to sell, or both. Investors might sometimes adopt a 'wait and see' attitude, expecting more news. It is difficult to construct a variable that consistently measures investor expectations about a stock and the direction of the changes in those expectations brought about by news, but it is likely that the effect of news is stable in each particular month in which I estimate the model.

$LReturn$ is generally negatively related to buys and positively related to sells, and this relation is much stronger for sells. The negative relation with sells is consistent with the disposition effect, in which individuals tend to sell their winning stocks and hold onto their losers. The results for buys indicate that investors tend to look for stocks that have recently fallen in value, possibly in the hope that they will rebound. $LVolume$ has no consistent relation to buys or sells.

The municipality-specific variables are also related to trading behavior. $Income$ is always positive and significant in most cases. Thus, municipalities with more income per investor trade more. Population density ($Popdens$) is generally positively related to trading, although the effect is not as strong as that of $Income$.

D. Economic Significance

To examine the economic significance of the results, I compute the estimated percentage change in the number of individual buys and sells for a one percent change[5] in each explanatory variable. The results are presented in Panel A of Table 5, and here I discuss only the variables that were statistically significant in the tables. A one percent change in $SIpi$ is associated with a two percent increase in the number of subsequent individual buys, and also a two percent increase in the number of individual sells. In comparison, A one percent change in the proportion of owners of the stock increases buys by 2 percent and sells by 7 percent. A one percent change in the number of news articles has a more modest effect, at one percent for both buys and sells. *Income* has a very large effect, and a one percent change is associated with 61 and 89 percent change in trading. Recall that this is a purely cross-sectional implication since I have only one income estimate in 2000 for each municipality. This is likely due to the presence of high-income Helsinki in the sample. In untabulated results, I remove Helsinki and the coefficient on income drops by 2/3 and is much less often statistically significant.

Table 5 Approximately Here

[5] I do not compute the effect of a one-standard deviation change in the variables because some have no time-series standard deviation, and the cross-sectional standard deviation is not a meaningful measure of variability for one municipality.

E. Returns

In a situation where a trade in one direction is likely to prompt others, investors cannot distinguish which trades convey information. The stock price is likely to change at each trade even when there is no new information, making reversals possible later. In this section, I test whether social trading affects stock returns.

Llorente, Michaely, Saar, and Wang (2002), show, in a sample of NYSE and AMEX stocks, that returns generated by trades that do not appear to contain information are subsequently reversed, while returns generated by trades they label as informed have a permanent impact on prices. To examine the effect of social trading on returns, I form an equal-weighted portfolio of the 20 stocks. I investigate the time-series relation between a monthly measure of the total number of buys and sells caused by social interaction, respectively $Socialbuys_{j,t} = \beta_{j,b,social} * S_{j,t} * I_{j,t}$ and $SocialSells_{j,t} = \beta_{j,s,social} * S_{j,t} * I_{j,t}$, equally weighted over firms j, and the raw monthly returns on the portfolio.

The results are presented in Table 6, Panel A. Heteroskedasticity-robust p-values are in parentheses and bolded terms are significant at the ten percent level. The table shows that returns are positively related to social buys in the current month and following month, but only the following month is statistically significant. The socially motivated sales paint a different picture. Social sales are negatively related to returns in the current month but not in the following month. The coefficient is positive in the following month but not significant, so we cannot conclude that there are reversals in the price effect of social trading. Since there are no apparent reversals in returns in the next month for the effects of social buys or sells, the information shared between investors seems to have some merit in predicting at least short-term stock returns.

Table 6 Approximately Here

Since contemporaneous returns are related to the amount of social buying and selling, can these return effects be predicted? The social variables are quite predictable. Adjusted R^2s for the prediction of $SocialBuys$ and $SocialSells$ based on their first two lags are .48 and .63, respectively. The results of regressing monthly returns on the predicted $\widehat{SocialBuys}$ and $\widehat{SocialSells}$ appear in Table 6, Panel A. Both $\widehat{SocialBuys}$ and $\widehat{SocialSells}$ are significantly related to returns.

As control variables in the model of returns, I include the total number of individual buys and sells. Total buys are negatively related to returns in the current and two subsequent months, and total sells are positively related to returns in the current month, but the relation is ambiguous for subsequent months. Linnainmaa (2007) conjectures that well-informed institutions pick off individuals' stale limit orders, so that contemporaneous returns vary in the opposite direction as individual investor trades. This effect is distinct from the effect of trades due to social interaction. While limit orders that get picked off by institutions are stale trades, likely from past days or weeks, trades motivated by recent social interaction are more likely to be active trades. In untabulated results, I re-estimate the model including buy and sell volume or lagged monthly returns. Inclusion of these variables does not change the significance of the social parameters. R^2s from the regressions in the table range from 0.06 to 0.55 for the full model.

Table 6, Panel B presents two of the results of Table 6, Panel A on a stock-by-stock basis. Some stocks do not exist for many months, so it is not possible to include all of the control variables, but the pattern is similar to that found in the equal-weighted index. For $SocialBuys$, 16 out of 20 coefficients are positive, and 15 out of 20 are negative for $SocialSells$. For $\widehat{SocialBuys}$, 17 out of 20 coefficients are positive, and 13 out of 20 are negative for $\widehat{SocialSells}$.

Last, Granger causality test results after a VAR with three lags, $SocialBuys$ and $SocialSells$ together Granger-cause returns ($p = .01$), but return does not Granger-cause either of these variables ($p = .26$ and $p = .96$, for $SocialBuys$ and $SocialSells$).

IV. Robustness Tests on the Specification

A. Omitted Variables

It is possible that a variable omitted from the model and correlated with the social variable is the true driver of trades. While this is difficult to imagine because the social variable varies daily and by municipality, I have re-estimated the results using several other control variables. Adding in the number of owners per investor, $Nholdpi$, in the buy model or the squared number of owners divided by the number of investors in either equation does not change the results. Adding the total population size of a municipality, its area, the average age and percentage of males also has no effect. Population density, the interaction of population density with $SIpi$, and the interaction of $Nholdpi$ with each of the other variables also does not affect the significance of $SIpi$, although the magnitude of the coefficient sometimes increases. Finally, past returns on each stock at monthly or yearly horizons, and past volume and number of buys and sells per investor at weekly or yearly horizons do not change the results.

Potentially, the dependent variable, although it is already a ratio of the number of trades per investor, is still related to population size. If the social interaction variable is also related to size, the significance of the results might be unduly increased. In robustness tests, I control for both total population size, number of investors, and lagged number of buys and sells per investor, and this does not affect the significance of the results.

B. Number of Areas

Most people reside and work in the same municipality, and the spatial granularity of the data was chosen to reflect this. However, it is reasonable to question whether the result is sensitive to this choice. The smaller the areas being considered, the more area-day observations there are but fewer trades can be identified as caused by social influence, since influence between areas is not measured. On the other hand, with larger areas there will be more trades per area and fewer area effects, and thus the parameters should be more precisely estimated. To investigate whether the result is robust to the chosen granularity of the data, I replicate the results for both the 20 major Finnish regions and 100 areas obtained by aggregating the 444 municipalities, and find similar results.

A related question is whether the coefficients vary with area size. Although controlling for area size does not dampen the significance of $SIpi$ as mentioned above, it is still plausible that the coefficients are different, since $SIpi$ tends to be much larger for large areas. Although this is unlikely given the results of the previous paragraph, potentially only one area size is driving the results. To investigate this possibility, I re-estimate the model for the lowest quartile (less than 133 investors), the middle half (133-578 investors), and the largest quartile of municipality sizes measured by the number of investors in each municipality. The untabulated results show that the coefficients are much larger for the smallest municipalities than for the larger municipalities as would be expected given the multiplicative nature of the variable, but remain generally significant across all size bins.

One possible reaction to this would be to divide $SIpi$ again by N. In effect, this would be modeling the proportion of new infections as the product of the proportion of infected times the proportion of susceptible people. Intuitively, this assumes that people interact only with a fixed number of people no matter what the population size of their area. The truth is likely to lie somewhere in between the two specifications.

Although such a setup is also occasionally used in epidemiology, a model with N^2 in the denominator is not appealing in my study for two reasons. While the assumption of a fixed number of contacts may be reasonable for sexually transmitted diseases for example, it does not describe the transmission of ideas well and in rumor models (Moreno, Nekovee, and Pacheco (2004)), which are closer in spirit to this paper, tend to use the original setup with N. The second reason that this variable would not work well here is that it is that $S \times I/N^2$ is typically very highly correlated with the number of owners per investor, I/N. While there is no reason to put I/N in an epidemic model for disease transmission, it is meaningful economically, especially when modeling sales per investor when short sales are not allowed.

C. Range of the Data

The model assumes that the population N of investors in the area remains stable over the (monthly) estimation period. In this case, the product of S and I is increasing while the number of infected make up less than half of the population, and decreasing in I thereafter. The number of people infected per period is uniformly increasing in $SIpi$, so the infection rate will slow down as more people become infected. Table 1, Panel B shows that the number of owners per investor remains in the range where $SIpi$ is increasing in I. The maximum mean number of owners per investor is for Sonera, where it is at .23 with a standard deviation of .15 The minimum average is for Tietoenator and Stonesoft, where 2 percent of investors own the stock. While it would be interesting to test if the number of buys per investor is still increasing in $SIpi$ when this variable is decreasing in the number of investors, the data do not permit this test. Given the increasing number of stocks that investors have to choose from, it is likely that the percentage of investors owning each particular security will continue to fall.

D. A Pure Time-Series Specification

One could also estimate time-series tobit models for each one of the regions, and investigate (and make sure there exists) a purely time-series relation of buys and sells to $SIpi$. The benefit of this specification is that one can see if $SIpi$ is related to trading in a time-series manner rather than in a more cross-sectional manner, and a monthly specification may not capture much variation in $SIpi$. The disadvantage of this type of model is that there is no consensus in the literature on how to correct for the large growth in participation and trading over the nine years of the data set.

For each stock j, I estimate the following tobit models on each municipality that trades the stock for at least 50 months during the sample period.

$$\begin{aligned}\text{Total Buys Per Investor}_{i,j,t} = {} & \beta_{j,b,social} * SIpi_{i,j,t} \\ & + \beta_{j,b,News} * News_{j,t} + \beta_{j,b,LR} * LReturn_{j,t} + \beta_{j,b,LV} * LVolume_{j,t} \\ & + Lag\,Total\ Buys\ Per\ Investor_{i,j,t}\end{aligned}$$

$$\begin{aligned}\text{Total Sells Per Investor}_{i,j,t} = {} & \beta_{j,s,social} SIpi_{i,j,t} + \beta_{j,s,Owners} * Nholdpi_{i,j,t} \\ & + \beta_{j,s,News} * News_{j,t} + \beta_{j,s,LR} * LReturn_{j,t} + \beta_{j,b,LV} * LVolume_{j,t} \\ & + Lag\,Total\ Sells\ Per\ Investor_{i,j,t}\end{aligned}$$

There are two differences between these models and the models for buys and sells presented in Table 4. First, municipality characteristics do not appear because this model is run individually on each municipality. Second, I include lagged total buys and total sells per investor in an attempt to correct for the trend in total buys and sells over time. While I include these as well in robustness checks in the model presented in Table 4, and they do not affect the results, this model spans over nine years, and so they are likely to be crucial.

In the model for buys, the median coefficients on $SIpi$ are positive in 19 cases out of 20 and significant in 12 of these cases. For sells, the coefficient on $SIpi$ is positive in 16 out of 20 cases, 9 of which are significant, and is significantly negative in one case. I choose the model presented in Table 4, however, to alleviate potential concerns about correctly controlling for the effects of participation rates and expected volume changes over the 9-year time period.

E. A Negative Binomial Model

As an alternative to the tobit specification, one could describe the number of individual trades with a count model. an appropriate count model for this setup is the zero-inflated negative binomial (ZINB) model, a more general variant of the Poisson model. The zero inflation is necessary because there are many 'zero' observations in this data. A zero-inflated model assumes that the data are from two processes, one of which generates only zeros. In this a model, the independent variables are the total number of investors, the social effect variable measured as the total number of owners times the number of non-owners, and the municipalities' total income, as well as the other control variables left as they are.

A ZINB model produces strong significance for both the social interaction factor and for the measure of total investor population. I choose the tobit model of trades per investor instead, however, because this eliminates the correlation between the measure of social interaction (S*I) and the measure of the number of investors $(S+I)$, which is sometimes high. Correlations like these can inflate coefficients and would preclude a study of the economic significance of the social effect. Linear regressions produce equally strong results, but are inappropriate due to the strictly positive dependent variable.

F. A Testable Prediction: Is Social Trading Related Across Municipalities?

Although it is consistent across different municipality sizes, the analysis in this paper measures social interactions inside municipalities only, and ignores any possible influence across municipalities. If there is in fact social influence on individual trading, some of this influence should spill over into neighboring municipalities. In this section, I use two measures of spatial correlation to address this question, Moran's I and Geary's C.

Moran's I divides the spatial autocovariance by the variance of the data. It is computed as follows:

$$\text{Moran's } I = \frac{N}{S_0} \frac{\Sigma_{i=1}^{N} \Sigma_{j=1}^{N} w(i,j)(x_i - \bar{x})(x_j - \bar{x})}{\Sigma_{i=1}^{N} (x_i - \bar{x})^2},$$

where N is the number of municipalities, and x is $\beta_{b,social}$ or $\beta_{s,social}$ estimated across all months value for each municipality, with year-month random effects. $\bar{x}$ is the mean of the x_i, $w(i,j)$ is 1 if regions i and j are neighbors and zero otherwise, and S_0 is the sum of all of the $w(i,j)$. I use the coefficients only and not the number of social trades, in order to analyze the propensity to trade socially in isolation of the opportunities for social influence, which are naturally spatially correlated due to population density.

The expected value of Moran's I is $-1/(N-1)$, so one cannot compare results across stocks where N may differ. A negative value of Moran's I signifies negative spatial correlation and a positive value signifies positive spatial correlation.

Geary's C divides the sum of squared differences between pairs of data, instead of deviations from the mean, by the variance of the data. This is perhaps more relevant in this study where there are many municipalities. The formula for Geary's C is as follows:

$$\text{Geary's } C = \frac{N-1}{2S_0} \frac{\Sigma_{i=1}^{N}\Sigma_{j=1}^{N} w(i,j)(x_i - x_j)^2}{\Sigma_{i=1}^{N}(x_i - \bar{x})^2}$$

The expected value of Geary's C is 1. A Geary's C above 1 signifies negative spatial correlation, while a value below 1 signifies positive spatial correlation.

These measures require a matrix of ones and zeros which conveys which municipalities are neighbors. I determine this by using the spatial coordinates of each municipality and by specifying a maximum distance between municipality centers for them to be defined as neighbors.

The theoretical bounds on Moran's I and Geary's C can be tighter than [-1,1] and [0,2], respectively, depending on the characteristics of the space and of the weight matrix. In this study, the weighting matrix is sparse because most of the 444 municipalities are not neighbors to most other municipalities. Since the weighting matrix is composed of zeros except where one region is a neighbor to the other, the realized measures of spatial correlation will be low in absolute value.

Table 7 shows the results of these calculations for both buys and sells for each stock. Bolded terms are significant at the ten percent level. The table shows that the two measures of spatial correlation are consistent in picking up positive spatial correlation, for both the 25 kilometer and 50 kilometer criteria for municipalities to be considered neighbors. Consistent with the theory that social effects are local, the coefficients are slightly weaker when the definition of neighbors is expanded to a 50 kilometer radius.

Table 7 Approximately Here

V. Alternative Explanations

Models of endogenous effects are subject to what Manski (1993) terms the "reflection problem." Inferring whether the average behavior of a group influences the behavior of an individual is difficult because one can not disentangle the effects of almost simultaneous actions on the part of the group and of the individual. The dynamic model of trading in this study avoids this problem because the social variable is measured before trading occurs on each day.

Although the model also controls for known determinants of individual investor trade and is robust to the inclusion of a variety of other variables and to different specifications, I investigate several alternative explanations for these results, including unobserved municipality-level characteristics, insider trading, local news, TV and radio, local stock brokers, and tax-loss trading.

A. Insiders and the Location of Firms

It could be that the effects found here are driven solely by employees of the firms. Employee trades will be correlated in time, clustering when they receive relevant information, and in space, since employees most likely live near their work place. To investigate whether employees are driving the results, I exclude all of the municipalities where each firm operates and re-estimate the model. The number of municipalities thus excluded for each firm can be found in Table 1 on the right-most column. About half of the firms have headquarters in one city which is usually Helsinki. The other half have multiple locations. One firm, Tietoenator, has 155 Finnish locations in 24 municipalities. In untabulated results,[6] The effect of social interaction is slightly stronger when the firm's locations are removed. This could be because there is less likely to be local news about the firm in an area far away from its location, and thus more need to rely on information gleaned from social interaction.

B. Current Owners Purchasing Again

Possibly, investors are not communicating but current share owners are buying the same stock repeatedly. I control for the number of owners in the sell equation because only owners may legally sell the stock, so this is only a concern for the buy equation. As specified in the robustness section, I control for both the number of owners per investor in the buy equation and the squared number of owners per investor in both equations, and find that they do not affect the results.

[6] Available upon request.

C. News Not Covered in National Newspapers

C.1. Local Newspapers

While I have controlled for the daily number of articles in the Finnish national and major European newspapers that investors are likely to read, I have not controlled for the number of articles from local newspapers. Potentially, daily local news about the companies could drive the results. It is unlikely that the daily local news about a stock is related to the prior day's product of the number of owners times the number of non-owners of a stock, unless the resulting discussions about the stock make it into the local news. Moreover, since I have controlled for national news and run the model without local companies in the prior section, the local news would have to be both about non-local stocks and also unrelated to the news in the national newspapers. Nevertheless, to test the possibility that local news is driving the effect, I investigate all 94 Finnish local newspapers listed on the website Onlinenewspapers.com. Of these, 74 have working web sites in May 2007. I search for a a section related to investing, and find that 17 newspapers have company news on the front page or a section labeled "Talous" (Finnish), or "Ekonomi" (Swedish) for "Economy." This is a broad topic, and 4 of the 17 newspapers do not mention any company name in this section. The most common sub-sections in these local newspapers seem to be variants of "Mielipide" (opinion), "Urheilu" (sports), and "Kulttuuri" (culture). This agrees well with statistics Finland's report that only 8 to 9 percent of local newspaper space was devoted to the Economy between 1991 and 2000. Given these results, I am confident that local newspapers are unlikely to cause the daily patterns in individual investor trades.

C.2. TV and Radio

According to Statistics Finland, The Finnish television market in 2000 was less than half the size of the newspaper market, which was 1,166 million euros in 2000. Approximately 56 percent of the Finnish population watched television on a given day during the period, and 85 percent listened to radio. Approximately 20 percent of the programming of the three main channels was either news or current affairs, which would include some firm-level news. While I cannot investigate the historical television and radio news stories, the firm-level news is likely to be correlated with that which is found in the daily newspapers, especially since it is predominantly national news. As with the newspapers, any local news would have to be about non-local stocks, since I have removed the local stocks in a previous robustness check.

D. Local Brokers

Possibly, the effect presented here is driven by local brokers in each municipality who are pushing stocks daily to their clients in a manner that is unrelated to daily news. Finland is much like the United States in terms of investing in individual stocks. There are approximately 150 members and 1200 authorized brokers on on the Helsinki exchange. Trading by individuals can take place in person at a branch, over the phone or via the internet. Given the many brokers and methods of trading that are available to each investor, I believe it is unlikely that individual stock brokers alone could influence significant numbers of traders. Furthermore, if local brokers are behind individual investor trades, one would expect that the number of buys and sells is related to the number of investors in a municipality, measured by the intercept, since this is a model of trades per investor. Although it is often significant, the intercept is not shown in the tables in order to preserve space and because it could capture many different unobserved municipality-level characteristics. In any case, the interaction term measuring social influence remains significant.

E. Tax-Loss Trading

Investors may trade solely to realize their losses and lessen their taxes. This type of trading could not be responsible for the entire effect measured here, because it should only affect the sale of securities and not the purchases. Nevertheless, I re-estimate the results after deleting all December estimates. The results are similar and are not reported.

VI. Characterization of Social Effects

A. The Determinants of Social Trading

To examine the factors that influence social trading, I regress median firm-level estimates of *avgsocial*, which is the average over all firms j of $(\beta_{i,j,b,social} + \beta_{i,j,s,social})$, for each municipality i, on municipality-level variables. I sum the two betas because they are each a positive measure of the propensity to trade socially. The municipality-level variables are from Statistics Finland and are summarized in Table 2.

The first variable that might explain the propensity to trade socially, *Swedish*, is the percent of Swedish-speaking people in the municipality. Swedish people are the largest minority in Finland, and possibly their social and investing habits are different from those of the majority. *Dtowork* is the average distance to work in kilometers. It is meant to capture possible differences in social investing if a person resides far away from his or her work, and thus may not have time to interact with colleagues in her leisure time (Note that this is not the same thing as population density, which I control for in the robustness section). I expect *Dtowork* to have a negative effect on social trading, but it is possible that large social networks exist outside of a person's work, in which case the predicted sign may be positive.

I also include *Univ*, the percentage of people who hold university degrees, and *Income*, the median income of the municipality. It is not a priori clear if these will help explain social-interaction-based trading. *T.O.*, the turnover of inhabitants of the municipality, should decrease the social trading effect by breaking social bonds, and *Kioskspp*, the number of kiosks per person in the municipality, is meant to proxy for news, an alternative source of information available to investors. If more kiosks means more availability of timely information about firms, investors may rely less on their acquaintances. Alternatively, availability of financial news might make stocks the topic of conversation more often.

The results of these cross-sectional regressions are presented by firm in Table 8. Panel A presents a correlation matrix, and Panel B presents the univariate and multivariate regressions. The coefficient of *Swedish* is insignificant, suggesting that Swedes and Finns have the same propensity to trade socially. *Dtowork* is significant and positive. It seems that access to work colleagues at non-work hours is not a determinant of increased social trading. *Univ* and *Income* are negative and significant on their own, but the significance goes away in the multivariate setting. Since their correlation coefficient is .85, they most likely are measuring similar things. This, and the sign of the coefficient on distance to work, hints that trades from rural municipalities are more likely to be social. *Turnover* is not a significant factor of social trading, and *Kioskspp* is negatively related to social trading, which supports the idea that availability of news lessens social influence on trading. In brief, social trading is not explained well by any of the static, municipality-level characteristics shown here.

Table 8 Approximately Here

B. Social Effects Over Time

An important question is whether, in the more recent days of the internet and easy access to news, social influence on trading behavior has changed. The first panel of Figure 2 shows the estimated average sum of daily social buys and sells per municipality over the sample period, which is $\beta_{b,social} S_t * I_t$ and $\beta_{s,social} S_t * I_t$. This figure shows an increasing pattern over time. The second panel of Figure 2 shows the equal weighted average of the buying parameters, $\beta_{b,social}$ and selling parameters, $\beta_{s,social}$. In the background is the average, $S * I$. This figure suggests that susceptibility to social influence is generally decreasing over time, but that the social factors, $S_t * I_t$, are increasing. There is a slight decrease near the end of the sample, which corresponds to the bursting of the technology bubble. Perhaps individual investors shrank away from the market at that time. The increase is most likely due to the increasing percentage of stock owners in the population. Thus, increased stock market participation in general, especially when the new investors are naive, may lead to unforseen consequences due to the influences of other traders.

Figure 2 Approximately Here

VII. Conclusion

Using a new measure of social influence on trading, this paper tests whether social influence is an important determinant of daily individual investor trades. Controlling for recent news, past returns, volume, and municipality-level characteristics like education and income, I find significant social effects on individual investor trading in data on all individual investor trades in the twenty most frequently-traded Finnish stocks between 1995 and 2003. The effects of social trading are economically significant.

I also show that socially motivated trading can predict stock returns. Individuals themselves over time have become less susceptible to social influence but they are more subject to it, and thus the number of trades caused by social influence increases slightly over the sample period. In robustness checks, I find that the effect measured by the social variable is not due to employees of the traded firms, to the model specification, or the granularity of the data. I also rule out several alternative explanations.

This study shows that investor location data may also shed light on the nature of price changes and on whether prices are away from fundamental value. The results suggest that the market is fairly efficient, because it would take more information than is easily available about trader location for an investor to spot potential mispricings before they correct themselves. It also implies that policies encouraging investors to collect their own information by lowering the cost of independent research or improving its effectiveness may lessen the amount of socially motivated trading and its effects on prices.

References

Avery, C., and P. Zemsky. "Multidimensional Uncertainty and Herd Behavior in Financial markets." *American Economic Review,* 88 (1998), 724-748.

Banerjee, A. V. "A Simple Model of Herd Behavior," *Quarterly Journal of Economics,* 107 (1992), 797-818.

Bange, M. "Do the Portfolios of Small Investors Reflect Positive Feedback Trading?" *Journal of Financial and Quantitative Analysis,* 35 (2000), 239-255.

Barber, B., and T. Odean. "All that Glitters: The Effect of Attention and News on the Buying Behavior of Individual and Institutional Investors." *Review of Financial Studies,* 21 (2008), 785-818.

Bikhchandani, S.; D. Hirshleifer; and I. Welch. "A Theory of Fads, Fashion, Custom, and Cultural Change as Informational Cascades." *The Journal of Political Economy,* 100 (1992), 992-1026.

Bris, A.; W. Goetzmann; and N. Zhu. "Short Selling," chap. *Short Sales in Global Perspective,* Wiley and Sons (2004).

Brown, J.; Z. Ivkovic; P. Smith; and S. Weisbenner. "Neighbors Matter: Community Effects and Stock Market Participation." *Forthcoming, Journal of Finance.*

Feng, L., and M. Seasholes. "Correlated Trading and Location." *Journal of Finance,* 59 (2004), 2117-2144.

Frieder, L., and A. Subrahmanyam. "Brand Perceptions and the Market for Common Stock." *Journal of Financial and Quantitative Analysis,* 40 (2005), 57-85.

Griffin, J. M.; F. Nardari; and R. M. Stulz. "Do Investors Trade More When Stocks Have Performed Well? Evidence from 46 Countries." *Review of Financial Studies,* 20 (2007), 905-951.

Grinblatt, M. and M. Keloharju. "The investment behavior and performance of various investor-types: A study of Finland's unique data set." *Journal of Financial Economics,* 55 (2000), 43-67.

Grinblatt, M.; M. Keloharju; and S. Ikaheimo. "Social Infludence and Consumption: Evidence from the Automobile Purchases of Neighbors." *Forthcoming, Journal of Economic Perspectives.*

Hong, H.; J. D. Kubik; and J. C. Stein. "Social Interaction and Stock Market Participation." *Journal of Finance,* 59 (2004), 137-163.

Hong, H.; J. D. Kubik; and J. C. Stein. "Thy Neighbor's Portfolio: Word of Mouth Effects in the Holdings and Trade of Money Managers." *Journal of Finance,* 60 (2005), 2801-2824.

Horst, U., and J. Scheinkman. "Equilibria in Systems of Social Interactions." *Journal of Economic Theory,* 130 (2006), 44-77.

Ivkovic, Z., and S. Weisbenner. "Information Diffusion Effects in Individual Investors Common Stock Purchases: covet Thy Neighbors Investment Choices." *Review of Financial Studies,* 20 (2007), 1327-1357.

Kermack, W. O., and A. G. McKendrick. "A Contribution to the Mathematical Theory of Epidemics." Proc. Roy. Soc. Lond, 115 (1927), 700-721.

Linnainmaa, J. "The Limit Order Effect." Working Paper, Chicago GSB (2007).

Llorente, G.; R. Michaely; G. Saar; and J. Wang. "Dynamic Volume-Return Relation of Individual Stocks." *The Review of Financial Studies,* 15 (2002), 1005-1047.

Manski, C. F. "Identification of endogenous social effects: the reflection problem." *Review of Economic Studies,* 60 (1993), 531-542.

Mollison. *Epidemic Models: Their Structure and Relation to the Data,* Cambridge, UK: Cambridge University Press (1995).

Moreno, Y.; M. Nekovee; and A. F. Pacheco. "Dynamics of rumor spreading in complex networks." *Physical Review,* 69 (2004), 066130 1-7.

Neyman, J., and E. Scott. "Consistent estimation from partially consistent Observations." *Econometrica,* 16 (1948), 1-32.

Odean, T. "Are investors reluctant to realize their losses?" *Journal of Finance,* 53 (1998), 1775-1798.

Odean, T. "Do individual Investors Trade Too Much?" *American Economic Review,* 89 (1999), 1279-1298.

Shefrin, H., and M. Statman. "The Disposition to Sell Winners Too Early and Ride Losers Too Long: Theory and Evidence." *Journal of Finance,* 40 (1985), 777-91.

Shiller, R. J. *Market Volatility,* Cambridge, Mass: MIT Press, (1989).

Shiller, R. J. "Conversation, Information, and Herd Behavior." *American Economic Review,* 85 (1995), 181-185.

Shumway, T., and G. Wu. "Does Disposition Drive Momentum?" Working Paper, University of Michigan.

Sorescu, S., and A. Subrahmanyam. "The Cross Section of Analyst Recommendations." *Journal of Financial and Quantitative Analysis,* 41 (2006), 139-168.

Wooldridge, J. *Econometric Analysis of Cross-Section and Panel Data,* Cambridge, MA: MIT Press (2002).

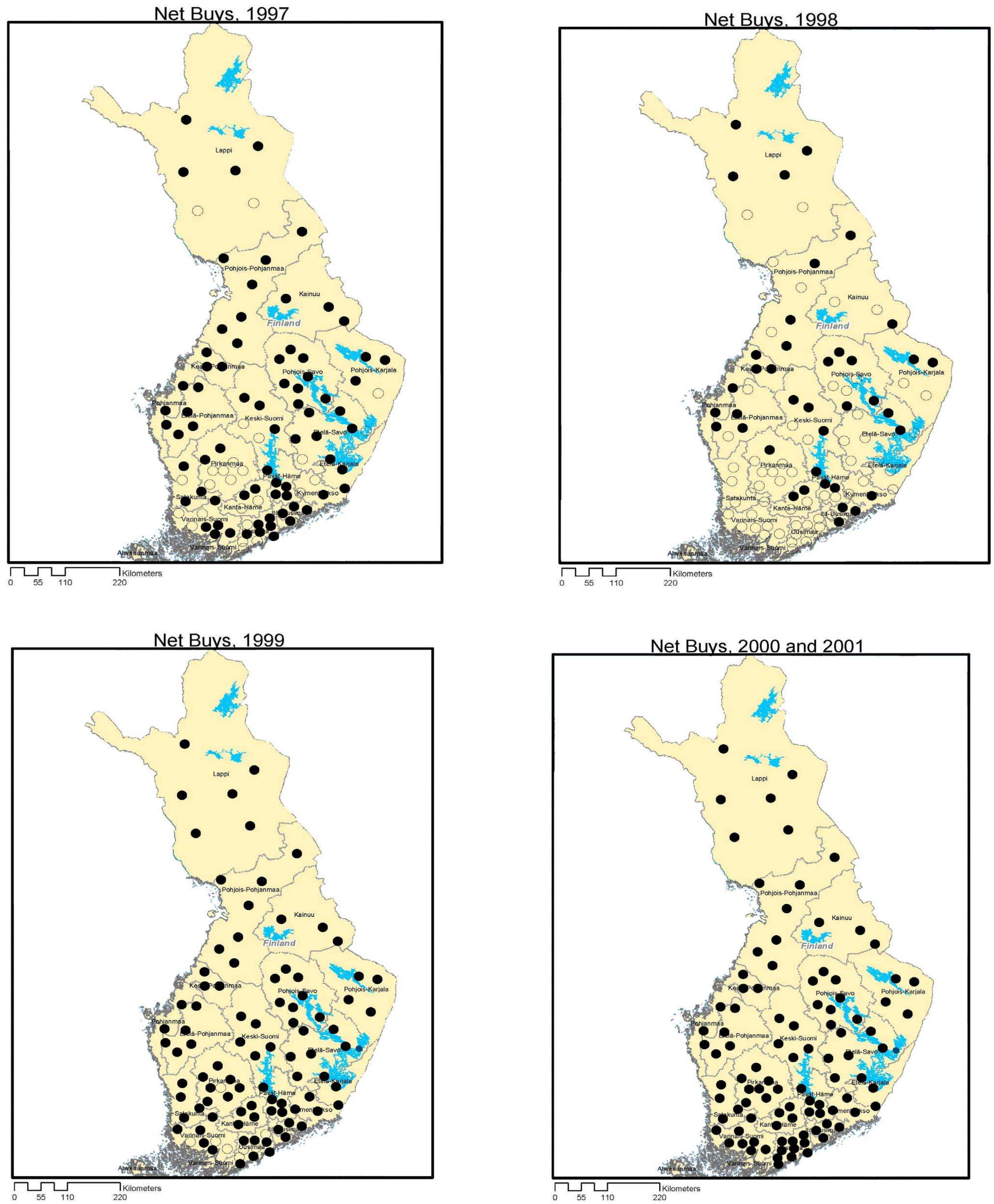

Figure 1. Evolution of the net buy orders in 100 zip code areas, 1997-2001. These maps represent the buy and sell orders of Nokia stock in 100 zip code areas, aggregated from the 444 municipalities. Zip code areas are 116 square miles on average. The empty circles represent areas where there are more sell orders than buy orders. The filled-in circles represent areas where there are more buy orders.

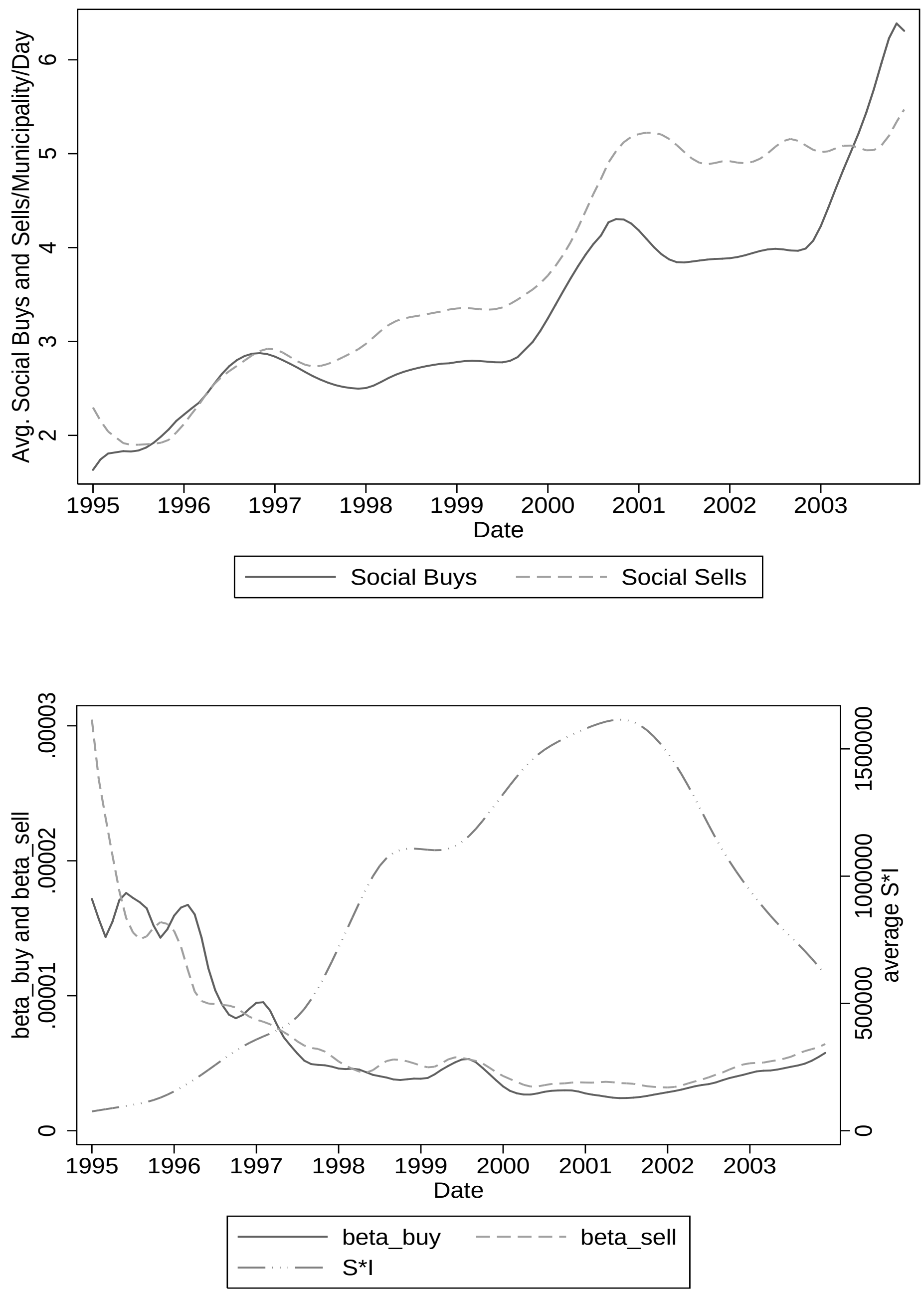

Figure 2. Time-series Plots The top plot is of the median number over the 20 stocks of buys and sells attributed to social interaction, $\beta_{b,social}SI$ and $\beta_{s,social}S_tI_t$, expressed per municipality and per day. The bottom plot shows medians of the number of owners*non-owners, S_tI_t, and of buy and sell social interaction parameters, $\beta_{b,social}$ and $\beta_{s,social}$.

Table 1: Firm Characteristics and Summary Statistics

Panel A: The 20 Most Traded Firms in Finland

Summary statistics of the 20 firms used in the estimation, making up 58 percent of individual investor trades. *% of Total* stands for the percent of total individual investor trades in the database. *Market capitalization* is in millions of Euros and the standard deviation is based on daily data. *Municipalities* is the number of municipalities in which the company has plants or offices.

Firm	Trades in	% of	*Market Cap*		Munici-	Months
Name	Database	Total	Mean	Std	palities	in Sample
Nokia	1,773,314	16.71	75,451	75,140	8	108
Sonera	902,538	8.50	14,052	13,719	1	51
Elektrobit	362,676	3.42	454	511	1	64
Raisio	303,728	2.86	252	237	6	91
UPM	272,228	2.56	6,517	2,456	24	92
Comptel	264,644	2.49	807	854	1	49
F-Secure	256,834	2.42	460	559	1	50
Merita A	232,936	2.19	263	52	7	63
Elisa	220,310	2.08	2,082	1,335	8	53
TJ Group	203,289	1.92	116	196	1	57
Fortum	175,439	1.65	4,419	1,010	1	61
Elcoteq	167,840	1.58	199	173	4	73
Nordea	145,610	1.37	17,015	4,207	2	47
Tietoenator	138,625	1.31	1,546	1,173	24	108
Stonesoft	138,416	1.30	309	385	1	57
Stora Enso	133,653	1.26	1,631	829	10	92
Perlos	130,039	1.23	758	616	9	54
Sampo	129,406	1.22	2,568	1,665	1	78
Eimo	126,703	1.19	153	112	2	57
Pohjola	113,000	1.06	489	344	1	108

Panel B: Firm-Level Summary Statistics

Daily buys and *Daily sells* are the average number of individual buys and sells per municipality per trading day. *SIpi* is the average value of the number of owners in a municipality times the number of non-owners, divided by the total number of investors. *News* is the number of news articles in the Finnish newspapers and the major European business news papers on each day and on the previous day. *Daily volume* is the total daily volume of the shares by all types of traders.

	Daily Buys		*Daily Sells*		*Sipi*		*Weekly Return %*		*Daily News*		*Daily Volume/000*		*Owners per investor*	
Firm	Mean	Std	Mean	Std	Mean	Std	Mean	Std	Mean	Std	Mean	Std	Mean	Std
Nokia	0.95	1.79	0.76	1.33	91.3	59.6	0.57	6.51	1.58	2.50	31,400	57,000	0.18	0.16
Sonera	0.92	1.56	0.87	1.48	128.7	72.2	0.24	9.92	0.40	1.16	14,000	14,400	0.23	0.15
Elektrobit	0.36	0.93	0.23	0.73	57.5	28.4	0.39	9.60	0.13	0.51	921	2,244	0.12	0.07
Raisio	0.16	0.59	0.11	0.46	42.2	25.1	0.39	9.59	0.24	0.67	629	1,624	0.15	0.08
UPM	0.14	0.45	0.14	0.39	90.3	7.0	0.28	4.67	0.65	1.24	3,807	6,046	0.15	0.05
Comptel	0.30	0.75	0.27	0.82	60.2	5.4	0.06	11.43	0.09	0.43	479	803	0.09	0.03
F-Secure	0.27	0.73	0.24	0.68	54.8	12.7	0.20	11.28	0.19	0.62	414	970	0.07	0.05
Merita	0.12	0.37	0.40	0.78	47.3	40.6	0.36	5.51	0.28	0.72	4,445	6,147	0.06	0.04
Elisa	0.05	0.26	0.06	0.24	44.8	13.7	0.07	7.34	0.57	1.17	752	1,044	0.11	0.04
TJ Group	0.21	0.64	0.16	0.56	40.5	60.5	0.13	12.01	0.07	0.31	214	595	0.06	0.03
Fortum	0.12	0.43	0.16	0.50	87.3	12.0	0.23	3.08	0.52	1.17	2,596	8,455	0.18	0.09
Elcoteq	0.13	0.49	0.11	0.41	17.4	7.0	0.13	4.46	0.15	0.51	171	326	0.03	0.02
Nordea	0.08	0.32	0.16	0.45	15.9	8.2	0.04	2.38	0.91	1.69	4,115	9,307	0.04	0.02
Tietoenator	0.04	0.21	0.03	0.20	5.9	3.4	0.82	7.44	0.30	0.68	802	1,565	0.02	0.01
Stonesoft	0.11	0.39	0.10	0.40	13.5	4.5	0.59	13.92	0.06	0.32	255	568	0.02	0.01
Stora Enso	0.08	0.31	0.06	0.25	26.4	7.1	0.29	5.20	0.57	1.08	5,982	10,000	0.04	0.02
Perlos	0.12	0.38	0.11	0.36	24.2	3.3	0.19	9.43	0.09	0.37	335	650	0.03	0.01
Sampo	0.08	0.31	0.06	0.28	57.1	8.9	0.44	5.42	0.41	1.12	2,303	5,412	0.14	0.05
Eimo	0.12	0.41	0.12	0.59	16.8	6.7	0.06	7.92	0.11	0.54	297	1,550	0.03	0.01
Pohjola	0.05	0.28	0.04	0.22	15.8	9.0	0.72	5.39	0.24	0.70	286	530	0.04	0.02

Table 2: Municipality-Level Summary Statistics

There are 444 municipalities grouped into 20 regions. #M is the number of municipalities in each region. *Pop* is the average municipality population. *Income* is the average individual yearly income in euros across all 444 municipalities. *Popdens* is the population per square km, *Swedish* is the percentage of Swedish speakers in the municipality, *Dtowork* is the average distance to work in km, and *Income* is the average income of the municipality. *T.O.* the proportion of the population that moves in or out each year, and *Kioskspp* is the number of news kiosks per inhabitant. *Univ* is the average percentage of people with a college education across all municipalities. All municipality-level data are from Statistics Finland.

	Municipality Averages								
Name	*#M*	*Pop*	*Income*	*Popdens*	*Swedish*	*Dtowork*	*T.O.*	*Kioskspp*	*Univ*
Uusimaa	24	55758	24681	197.7	7	22	0.0020	0.00035	18
Varsinais-Suomi	56	8079	19068	41.6	5	14	0.0028	0.00029	11
Satakunta	28	8385	17450	26.8	0	11	-0.0014	0.00032	8
Kanta-Hme	16	10416	18265	29.2	0	13	0.0047	0.00028	8
Pirkanmaa	33	13858	18833	31.9	0	14	0.0058	0.00025	11
Pijt-Hme	12	16536	17849	31.7	0	12	0.0024	0.00037	8
Kymenlaakso	12	15472	18508	33.2	0	12	0.0002	0.00036	7
S. Karelia	14	9736	17757	18.8	0	13	0.0005	0.00037	8
Etel-Savo	20	8115	16019	8.6	0	12	-0.0023	0.00032	7
Pohjois-Savo	25	10054	16488	12.3	0	13	-0.0014	0.00028	8
N. Karelia	19	8902	15603	7.8	0	15	-0.0017	0.00034	8
Central Finland	30	8869	17188	13.4	0	13	0.0026	0.00029	10
S. Ostrobothnia	27	7183	16172	13.8	0	12	-0.0005	0.00025	6
Ostrobothnia	18	9617	18233	22	52	13	-0.0008	0.00023	10
C. Ostrobothnia	12	5882	16516	12.8	9	13	-0.0046	0.00034	7
N. Ostrobothnia	40	9298	17791	10	0	17	-0.0009	0.00028	11
Kainuu	10	8657	15492	3.5	0	15	-0.0064	0.00023	7
Lapland	22	8496	16370	1.8	0	23	-0.0044	0.00038	7
It-Uusimaa	10	9169	21141	32.4	33	13	0.0064	0.00037	10
Åland	16	1647	23059	16.9	92	49	0.0038	0.00053	9
Total	444	5219732	19463	15.4	5	17	0.0011	0.00031	11

Table 3. Univariate Panel Tobit for Buys and Sells

The dependent variables are daily buys per investor and daily sells per investor, with municipality random effects. Median parameter values by stock. *SIpi* is the owners times non-owners of the stock per investor in the municipality. Coefficients are multiplied by 10,000. Percentage of positive coefficients and median p-values are below estimates. Bolded terms have median p-values below .10 and have 90 percent of estimates the same sign.

	Buys		Sells	
Firm	*SIpi*	Constant	*SIpi*	Constant
Nokia	**0.02**	**80.63**	**0.03**	**83.78**
	100, 0.00	95, 0.00	95, 0.00	95, 0.00
Sonera	**0.02**	**62.24**	**0.02**	**68.22**
	100, 0.00	100, 0.00	100, 0.00	100, 0.00
Elektrobit	**0.08**	**13.23**	**0.04**	**57.84**
	100, 0.00	100, 0.00	100, 0.00	100, 0.00
Raisio	**0.18**	**2.16**	**0.20**	**2.65**
	100, 0.00	100, 0.00	100, 0.00	100, 0.00
UPM	**0.03**	**1.93**	**0.03**	**1.95**
	100, 0.00	100, 0.00	100, 0.00	100, 0.00
Comptel	**0.06**	**52.83**	**0.06**	**57.81**
	100, 0.00	100, 0.00	100, 0.00	100, 0.00
F-Secure	**0.05**	**2.74**	**0.06**	**2.93**
	100, 0.00	100, 0.00	100, 0.00	100, 0.00
Merita	**0.07**	**2.02**	**0.08**	**3.63**
	100, 0.00	100, 0.00	100, 0.00	100, 0.00
Elisa	**0.18**	**1.91**	**0.21**	**1.66**
	100, 0.00	100, 0.00	100, 0.00	100, 0.00
TJ Group	**0.10**	**3.42**	**0.15**	**3.58**
	100, 0.00	100, 0.00	100, 0.00	100, 0.00
Fortum	**0.05**	**1.61**	**0.05**	**2.10**
	100, 0.00	100, 0.00	100, 0.00	100, 0.00
Elcoteq	**0.16**	**1.50**	**0.18**	**1.82**
	100, 0.00	100, 0.00	100, 0.00	100, 0.00
Nordea	**0.12**	**1.25**	**0.12**	**1.41**
	100, 0.00	100, 0.00	100, 0.00	100, 0.00
Tietoenator	**0.10**	**0.76**	**0.12**	**1.35**
	100, 0.00	100, 0.00	100, 0.00	100, 0.00
Stonesoft	**0.13**	**2.01**	**0.15**	**31.31**
	100, 0.00	100, 0.00	100, 0.00	100, 0.00
Stora Enso	**0.09**	**1.03**	**0.09**	**1.24**
	100, 0.00	100, 0.00	100, 0.00	100, 0.00
Perlos	**0.12**	**1.99**	**0.13**	**1.99**
	100, 0.00	100, 0.00	100, 0.00	100, 0.00
Sampo	**0.05**	**1.27**	**0.06**	**1.31**
	100, 0.00	100, 0.00	100, 0.00	100, 0.00
Eimo	**0.19**	**2.05**	**0.26**	**1.89**
	100, 0.00	100, 0.00	100, 0.00	100, 0.00
Pohjola	**0.09**	**0.68**	**0.11**	**1.09**
	100, 0.00	100, 0.00	100, 0.00	100, 0.00
Avg.	**0.09**	**11.86**	**0.11**	**16.48**

Table 4. Panel Tobit for Buys (Panel A) and Sells (Panel B)

The dependent variables are buys and sells per investor with municipality random effects. Median parameter values by stock. *SIpi* is the owners times non-owners of the stock per investor in the municipality. *News* is the number of articles about the firm on the current and previous day. *LReturn* and *LVolume* are the past week's stock return and past day's volume. *Income*, and *Popdens* represent average income and population density. *Nholdpi* is the percentage of investors who are owners of each stock. The coefficient of *Lvolume* is multiplied by 10^9, and *Income* multiplied by 1 million, others are multiplied by 10,000.

Percentage of positive coefficients and median p-values are below estimates. For example, in Panel A, the median monthly coefficient for Nokia on *SIpi* was .01/10,000, 95 percent of the coefficients were positive, and the median p-value was 0.00. Bolded terms have median p-values below .10 and have 90 percent of estimates the same sign. Constants not shown.

Panel A: Y=Buys Per Investor

Firm	*SIpi*	*Nholdpi*	*News*	*Lreturn*	*Lvolume*	*Income*	*PopDens*
Nokia	0.01	148.7	2.21	-155.3	0.01	**0.62**	**4.15**
	97, 0.16	89, 0.05	69, 0.00	31, 0.00	55, 0.01	99, 0.00	95, 0.04
Sonera	**0.01**	75.3	0.33	-54.4	-0.02	**0.57**	2.57
	96, 0.00	79, 0.00	56, 0.00	40, 0.00	45, 0.00	98, 0.02	100, 0.11
Elektrobit	**0.08**	**204.2**	4.54	38.7	-0.08	**0.61**	-1.06
	100, 0.00	94, 0.00	63, 0.01	64, 0.00	45, 0.02	100, 0.00	23, 0.23
Raisio	**0.13**	-21.0	4.82	10.9	0.01	**0.57**	**-2.80**
	100, 0.00	41, 0.06	67, 0.01	54, 0.01	48, 0.06	100, 0.00	5, 0.02
UPM	**0.01**	**102.2**	1.85	-42.9	-0.01	**0.52**	1.96
	100, 0.00	99, 0.00	60, 0.06	49, 0.01	43, 0.16	100, 0.00	77, 0.15
Comptel	**0.03**	**118.0**	5.80	2.2	-0.21	**0.57**	**3.03**
	100, 0.00	94, 0.04	61, 0.00	51, 0.00	45, 0.01	100, 0.00	98, 0.05
F-Secure	**0.02**	**319.2**	5.01	44.3	0.05	**0.55**	**2.04**
	98, 0.00	100, 0.00	73, 0.00	65, 0.00	50, 0.02	100, 0.00	92, 0.13
Merita	**0.05**	212.7	0.35	40.2	-0.01	**0.45**	1.35
	100, 0.00	85, 0.00	51, 0.08	59, 0.00	46, 0.05	100, 0.00	67, 0.33
Elisa	**0.14**	-63.4	2.50	-25.1	-0.11	**0.30**	**10.29**
	100, 0.01	20, 0.12	69, 0.07	46, 0.11	44, 0.10	98, 0.07	93, 0.00
TJ Group	**0.08**	215.8	3.50	31.3	-0.47	**0.51**	-0.76
	100, 0.00	75, 0.01	54, 0.04	61, 0.00	42, 0.13	100, 0.00	46, 0.23
Fortum	**0.04**	-65.4	2.30	-96.1	0.01	0.60	-0.70
	100, 0.00	34, 0.07	72, 0.01	44, 0.03	54, 0.16	100, 0.00	26, 0.56
Elcoteq	**0.11**	-1.7	3.74	-45.0	0.25	**0.39**	0.09
	100, 0.00	73, 0.49	68, 0.01	38, 0.01	53, 0.04	100, 0.00	55, 0.43
Nordea	**0.17**	9.8	1.49	**-341.7**	0.02	0.10	**6.03**
	100, 0.00	51, 0.19	70, 0.01	9, 0.00	57, 0.09	79, 0.11	100, 0.00
Tietoenator	**0.05**	-36.8	1.81	-11.8	0.00	**0.27**	1.18
	97, 0.00	41, 0.33	56, 0.13	45, 0.11	51, 0.20	95, 0.03	81, 0.12
Stonesoft	**0.07**	123.7	4.33	13.2	-0.52	**0.39**	1.03
	100, 0.00	67, 0.33	53, 0.03	56, 0.00	37, 0.06	100, 0.00	75, 0.16
Stora Enso	**0.05**	**160.4**	0.54	-51.9	0.02	**0.40**	0.86
	100, 0.00	90, 0.00	53, 0.14	38, 0.04	53, 0.12	100, 0.00	66, 0.35
Perlos	**0.09**	**299.2**	2.99	-20.6	0.04	**0.46**	0.00
	100, 0.00	100, 0.00	59, 0.01	41, 0.02	50, 0.03	100, 0.00	50, 0.46
Sampo	**0.04**	**-121.6**	2.05	0.2	-0.03	**0.40**	**-0.58**
	100, 0.00	1, 0.01	44, 0.05	50, 0.08	42, 0.15	85, 0.06	36, 0.28
Eimo	**0.17**	295.0	6.37	15.2	0.05	0.44	-1.01
	100, 0.00	88, 0.00	76, 0.04	53, 0.01	52, 0.24	100, 0.00	16, 0.30
Pohjola	**0.05**	71.9	-0.26	2.9	0.26	**0.36**	1.42
	97, 0.02	63, 0.31	44, 0.24	50, 0.06	57, 0.20	100, 0.00	78, 0.29
Avg.	**0.07**	**102.3**	**2.81**	**-32.3**	**-0.04**	**0.45**	**1.45**

Panel B: Y=Sells per investor

Firm	*SIpi*	*Nholdpi*	*News*	*Lreturn*	*Lvolume*	*Income*	*PopDens*
Nokia	0.01	**448.7**	2.88	108.1	-0.01	**0.75**	**4.43**
	97, 0.12	100, 0.00	70, 0.00	67, 0.00	43, 0.00	99, 0.00	96, 0.01
Sonera	**0.01**	**219.0**	1.57	9.0	0.00	**0.77**	**2.48**
	100, 0.01	94, 0.00	60, 0.00	53, 0.00	49, 0.00	100, 0.00	92, 0.07
Elektrobit	**0.11**	**234.5**	3.70	92.1	-0.43	**0.89**	-1.63
	100, 0.00	98, 0.00	59, 0.04	67, 0.01	28, 0.07	100, 0.00	23, 0.26
Raisio	**0.15**	-23.6	3.83	30.6	0.11	**0.65**	**-3.62**
	100, 0.00	35, 0.04	67, 0.02	63, 0.09	57, 0.21	99, 0.00	2, 0.02
UPM	**0.02**	**112.5**	0.88	212.4	-0.02	**0.53**	2.07
	100, 0.00	100, 0.00	58, 0.05	83, 0.00	35, 0.14	100, 0.00	88, 0.13
Comptel	**0.04**	165.8	2.66	34.5	-0.30	**0.62**	2.39
	100, 0.00	86, 0.01	61, 0.04	51, 0.01	47, 0.09	100, 0.00	96, 0.12
F-Secure	**0.03**	**495.6**	3.63	54.3	-0.01	**0.72**	1.71
	100, 0.00	100, 0.00	66, 0.06	64, 0.00	50, 0.03	100, 0.00	68, 0.18
Merita	**0.03**	258.3	-1.35	61.0	-0.01	**0.45**	**2.28**
	100, 0.00	85, 0.00	38, 0.00	64, 0.02	46, 0.01	100, 0.00	98, 0.10
Elisa	**0.17**	57.3	1.01	64.0	-0.02	**0.16**	**8.47**
	100, 0.01	87, 0.01	59, 0.06	69, 0.09	46, 0.31	91, 0.09	91, 0.01
TJ Group	**0.12**	311.2	2.63	57.1	-0.30	**0.74**	-1.13
	100, 0.00	89, 0.01	53, 0.11	65, 0.02	47, 0.15	100, 0.00	33 0.23
Fortum	**0.04**	-38.4	0.19	219.8	0.03	**0.66**	-0.89
	100, 0.00	34, 0.25	52, 0.02	74, 0.02	54, 0.08	100, 0.00	23, 0.52
Elcoteq	**0.14**	153.7	4.29	206.3	0.66	**0.43**	0.26
	100, 0.00	86, 0.23	62, 0.02	82, 0.00	59, 0.07	100, 0.00	59, 0.39
Nordea	**0.18**	42.8	0.35	**399.8**	0.03	0.09	**6.62**
	100, 0.00	53, 0.02	53, 0.05	94, 0.00	66, 0.04	89, 0.13	100, 0.00
Tietoenator	**0.07**	333.9	1.58	6.0	-0.11	**0.35**	1.19
	99, 0.00	85, 0.16	56, 0.12	54, 0.10	45, 0.19	100, 0.00	55, 0.19
Stonesoft	**0.09**	**534.2**	4.97	18.3	-0.37	**0.45**	1.05
	98, 0.00	91, 0.07	54, 0.04	61, 0.07	37, 0.20	100, 0.22	70, 0.19
Stora Enso	**0.06**	200.2	0.25	158.0	-0.04	**0.40**	0.74
	100, 0.00	85, 0.01	48, 0.12	82, 0.01	37, 0.05	100, 0.00	67, 0.47
Perlos	**0.10**	**304.1**	0.96	29.7	-0.20	**0.50**	-0.06
	100, 0.00	100, 0.00	56, 0.28	63, 0.08	48, 0.15	100, 0.00	50, 0.44
Sampo	**0.06**	**-91.6**	-0.09	32.9	-0.07	0.48	-1.36
	100, 0.00	9, 0.03	32, 0.25	60, 0.09	42, 0.10	88, 0.10	23, 0.27
Eimo	**0.20**	**368.9**	5.43	38.1	0.26	**0.50**	-0.97
	100, 0.00	100, 0.00	71, 0.04	59, 0.06	52, 0.12	100, 0.00	34, 0.35
Pohjola	**0.07**	294.8	-0.56	42.1	0.17	**0.47**	**1.11**
	99, 0.01	94, 0.06	43, 0.21	60, 0.16	56, 0.20	100, 0.00	76, 0.00
Avg.	**0.08**	**219.1**	**1.94**	**93.7**	**-0.03**	**0.53**	**1.26**

Table 5: Average effect on buys and sells of a one percent increase in variables at their means. $SIpi$ is the number of owners times the number of non-owners of the stock per investor, $Nholdpi$ is the number of owners of the stock per investor (only relevant for sales), $News$ is the number of news articles in the Finnish and major European business newspapers in the current and previous day, *LReturn* is the return on the stock in the previous week, *Lvolume* is the volume on the previous day, $Income$ is the average income of the people in the municipality, and *Popdens* is the population density. For example, the the effect on the number of daily individual investor buys of an average stock of a one percent increase in $SIpi$ is the average over all of the stocks of $\beta_{buys} * average_t(SIpi) * average_t(\#investors/municipality) * 444$ municipalities $* .01$ divided by the average number of daily buys, where $average_t$ signifies average over all of the months in which the stock is traded.

Average percent increase in buys and sells for a one percent increase in variables							
Obs	*SIpi*	*Nholdpi*	*News*	*Lreturn*	*Lvolume*	*Income*	*Popdens*
Buys	0.02	0.02	0.01	-0.03	0.00	0.61	0.00
Sells	0.02	0.07	0.01	0.32	0.00	0.89	0.00

Table 6, Panel A: Monthly Portfolio Returns

Equal weighted portfolio regressions use an equal weighted portfolio composed of the stocks present in the sample during each month. *SocialBuys* is the estimated number of buy transactions due to social interaction. *SocialSells* is the estimated number of sell transactions due to social interaction. Both are equally weighted across the stocks present in the sample in each month. *Buys* and *Sells* are the equally weighted number of buys and sells by individuals. A hat on a variable signifies that it is the predicted value of that variable based on its own two lags. Coefficients are multiplied by 10,000. Heteroskedasticity-robust p-values are in parentheses.

	Model					
Parameter	1	2	3	5	6	7
$SocialBuys$	4.13	12.09		1.66		
	(0.78)	(0.29)		(0.91)		
$SocialSells$	**-82.01**	**-43.12**		**-38.59**		
	(0.00)	(0.01)		(0.01)		
$LagSocialBuys$			7.65	**21.15**		
			(0.31)	(0.09)		
$LagSocialSells$			-16.18	1.56		
			(0.54)	(0.94)		
$Buys$		**-1.19**		**-1.08**		
		(0.00)		(0.00)		
$Sells$		**1.54**		**1.91**		
		(0.00)		(0.00)		
$LagBuys$			**-0.58**	0.03		
			(0.02)	(0.40)		
$LagSells$			**0.63**	**-0.59**		
			(0.06)	(0.03)		
$\widehat{SocialBuys}$					**256.22**	**211.40**
					(0.04)	(0.07)
$\widehat{SocialSells}$					**-361.77**	**-289.98**
					(0.01)	(0.02)
$\widehat{Buys}$						-0.64
						(0.10)
$\widehat{Sells}$						0.58
						(0.27)
$Constant$	**1170.85**	216.94	316.36	142.57	**1792.47**	**1628.69**
	(0.02)	(0.46)	(0.41)	(0.55)	(0.08)	(0.04)
N	108	108	107	107	105	105
R^2	0.09	0.45	0.09	0.52	0.09	0.15

Table 6, Panel B: Monthly Returns by Firm

SocialBuys is the estimated number of buy transactions due to social interaction. *SocialSells* is the estimated number of sell transactions due to social interaction. $\widehat{SocialBuys}$ and $\widehat{SocialSells}$ are the predictions of *SocialBuys* and *SocialSells* based on the first two lags. Adjusted R^2s are presented under N, the number of observations. Heteroskedasticity-robust p-values are in parentheses.

	Current month: Y=Raw Return			Predictability: Y= Raw Return		
Firm	$SocialBuys$	$SocialSells$	N/R^2	$\widehat{SocialBuys}$	$\widehat{SocialSells}$	N/R^2
Nokia	0.002	**-0.010**	108	0.006	-0.011	106
	(0.69)	(0.08)	4%	(0.74)	(0.91)	3%
Sonera	-0.025	**-0.023**	51	0.023	-0.007	50
	(0.24)	(0.01)	4%	(0.67)	(0.81)	0%
Elektrobit	-0.003	**0.004**	63	-0.006	**0.057**	
	(0.59)	(0.09)	5%	(0.64)	(0.01)	8%
Raisio	**0.000**	0.001	90	0.004	-0.015	89
	(0.08)	(0.29)	1%	(0.52)	(0.23)	2%
UPM	**0.012**	**-0.011**	91	0.003	0.033	90
	(0.01)	(0.06)	10%	(0.79)	(0.33)	2%
Comptel	**0.039**	**-0.031**	48	0.040	0.028	47
	(0.03)	(0.01)	9%	(0.39)	(0.39)	8%
F-Secure	0.014	-0.012	49	-0.007	0.018	48
	(0.32)	(0.49)	1%	(0.87)	(0.55)	5%
Merita	**0.019**	-0.015	64	-0.007	0.006	62
	(0.02)	(0.26)	7%	(0.35)	(0.55)	3%
Elisa	0.011	-0.010	53	0.052	-0.020	52
	(0.50)	(0.24)	1%	(0.51)	(0.28)	2%
TJ Group	-0.002	-0.014	56	-0.010	0.044	55
	(0.72)	(0.12)	0%	(0.59)	(0.69)	1%
Fortum	0.006	**-0.007**	60	-0.006	-0.003	59
	(0.11)	(0.06)	6%	(0.66)	(0.85)	0%
Elcoteq	**0.035**	-0.023	72	0.006	**-0.205**	70
	(0.02)	(0.11)	9%	(0.88)	(0.08)	3%
Nordea	0.000	0.000	47	**0.004**	**-0.003**	46
	(0.78)	(0.81)	2%	(0.05)	(0.03)	8%
Tietoenator	-0.001	0.000	51	-0.004	-0.030	51
	(0.33)	(0.81)	1%	(0.45)	(0.41)	2%
Stonesoft	-0.013	0.008	56	-0.018	-0.007	55
	(0.33)	(0.37)	1%	(0.50)	(0.85)	2%
Stora Enso	0.006	-0.009	78	**0.064**	**-0.065**	76
	(0.18)	(0.58)	2%	(0.03)	(0.00)	12%
Perlos	**0.033**	-0.006	54	0.243	-0.062	52
	(0.06)	(0.70)	4%	(0.19)	(0.47)	9%
Sampo	-0.004	-0.006	78	0.000	**-0.021**	75
	(0.61)	(0.16)	6%	(0.99)	(0.04)	5%
Eimo	0.004	-0.014	57	-0.009	-0.004	56
	(0.60)	(0.20)	2%	(0.85)	(0.94)	0%
Pohjola	0.000	-0.004	108	-0.004	-0.006	106
	(0.88)	(0.11)	1%	(0.61)	(0.47)	3%
Avg.	**0.007**	**-0.009**		**0.019**	**-0.003**	

Table 7. Spatial Correlation of Social Buy and Sell Propensities Among Municipalities.

Spatial correlation is measured by Moran's I and Geary's C. The expected value of Moran's I is -1/(N-1). A negative value signifies negative correlation, and a positive value signifies positive correlation. The expected value of Geary's C is 1. Values below 1 signify positive correlation, and values above 1 signify negative correlation. Bolded terms are significant at the 10% level. The measures are computed as follows:

Moran's $I = \frac{N}{S_0} \frac{\Sigma_{i=1}^{N} \Sigma_{j=1}^{N} w(i,j)(x_i - \bar{x})(x_j - \bar{x})}{\Sigma_{i=1}^{N} (x_i - \bar{x})^2}$, and

Geary's $C = \frac{N-1}{2S_0} \frac{\Sigma_{i=1}^{N} \Sigma_{j=1}^{N} w(i,j)(x_i - x_j)^2}{\Sigma_{i=1}^{N} (x_i - \bar{x})^2}$,

where N is the number of municipalities, and x is $\beta_{b,social}$ or $\beta_{s,social}$ estimated across all months value for each municipality, with all control variables and year-month random effects. $\bar{x}$ is the mean of the x_i, $w(i,j)$ is 1 if regions i and j are neighbors and zero otherwise, and S_0 is the sum of all of the $w(i,j)$.

	Neighbors=25km				Neighbors=50km			
	Buys		Sells		Buys		Sells	
Firm	Moran	Geary	Moran	Geary	Moran	Geary	Moran	Geary
Nokia	0.02	0.89	-0.03	0.97	0.00	0.89	0.01	**0.84**
	(0.32)	(0.28)	(0.25)	(0.41)	(0.49)	(0.12)	(0.34)	(0.01)
Sonera	**0.05**	**0.71**	0.05	0.94	0.02	**0.87**	0.00	0.98
	(0.10)	(0.01)	(0.11)	(0.31)	(0.11)	(0.03)	(0.49)	(0.39)
Elektrobit	0.02	**0.79**	**0.05**	**0.87**	0.01	0.98	0.02	**0.90**
	(0.25)	(0.08)	(0.10)	(0.07)	(0.34)	(0.38)	(0.18)	(0.02)
Raisio	0.00	1.05	0.01	1.03	0.02	0.96	0.01	0.98
	(0.45)	(0.34)	(0.38)	(0.36)	(0.12)	(0.29)	(0.25)	(0.28)
UPM	**0.07**	**0.77**	-0.01	**0.88**	**0.03**	0.96	0.02	0.99
	(0.03)	(0.03)	(0.42)	(0.08)	(0.04)	(0.25)	(0.11)	(0.39)
Comptel	0.05	0.94	**0.06**	**0.82**	-0.02	1.05	**-0.05**	1.04
	(0.12)	(0.31)	(0.10)	(0.01)	(0.16)	(0.23)	(0.02)	(0.17)
F-Secure	0.01	**0.81**	0.03	0.93	0.00	**0.91**	0.02	0.96
	(0.43)	(0.02)	(0.24)	(0.21)	(0.39)	(0.03)	(0.15)	(0.17)
Merita	-0.02	0.83	**-0.08**	1.07	0.00	**0.89**	-0.01	1.00
	(0.37)	(0.11)	(0.04)	(0.21)	(0.47)	(0.07)	(0.31)	(0.48)
Elisa	0.01	**0.81**	**0.07**	**0.79**	0.01	**0.92**	0.00	**0.89**
	(0.44)	(0.07)	(0.08)	(0.01)	(0.32)	(0.10)	(0.41)	(0.01)
TJ Group	0.01	1.00	-0.04	0.97	-0.01	1.00	-0.02	0.97
	(0.37)	(0.50)	(0.23)	(0.36)	(0.31)	(0.48)	(0.27)	(0.24)
Fortum	-0.02	0.99	0.04	**0.78**	-0.01	0.99	0.01	0.98
	(0.30)	(0.47)	(0.15)	(0.00)	(0.44)	(0.45)	(0.27)	(0.40)
Elcoteq	-0.01	0.96	**0.11**	**0.83**	-0.01	**0.91**	**0.03**	**0.90**
	(0.40)	(0.37)	(0.01)	(0.02)	(0.42)	(0.08)	(0.10)	(0.01)
Nordea	**0.06**	0.87	-0.03	**1.11**	0.02	**0.89**	-0.03	**1.06**
	(0.09)	(0.11)	(0.26)	(0.10)	(0.15)	(0.02)	(0.12)	(0.09)
Tietoenator	0.00	0.98	**0.08**	0.93	**0.03**	**0.89**	**0.07**	**0.94**
	(0.49)	(0.43)	(0.06)	(0.21)	(0.06)	(0.03)	(0.00)	(0.08)
Stonesoft	**0.06**	**0.77**	0.02	**0.78**	**0.03**	0.98	**-0.06**	1.04
	(0.08)	(0.03)	(0.35)	(0.01)	(0.08)	(0.36)	(0.03)	(0.18)
Stora Enso	0.02	0.91	-0.01	**0.82**	-0.03	0.99	**0.04**	**0.92**
	(0.26)	(0.20)	(0.39)	(0.02)	(0.14)	(0.32)	(0.02)	(0.02)
Perlos	0.03	0.98	0.01	**0.79**	**-0.06**	**1.08**	0.00	**0.92**
	(0.26)	(0.41)	(0.44)	(0.01)	(0.01)	(0.04)	(0.46)	(0.02)
Sampo	0.00	0.92	**0.13**	0.90	0.02	**0.82**	0.02	0.97
	(0.47)	(0.24)	(0.00)	(0.11)	(0.19)	(0.00)	(0.18)	(0.19)
Eimo	-0.02	1.01	-0.02	0.98	0.03	0.97	0.00	0.96
	(0.38)	(0.47)	(0.40)	(0.42)	(0.11)	(0.30)	(0.41)	(0.16)
Pohjola	0.03	**0.70**	-0.02	1.02	0.00	**0.92**	-0.01	1.01
	(0.22)	(0.01)	(0.39)	(0.42)	(0.43)	(0.10)	(0.33)	(0.46)
Avg.	NA	0.88	NA	0.91	NA	0.94	NA	0.96

Table 8. Explaining Social Trading With Municipality-Level Data. Details about the variables are presented in Table 2. The dependent variable is $Social = \beta_{buy} + \beta_{sell}$ estimated at the municipality level with year-month fixed effects. *Swedish* is the percentage of people in a municipality who are Swedish. *Dtowork* is the average commute in kilometers. *Popdens* is the population density of a municipality. *Univ* is the proportion of inhabitants with a university degree. *Income* is the average income in Euros. *Turnover* is the proportion of the population that moves in or out each year. *Kiosksppp* is the number of news kiosks per inhabitant. Coefficients are multiplied by 10,000 except *Kiosksppp*. Heteroskedasticity-robust p-values are in parentheses. Bolded terms are significant at the ten percent level.

Panel A: Correlation Table

	AvgSocial	*Swedish*	*Dtowork*	*Popdens*	*Univ*	*Income*	*Turnover*
AvgSocial	1						
Swedish	-0.09	1					
Dtowork	0.08	-0.12	1				
Popdens	-0.02	0.04	-0.14	1			
Univ	-0.05	0.14	-0.10	0.61	1		
Income	-0.06	0.27	-0.20	0.51	0.85	1	
Turnover	0.01	-0.15	0.23	0.21	0.28	0.29	1
Kiosksppp	-0.17	0.13	0.12	0.09	0.05	0.05	0.12

Panel B: Regressions

Y= $AvgSocial$ = average over 20 securities of $\beta_{buy} + \beta_{sell}$

	1	2	3	4	5	6	7	8
Swedish	30.40							2.44
	(0.83)							(0.46)
Dtowork		**30.40**						**32.96**
		(0.09)						(0.08)
Popdens			-0.25					**0.47**
			(0.13)					(0.06)
Univ				**-38.13**				-39.79
				(0.07)				(0.37)
Income					**-0.05**			-0.01
					(0.09)			(0.90)
Turnover						12.48		-1.33
						(0.80)		(0.98)
Kiosksppp							-30.04	**-54.84**
							(0.48)	(0.23)
Constant	0.02	-0.04	**0.02**	**0.05**	**0.10**	0.00	0.03	0.01
	(0.09)	(0.20)	(0.08)	(0.06)	(0.07)	(0.99)	(0.11)	(0.92)
Obs.	381	381	381	381	381	381	381	381
Adj. R^2	0.00	0.03	0.00	0.00	0.01	0.00	0.01	0.04