Who Trades With Whom? Individuals, Institutions, and Returns*

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Abstract

Using all trading in Finland over a fifteen-year period, I study the relation between price changes and the trading of individuals and financial institutions. On average, prices increase when institutions buy from individuals, and decrease when institutions sell to individuals. No such consistent pattern is observed when individuals trade with other individuals, or when institutions trade with other institutions. If prices do move while individuals trade among themselves, they quickly revert. These reversals occur as institutions trade with individuals in a direction that pushes prices toward previous levels.

Keywords: Institutional investors; Individual investors; Liquidity provision; Price impact
JEL Classification Codes: G10, G12, G14

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Models of market microstructure posit the existence of three types of financial market participants: informed investors, uninformed "noise traders," and market-makers (Glosten and Milgrom, 1985; Kyle, 1985). An important question in economics, dating back at least to Keynes (1936) is to what extent prices are distorted by noise traders.[1] Friedman (1953) argues that rational, informed investors quickly exploit arbitrage opportunities caused by mispricing. But De Long, Shleifer, Summers, and Waldmann (1991) show how noise traders can have long-term effects on prices, and Shleifer and Vishny (1997) and Abreu and Brunnermeier (2003) explain why arbitrageurs may be unable to take advantage of known mispricing. If noise traders do distort prices, then prices must move in response to their trading. This paper examines that possibility.

Who are the proverbial noise traders? While they may have an exogenous liquidity motive for trade, Black (1986) defines noise trading as "trading on noise as if it were information." The literature provides considerable evidence that individual investors play this role.[2] For example, individual investors make rather poor investment decisions; typically, stocks heavily bought by individuals subsequently underperform those heavily sold.

There are two possible explanations for this phenomenon. The first, suggested by Barber, Odean, and Zhu (2009) and Hvidkjær (2008), is that individual investors could push prices away from fundamentals, and the subsequent reversal to fundamental value leads to poor performance. The second, supported by Kaniel, Saar, and Titman (2008), Campbell, Ramadorai, and Schwartz (2009), and Kelley and Tetlock (2013) is that well-informed institutions buy undervalued stocks from individuals and sell overvalued stocks to individuals, and prices subsequently move toward fundamentals. Under the first explanation, individuals distort prices; under the second, institutional demand for trading is met by individuals whose trading supplies liquidity.

[1]Keynes (1936, p. 155), describes investing as a "battle of wits to anticipate the basis of conventional valuation a few months hence, rather than the prospective yield of an investment over a long term of years…"

[2]See Barberis and Thaler (2005), especially Section 7 and the references therein.

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In this paper, I use the complete daily records for all trading in Finland over a fifteen-year period to examine these competing hypotheses. First, in contrast to the existing literature, I identify how much trading occurs not only *between* individuals and institutions, but also *within* each group. I document that, while about one quarter of trading activity is between individuals and institutions, almost the same amount occurs just between households, and another 14% occurs between institutions. (The remaining trade involves other kinds of traders.) This is particularly interesting given the herding that has been documented among both individuals (Odean, 1998) and institutions (Wermers, 1999), which implies that trading within groups should be rare—if all individuals are buying, for example, they cannot buy from other individuals.

Second, I show that prices move consistently when institutions trade with individuals: on average, when households[3] buy shares from institutions, prices decline; and when they sell shares to institutions, prices increase. Of course, this implies that prices fall when institutions sell shares to individuals, and rise when institutions buy shares from individuals. In other words, the pattern that emerges from the regressions is that prices tend to move in the direction of institutional trading, and individuals supply liquidity to meet the trading demand.[4] I find these results at horizons ranging from intra-daily to monthly, and with vector autoregressions.

In contrast to the trading between households and institutions, we see no consistent price changes on average when trading occurs just between individuals or just between institutions. However, the third main finding in the paper is that when prices do move as a result of trading among households, they tend to subsequently revert. This price reversion is consistent with the trading of individuals generally being uninformed. Moreover, I show that these price reversions occur as institutions subsequently trade with individuals in a direction that

[3]Throughout the paper, I use the terms "individual" and "household" interchangeably.

[4]My tests cannot differentiate between two alternatives that are observationally quite similar. In the first, institutional trading moves prices, while in the second the fundamental price changes and institutions react to the price change by trading with individuals. I thank the referee for pointing out this important caveat.

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pushes prices back toward previous levels. No such reversion is seen with trading between institutions.

My data include the trading records of all households, financial institutions and other entities that trade stocks on the Helsinki Stock Exchange between January, 1995 and June, 2009. There are three notable features of these data that make them particularly well-suited to examining the relation between trading and price changes. First, the data include account identifiers that classify the investor as a household, financial institution, or one of several other entities. Therefore, there is no need to estimate an investor classification as there is in most data sets available for the U.S.[5] Second, whereas data available in the U.S. are either available quarterly or from proprietary data sets covering small samples of traders and/or short time periods, the Finnish data record all transactions placed each day by each investor. This allows me to analyze the interaction of investors at a high frequency without relying on an estimation technique such as the one developed by Campbell et al. (2009). Third, the data cover a fifteen-year period for the entire Finnish stock market, including both the "bubble" period in technology stocks during which many Finnish stocks rose dramatically, as well as periods before and after this rise. This helps ensure that the results are generally applicable to a variety of market conditions, and not driven by rare events.

The poor performance of individual investors documented by Odean (1998, 1999) and Barber and Odean (2000, 2001) can result either because they trade with better-informed institutional investors, or because they push prices above or below fundamentals and subsequently lose money in the ensuing correction. Dorn, Huberman, and Sengmueller (2008), Hvidkjær (2008), and Barber et al. (2009) present evidence that the trading of individual investors moves prices, which then slowly revert. Because of constraints on the data available for the U.S. market, these authors adopt a clever strategy to identify the trading of individual investors: they examine the imbalance of buyer- and seller-initiated transactions for small

[5]The TORQ data (available for 144 stocks during three months in 1990–1991) and the proprietary data used by Kaniel et al. (2008) are exceptions.

quantities of trades and classify this as the trading of individuals. Barber et al. (2009) show that this order-imbalance is correlated with the order-imbalance among a sample of investors at a discount brokerage firm. In contrast to these results, Kaniel et al. (2008), Campbell et al. (2009), Linnainmaa (2010), and Kelley and Tetlock (2013) find that individual investors supply liquidity to meet institutional demand for immediacy. Compared to these papers, the data studied in this paper cover a considerably longer time period, and I focus on daily data.[6] (While Kaniel et al. (2008) have daily data, they aggregate their data to weekly observations for all of their reported analysis.)

I contribute to this literature by documenting the extent to which within-group trading occurs, and how trading both within and between groups is related to contemporaneous returns at a daily frequency. I also examine how institutional traders respond to price changes that do occur as individual investors trade amongst themselves.

1 Hypotheses

As discussed above, the low returns earned by stocks following high levels of buying by individuals could arise either from individuals pushing prices above fundamental value, or by institutions selling overvalued stocks to individuals. To differentiate between these alternatives, I develop and test three hypotheses.

While researchers typically think of liquidity provision as submitting a limit order that gives others the option to trade, Kaniel et al. (2008, p. 296) note that practitioners think of a buy order placed when prices are falling—or a sell order placed when prices are rising—as supplying liquidity, regardless of whether the trader submits a limit or market order. This is the sense in which I use the term "liquidity provision" in the paper. Individual investors

[6] Griffin, Harris, and Topaloglu (2003) also examine daily trading, using a data set of Nasdaq 100 securities during a ten-month period beginning in May, 2000. They focus on the relation between returns and the buy-sell imbalance of individuals and institutions—not the total amount of trading within and between groups examined in my paper—and they are careful to note that the patterns they observe may not be representative of other markets or time periods.

may not set out to provide liquidity to institutions, actively posting limit buy and sell orders and taking the spread as compensation for their services; rather, they may respond to price changes resulting from institutional trading and end up supplying liquidity. One way this can occur is if individuals have "latent" limit orders—prices at which they plan to buy or sell in the future—and these orders get triggered by price movements. For example, individuals who suffer from the disposition effect are more likely to sell a stock after seeing its price rise. The "limit order effect" of Linnainmaa (2010) can also contribute to this phenomenon.

Before stating the hypotheses, it is useful to consider possible price paths surrounding a trade, as shown in the stylized examples in Figure 1. The figure shows four price paths following a trade at time t_0. In the top two graphs, the trade is buyer-initiated. The bottom two graphs depict seller-initiated trades. The left two graphs show trade between an informed buyer and an uninformed seller, while the right two graphs show trade between an uninformed buyer and an informed seller. When the trade is initiated by an uninformed trader, prices subsequently revert, as seen in the upper-left and lower-right quadrants. If the trade initiator is informed, however, no such reversion takes place. This price reversion is a feature of models with asymmetric information: in contrast to the permanent price impact of informed trades, uninformed trading causes immediate price changes to compensate liquidity providers, but expected future cash flows have not changed.[7] The reversion can stem from bid-ask "bounce," and is critical to the estimation of liquidity measures such as Roll's (1984) spread and Pastor and Stambaugh's (2003) liquidity factor.

Given the poor performance of individual investors discussed above, the question studied in the paper is whether individuals demand liquidity and actively move prices (top right of Figure 1) or supply liquidity as prices move (bottom left of the figure). If institutions are more likely to be informed, and individuals provide institutions liquidity in the sense defined

[7] See Glosten and Milgrom (1985), Kyle (1985), Easley and O'Hara (1987), Campbell, Grossman, and Wang (1993), Llorente, Michaely, Saar, and Wang (2002), Chordia and Subrahmanyam (2004), and Avramov, Chordia, and Goyal (2006), among others.

above, then this stylized example leads to a number of hypotheses. First, when institutions trade with individuals, prices should move. This leads to:

Hypothesis 1 *When institutions purchase shares from individuals, prices contemporaneously increase. When institutions sell shares to individuals, prices contemporaneously decrease.*

Price increases accompanying institutional buying, and decreases accompanying institutional selling, are consistent with institutions demanding liquidity. In contrast, evidence against Hypothesis 1 would indicate that institutions supply liquidity. To test this hypothesis, I regress daily returns on a set of variables that summarize the amount of trading that took place between each investor group on each day. I also test the relation using weekly and monthly horizons. Details of the estimation procedure and results of tests of Hypothesis 1 are presented in Section 3.2.

Second, the stylized examples in the Figure 1 indicate that prices will change predictably after trading, depending on which types of investors caused the price change, which leads to:

Hypothesis 2 *Price reversion is more likely following days when individuals trade with other individuals than days when individuals trade with institutions.*

Tests of this hypothesis are similar to those of Hypothesis 1, but instead of examining the contemporaneous relation between returns and trading by different groups, I investigate how returns change in the period following trading by individuals and institutions. In particular, I use a regression framework to test whether negative autocorrelation in daily returns is stronger following days when more trading takes place between two individuals than days when more trading occurs between individuals and institutions.

If Hypothesis 2 is true, it is also interesting to determine *whose* trading leads to price reversion. In particular, if trading comes primarily from individuals trading among themselves and prices change, we might expect institutions to react to the price movement by trading in a direction that pushes prices back to previous levels. That is, we would expect institutions to cause the price reversion by trading subsequently with individuals. This leads to the third hypothesis:

Hypothesis 3 *Institutions react to price changes caused when individuals trade with each other by subsequently trading with individuals to move prices back toward previous levels.*

To test Hypothesis 3, I examine the relation between institutional trading and the previous day's proportion of individual trading interacted with the price changes. I use a regression framework to test (a) whether institutions are more likely to *sell* to individuals following days that have both *high* returns and more intragroup individual trading; and (b) whether institutions are more likely to *buy* from individuals following days that have both *low* returns and more intragroup individual trading. Details of the estimation procedure and results for Hypotheses 2 and 3 are presented in Section 3.3.

2 Data and methods

In this section, I begin by describing the salient features of the data used in this study. I then discuss the procedures I use to classify investors into different groups, as this is key to the empirical implementation in the paper.

2.1 Data description

The data set used in this paper comes from the central register of shareholdings in Finnish stocks maintained by the Nordic Central Securities Depository (CSD), which is responsible for clearing and settlement of all trades. Finland has a direct holding system, in which individual investors' shares are held directly with the CSD. Since the data come from the CSD, they reflect the official record of holdings and are therefore of extremely high quality. In particular, shares owned by individuals but held in street name by a brokerage firm are identified as belonging to the individual, and shares for each individual are aggregated across brokerage accounts, regardless of whether they are held in street name. This allows a clean identification of which investor owns which shares on a daily basis, and since all trading is recorded in the data, it is possible to construct measures of trader interaction that are not feasible with data sets that include small samples of the population.

The data cover daily trading in all stocks trading on the Helsinki Stock Exchange from January, 1995 through June, 2009. Grinblatt and Keloharju (2000, 2001a, 2001b) use a subset of the same data, comprising the first two years of my sample period.

I impose several filters to ensure that the sample of firms is generally similar to firms in the United States and other developed economies. In particular, I require that each firm has a market capitalization of at least €50M on the day its stock begins trading; has an average of at least 40 trades per day; has trades on at least 500 trading days; is domiciled in Finland (i.e., its ISIN security identifier begins with "FI"); and has returns available in Datastream.

These filters leave a sample of 111 firms. (The qualitative results in the paper are not sensitive to variations in the sample.) Panel A of Table 1 presents summary statistics about this sample. Average firm size (calculated quarterly) is €2.1B, which is between the 50th and 75th percentile of the size distribution for NYSE-listed stocks. The average number (value) of trades per day is 134 (€2.9M), ranging from 40 (€0.3M) for the smallest third of firms in the sample to 250 (€5.8M) for the largest third. The table also reports the average number of unique accounts that trade stocks each day and the average number of shareholders, calculated quarterly. The last row of Panel A reports statistics just for Nokia, which is by far the largest firm in the Finnish market, accounting for 36% of the total stock market capitalization on average during the sample period (ranging daily from 16% to a high of 64% at one point in 2000). Because Nokia is so large, I confirm that none of the results in the paper is driven by this one firm.

During the period studied in the paper, trading on the Helsinki Stock Exchange opened and closed with a call market, and continuous trading during regular hours was conducted through a limit order book. The transaction data include the number of shares bought or sold, corresponding transaction prices, and the trade and settlement dates.[8] As well, each trade is assigned an account identifier that uniquely identifies the person or institution that placed the trade. Each account is classified by the CSD as being one of the following six types of investor: Households, Financial institutions, Non-financial corporations, Government agencies, Non-profit institutions, and Foreigners. (Only foreign investors directly registered with the CSD are identified as foreigners. These are typically foreign firms or organizations, but can also be individual investors.) I filter out trades by so-called "nominee" accounts, which are certain foreign investors or Swedish- and American-listed depository receipts, which trade through financial firms without registering and cannot be identified as originating with individuals or institutions.

Panel B of Table 1 presents statistics about the accounts that trade the stocks in the sample. There are 761,792 accounts and 57 million trades. Approximately 70% of the trades are placed either by households or by institutional investors, and in the remainder of the paper I focus on these two groups of investors. I do this primarily because the other groups' motives for trade may differ significantly from institutions and households, and any inference from their trading may be less applicable internationally. Moreover, foreign investors could either be households or institutions, making results more difficult to interpret. Nevertheless, in unreported tests I verify that including these groups makes no meaningful change to any of the results reported in the paper. The remaining columns in Panel B report the average number and value of shares traded by each investor group as well as the number of stocks an account trades. Not surprisingly, individuals make considerably smaller trades than insitutions, with an average trade value of €7,900 for individuals and €60,000 for institutions. Individuals also typically trade fewer than five stocks (among the filtered sample), while institutions trade about 24 stocks on average.

[8] Detailed transaction prices are missing for the first three months of the sample, which affects only the intraday tests discussed in the Appendix.

I augment the transactions data with stock-level data from the Thomson Datastream database. In particular, this is the source for returns (including dividends and adjusted for splits), shares outstanding, closing prices, and trading volume.

2.2 Identifying investor interaction

The aim of the paper is to understand how trading within and between groups of investors affects prices. Unfortunately, the data provide no direct match between the buy-side and sell-side of a transaction. For each trade, at least two observations are recorded in the data: the purchase(s) and sale(s) records. (Some trades are comprised of shares purchased or sold by more than one account, and in these situations there can be more than two records per trade.) To be clear, suppose investor A buys 100 shares of Nokia and investor B sells 100 shares at the same price; they may have traded with each other, but no link between these transactions is recorded in the data. This necessitates developing a method to identify the amount of trading that occurs between groups.

Given a classification of investors into groups, as in my data, it is possible to estimate the amount of trading that occurred between and within groups. For example, suppose trading in one stock on one day at one particular price is summarized as follows:

	Shares Bought	Shares Sold
Group A	250	450
Group B	2000	1800
Group C	250	250
Total	2500	2500

While we cannot be certain how much trade occurred between or within each group of investors, we may approximate these quantities by assuming that trade occurs in proportion to the amount of buying or selling accounted for by each group. Of the 250 shares purchased by Group A, we would therefore estimate that $450/2500 = 18\%$, or 45 shares, were purchased from other members of Group A; $1800/2500 = 72\%$, or 180 shares, were purchased from members of Group B; and the remaining 25 shares from Group C. Continuing with this example, we would estimate the amount of trading within and between Groups A, B, and C as follows:

	Seller		
Buyer	A	B	C
A	45	180	25
B	360	1440	200
C	45	180	25

While this procedure is an approximation technique, it often yields an *exact* identification of the amount of trading that occurred between two groups. To see this, note that in the example (as is frequently the case in the data) only one group (B) accounts for much of both the buying and selling activity. Since Group B accounts for so much of the trading, much of the trading must have occurred within this group—there simply is not enough selling by Groups A and C to meet the large demand for shares from Group B.

By applying the procedure for *each price* at which the stock traded in a day and then aggregating to get a daily measure, I maximize the frequency with which this exact identification can occur. Especially for all but the most frequently traded stocks, it is common for groups of investors to have only purchased or sold shares—but not both—at a particular price; it is therefore frequently possible to know with certainty exactly how much trading occurred between groups. For example, if institutions purchased 800 shares and sold 1000 shares, while households purchased 200 shares and sold no shares, the institutions must have sold 200 shares to the households and 800 shares to other institutions—there is no ambiguity here, and no estimation is required.

Table 2 summarizes how often this exact identification occurs in the data. For each stock and day, I calculate the proportion of trades (Panel A) or volume of shares traded (Panel B) that is exactly identified using this procedure. I then average across either all stocks, or across stocks within size tertiles. Across all stocks, the algorithm can exactly identify the type of buyer and seller in 80.1% of trades and 86.5% of trading volume. A higher proportion is identified among smaller stocks, since with lower trading volume there is a higher chance that one or two groups will be the only traders at any particular price. (Among small stocks, the median stock-day has 100% of trades or trade volume exactly identified.) On the other hand, large stocks tend to have more trading by institutions, which sometimes trade large blocks and are therefore easy to identify; this may explain why the lower percentiles of the distribution are higher for large stocks than for small stocks. The final row of each panel reports cross-sectional results of firm-level averages, which are similar to the earlier results.

The takeaway from Table 2 is that much of the trade interaction is *calculated*, not *estimated*. Even when interaction must be estimated, the range of possible values is frequently quite small, so the estimates are generally quite precise. The results reported in the paper are derived from the combined data with both exact and estimated interaction quantities, but all of the results continue to hold if I use only the exactly-identified data.

3 Results

3.1 Investor interaction

Turning to the main results, I begin by quantifying the amount of trading that occurs among institutions and households. Panel A of Table 3 presents the average proportion of trading by households and institutions in each stock. I first calculate the volume of shares traded from each group in each stock and day, and then take the average across stocks or size tertile. Across all firms, 43.7% of trading comes from institutions and 33.1% is from households. Institutions account for much more trading in the largest tertile (61.8% compared to 16.5% from households) but individuals account for more trading among the smallest stocks (45.0% compared to 28.8% from institutions.) The remaining trading is accounted for by unreported groups.

Panel B of the table shows the proportion of trade interaction between households and institutions. Columns 2 and 3 present estimates of actual interaction calculated using the method described in the previous section. I estimate the amount of trading that occurs between and within each investor group on each day for each stock, and then calculate the time-series average for each stock. The table reports the cross-sectional averages and standard errors (across stocks and across size tertiles) of this quantity.

For comparison, Columns 4 and 5 present a back-of-the-envelope estimate of the amount of trading that would be expected between each group if trade occurred randomly, determined only by the proportion of trading that comes from each group. For each stock, I calculate the average amount of trading that comes from each group during the sample period. I then calculate the amount of trading that would be expected if we were to randomly draw traders with these respective probabilities; for example, if individuals account for 30% of trading and institutions account for 50% of trading for one particular firm, then we would expect $0.3 \times 0.5 \times 2 = 30\%$ of trading in this stock to take place between institutions and households. I do this calculation for each stock, and then report the cross-sectional average as a measure of how much trading we would expect between each group.

A surprising amount of trading occurs between household investors. The amount of trading by households across all firms would suggest that 15% of trading should be between two households, but the actual amount is 23%. Similar results are seen in small and large firms. In contrast, trading among institutions or between institutions and households is about what would be expected. (This is somewhat less true among the largest firms, where it appears that institutions trade less with each other, and more with households, than would be expected.)

Previous research has documented herding behavior among both individuals and institutions; in other words, within-group trading is positively correlated. This means that trading within groups should be rare—if all households are buying, they cannot trade with each other. But the results presented here show that the previous findings of herding mask an important fact: a great deal of trading occurs between two individuals or between two institutions. In these data, individuals are more than twice as likely to trade with other individuals than their trading volume would suggest, and trading between individuals accounts for approximately as much trading as what occurs between individuals and institutions.

What explains the discrepancy between the actual and expected amount of trading among individuals? There are several possibilities, each of which could partially explain the result. First, institutions can arrange large block trades with each other away from the regular limit-order book, so for a fixed amount of trading, less volume will take place between individuals. Second, informed investors might trade only when there has been an information event, as in the model of Easley and O'Hara (1987). If institutions tend to be informed, they will be less likely to trade when no information event has occurred, and any trading by households will tend to be with other households. Indeed, Easley et al. (2008) find that uninformed orders are clustered in time, but also that uninformed investors avoid trading when informed investors are likely to be present. A related explanation is offered by Barber and Odean (2008), who document that individual investors are more likely to trade following events that get media attention.

The amount of trading coming from each group determines how much power there is to find a relation between either group's trading activity and price changes. If almost all trading came from institutions, it would be difficult to find a relation between price changes and the trading of either households or institutions, because returns (the left hand side variable in my regressions) would vary, but the proportion of trading from each group (the right hand side variables) would not. The percent of trading reported in Table 3 suggests that trading is sufficiently spread among the groups so as to provide adequate power for the tests.

The results in this sections show that there is considerable variation across stocks in how much trading occurs between and within groups. Overall, individuals account for approximately one third of trading in the Finnish stock market, which is certainly sufficiently large for the trading of individual investors to have substantial price effects. About half of individual investors' trading is with other individuals, and half is with institutions. The key question, which is the focus of the next section, is which of these types of trading is associated with price changes.

3.2 Daily returns

To understand how prices are determined by the interaction of different investors in the market, I examine the relation between stock returns and the proportion of trading within and between each type of investor. In particular, I estimate the regression

$$R_{i,t} = \alpha_i + \beta_{HH} H/H_{i,t} + \beta_{HI} H/I_{i,t} + \beta_{IH} I/H_{i,t} + \beta_{II} I/I_{i,t} + \sum_{k=1}^{3} \gamma_k R_{i,t-k} + \sum_{k=0}^{3} \beta_k R^M_{t-k} + \sum_{k=0}^{3} \delta_k ABNTO_{i,t-k} + \epsilon_{i,t}, \quad (1)$$

where the "trade variables" denoted by $A/B_{i,t}$ represent the fraction of trading in stock i on date t that is accounted for by traders of type A buying from traders of type B, and the types "H" and "I" indicate households and institutions, respectively. As controls, I include three lags of the stock's daily return, and the contemporaneous value and three lags of both the return on the market portfolio, R^M, and the stock's abnormal turnover ($ABNTO$, the daily turnover divided by its trailing 40-day average).

Importantly, the trade variables do not sum to one, so there is no problem of perfect collinearity. These variables do not account for all trading activity, but I focus in the analysis only on the trading of households and institutions because other investor groups tend to account for a relatively small proportion of trading, and interpreting their trading behavior is not as clear as it is for individuals or financial institutions. (For example, registered foreigners may include individuals or institutions, and government funds may have incentives to trade beyond a pure profit motive.) Nevertheless, the main conclusions of the paper are not altered if I include the other investor groups in the regressions, or if I rescale the trade variables so they do sum to one and drop the intercept from the estimation.

I begin by estimating the regression at a daily horizon, but confirm in section 3.5 that similar results obtain at longer horizons.[9] If trading between or within household and institutional investors is associated with price changes, then contemporaneous returns will be positive or negative, and the estimated β coefficient for the relevant combination of trade will be significant. For example, if trading between institutions is largely responsible for moving prices, we would expect days with high values of I/I to have more price movements, and returns should be larger in absolute value. In other words, β_{II} would be significantly different from zero. If neither group has a consistent effect on prices, then the four trade variables will be economically small and statistically insignificant.

I estimate regression (1) using the approach of Fama and MacBeth (1973) in two ways: averaging results from either time-series regressions by stock, or from cross-sectional regressions by date. (The market return variables are excluded from the cross-sectional regressions to avoid perfect collinearity.) The latter approach results in a time-series of estimates, which may be autocorrelated. Therefore, I use the robust standard error calculation of Newey and West (1987) with five lags, which corresponds to one week of trading. The adjustment for autocorrelation is unnecessary for the cross-section of estimates obtained from the stock-by-stock regressions. It is also worth noting that there may be another type of correlation that could lead to a downward bias in the estimated standard errors: if daily trading by a group of investors is correlated across stocks then it may not be entirely correct to count each stock as an independent observation. The average correlation of the trade variables across stocks each day, however, is only about 0.03. These low correlations, combined with the magnitude and robustness of the results reported below indicates that this is unlikely to be driving the findings.

Estimating the regression separately along each dimension allows me to check whether the results are driven by a cross-sectional relation, a time-series relation, or both. For example,

[9]In addition, the Appendix presents results from a test designed to infer the pattern at an intraday frequency.

the cross-sectional results allow me to confirm that my findings are not driven by particular stocks. Using a panel regression with clustered standard errors yields similar results.

Coefficient estimates for regression (1) are presented in Table 4, and provide an interesting picture of how prices are affected by the interaction of individual and institutional investors in the market. Panel A presents results with the trade variables calculated as a percentage of the number of trades, while in Panel B it is as a proportion of trading volume. The left panel, "FM by stock," summarizes the results from 111 time series regressions, while the right panel, "FM by date," summarizes the 3543 daily cross-sectional regressions. For each regression I report the average estimate and the t-statistic. Since the means and standard deviations of the trade variables are quite different, I also report the average of the standardized estimate (the estimate multiplied by the ratio of the dependent variable's standard deviation to that of the independent variable) to get a sense of the economic magnitude of the results. Finally, I report the percentage of regressions in which the coefficient is significant at the 1% level.

Consider first the "FM by stock" regressions. In both panels A and B, trading among households is not related to contemporaneous price changes: the H/H coefficient is small and insignificant in the cross section. Similarly insignificant results are found among institutions. In sharp contrast, the coefficients on H/I and I/H are economically large and highly significant.

It is important to stress that the large t-statistics on H/I and I/H are observed even though the statistic is calculated from just 111 stocks; clearly, the estimates do not vary much across stocks. And, while looking at the standard error of first-stage Fama-Macbeth regression estimates is not usually part of the analysis, it provides an additional sense of the strength of the results: most regressions, ranging from 65% to 87%, yield coefficient estimates on H/I and I/H that are significant at the 1% level.[10]

The coefficient estimates on H/I and I/H both dwarf the estimates on H/H and I/I, but it is also interesting to note that H/I is somewhat larger than I/H. That is, the effect

[10] Stock-by-stock results are presented in Table A2 of the appendix.

on returns (in absolute terms) is greater when institutions sell to households than when institutions buy from households. In other words, institutions appear to have larger price impact when they sell than when they buy. Campbell et al. (2009) find a similar asymmetry, and suggest that it could stem from the inability of some institutions to use short sales. They argue that an institution wishing to increase its exposure to a particular risk factor can minimize its price impact by spreading its purchases over different stocks that load on the factor, while an institution wanting to reduce exposure to a factor—and subject to short sale constraints—can only sell stocks it currently owns. This forces some institutions to sell more aggressively leading to larger price impact. We shall see below that this result holds at longer horizons as well.

This is the first direct evidence in favor of Hypothesis 1: days with higher levels of household buying from institutions are days with lower returns, while days with higher levels of institutional buying from households are days with higher returns. When institutions buy from households, prices rise, and when they sell to households, prices fall.

The results from cross-sectional regressions reported in the right panel are similar. While there is some evidence that trading among households or among institutions is associated with negative returns, the estimates are far larger and more significant for trading between the groups. (The number of regressions with coefficients that are significant at the 1% level is considerably smaller because each regression now only has at most 111 observations. Note also that the return on the market is excluded as a control because it is the same for all stocks on each day.)

The fact that the coefficient estimates for H/H and I/I are much smaller than the coefficients for intergroup trading could occur even if trading within groups is regularly associated with price movements, but not consistently in the same direction. For example, if prices sometimes increased and sometimes decreased when individuals trade with each other, regression (1) could yield an insignificant estimate of H/H. To investigate this further, Panel C of Table 4 reports results from the same regression, but with the dependent variable replaced by $|R_{it}|$. (Control variables that are returns are also replaced by their respective absolute values.) This regression ignores the direction of any effect and just asks whether the magnitude of returns is greater on days when different groups trade. The results show that days with more trading between individuals or between institutions are associated with no significant increase in absolute returns.

Despite the large portion of trading that comes from institutions trading with other institutions and households trading with other households, price changes are primarily associated with trading between these groups. To date, the literature has not been able to address the importance of price changes that occur when investors trade with other investors of the same type, but the results in Table 4 make clear that there is little in the way of price changes when trading takes place within each investor group, especially for trading among individual investors.

3.3 Returns following trade

The second hypothesis to be tested is that price reversion is more likely following days when trading is dominated by trading among households. It is possible that when the bulk of trading is between individuals, without much institutional trading, prices are pushed away from fundamental values. If this is the case, we might expect prices to revert in subsequent trading. To examine this, I estimate the regression

$$R_{i,t} = \alpha_i + \beta_1 H/H_{i,t-1} \times R_{i,t-1} + \beta_2 I/I_{i,t-1} \times R_{i,t-1} + \text{Controls} + \epsilon_{i,t}, \tag{2}$$

for stock i on date t. Here, the control variables include one lag for each of the trade variables, H/H, I/I, H/I, and I/H, as well as the same controls from earlier regressions (stock return, market return, and abnormal turnover, with three lags).

If returns tend to revert after days with high levels of trading among households and large (positive or negative) returns, β_1 should be negative. As shown in the results presented in

Panel A of Table 5, this is precisely what we find. The negative relation appears in both the cross-section and time-series Fama-MacBeth regressions. Moreover, there is no such effect for intragroup institutions trading: β_2 is insignificant in the time-series regressions while in the cross-sectional regressions it is positive, indicating that prices continue to move in the direction established when institutions traded with each other. These results strongly support Hypothesis 2, that price reversion is more likely after intragroup trading by individuals than after trading between the groups.

The price reversion that we observe must be caused by trading between or within the groups. One possibility is that institutions react to price movements that occur as individuals trade by subsequently purchasing (selling) underpriced (overpriced) shares from (to) individuals. To investigate this, I examine the relation between institutional trading with households on date t and intragroup trading by households on date $t-1$. Specifically, I estimate regressions similar to (2), but with either H/I or I/H as the dependent variable.

Suppose trading on date $t-1$ came largely from individuals trading with other individuals, and that returns were positive. If this trading moved prices above fundamentals, then we would expect institutions to be less likely to buy shares from households, and more likely to sell shares to households, on date t. That is, we would expect a positive coefficient on $H/H_{i,t-1} \times R_{i,t-1}$ in the regression with $H/I_{i,t}$ as the dependent variable, and similarly we would expect a negative coefficient on $H/H_{i,t-1} \times R_{i,t-1}$ in the regression with $I/H_{i,t}$ as the dependent variable. As shown in Panels B and C of Table 5, this prediction is borne out by the data. If trading among households moves prices up, institutions subsequently sell more to households (Panel B) and buy less from households (Panel C), which serves to cause prices to revert.

Combining the results from the three panels of Table 5 indicates that when prices do move as households trade with each other, institutions subsequently trade with individuals in a way that puts pressure on prices to revert. This evidence provides strong support for Hypothesis 3.

3.4 Vector autoregressions

Another approach to examining the relation between group trading and price changes is to estimate a vector autoregression as in Hasbrouck (1991). There are a number of benefits to this approach. First, allowing the trade variables and returns to depend on lags of each other provides a way to examine potentially complicated dynamics among the variables. Second, the lag structure of the VAR allows me to plot contemporaneous price impact and subsequent price changes. These plots are the empirical analogue of the stylized price paths shown in Figure 1.

Let $\mathbf{y}_{i,t} \equiv (H/H_{i,t}, I/I_{i,t}, H/I_{i,t}, I/H_{i,t}, R_{i,t})'$. As above, the notation $H/I_{i,t}$ denotes the proportion of trading in stock i on date t that comes from households purchasing shares from institutions, and so on. The reduced-form VAR for each stock, i, is

$$\mathbf{y}_{i,t} = \sum_{k=1}^{p} \mathbf{\Phi}_k \mathbf{y}_{i,t-k} + \sum_{k=0}^{s} \mathbf{\Theta} \mathbf{x}_{i,t-k} + \boldsymbol{\epsilon}_{i,t}, \tag{3}$$

where $\mathbf{x}$ is a vector of exogenous controls. In order to allow returns to depend contemporaneously on the trade variables, I estimate a dynamic structural VAR (see Hamilton (1994, Section 11.6)). In particular, triangular factorization of the error covariance matrix, $\mathbf{\Sigma} \equiv E(\boldsymbol{\epsilon}_t \boldsymbol{\epsilon}_t')$, yields a lower-diagonal matrix, $\mathbf{A}_0$, with ones on the principal diagonal such that $\mathbf{A}_0 \mathbf{\Sigma} \mathbf{A}_0' = \mathbf{\Sigma}^d$ where $\mathbf{\Sigma}^d$ is a diagonal matrix with all positive elements. Multiplying both sides of equation (3) by $\mathbf{A}_0$ gives the dynamic structural VAR

$$\mathbf{A}_0 \mathbf{y}_{i,t} = \sum_{k=1}^{p} \mathbf{A}_k \mathbf{y}_{i,t-k} + \sum_{k=0}^{s} \mathbf{C}_k \mathbf{x}_{i,t-k} + \boldsymbol{\eta}_{i,t}, \tag{4}$$

where $\mathbf{A}_k = \mathbf{A}_0 \mathbf{\Phi}_k$, $\mathbf{C}_k = \mathbf{A}_0 \mathbf{\Theta}_k$, and $\boldsymbol{\eta}_t = \mathbf{A}_0 \boldsymbol{\epsilon}_t$. The shocks in this system are uncorrelated, since $E(\boldsymbol{\eta}_t \boldsymbol{\eta}_t') = E(\mathbf{A}_0 \boldsymbol{\epsilon}_t \boldsymbol{\epsilon}_t' \mathbf{A}_0') = \mathbf{\Sigma}^d$. Moreover, since $\mathbf{A}_0$ is lower-diagonal, this specification allows each variable in $\mathbf{y}_{i,t}$ to depend on contemporaneous realizations of the variables that precede it in the vector:

$$H/H_{i,t} = \sum_{k=1}^{p} \mathbf{A}_{1k}\mathbf{y}_{t-1} + \eta_{i,1t}, \tag{5a}$$

$$I/I_{i,t} = \sum_{k=1}^{p} \mathbf{A}_{2k}\mathbf{y}_{t-1} - a_{21}H/H_{i,t} + \eta_{i,2t}, \tag{5b}$$

$$H/I_{i,t} = \sum_{k=1}^{p} \mathbf{A}_{3k}\mathbf{y}_{t-1} - a_{31}H/H_{i,t} - a_{32}I/I_{i,t} + \eta_{i,3t}, \tag{5c}$$

$$I/H_{i,t} = \sum_{k=1}^{p} \mathbf{A}_{4k}\mathbf{y}_{t-1} - a_{41}H/H_{i,t} - a_{42}I/I_{i,t} - a_{43}H/I_{i,t} + \eta_{i,4t}, \tag{5d}$$

and

$$R_{i,t} = \sum_{k=1}^{p} \mathbf{A}_{5k}\mathbf{y}_{t-1} - a_{51}H/H_{i,t} - a_{52}I/I_{i,t} - a_{53}H/I_{i,t} - a_{54}I/H_{i,t} + \eta_{i,5t}, \tag{5e}$$

where $\mathbf{A}_{jk}$ denotes the jth row of $\mathbf{A}_k$, and a_{mn} denotes the (m, n)-th element of $\mathbf{A}_0$.

The order in which the variables appear in the $\mathbf{y}_{i,t}$ vector determines which variables are allowed to affect which other variables *contemporaneously*, so there is a strong theoretical reason to put returns last: we want to allow all trade variables to affect the same-day return. But the order of variables in the vector has no effect on the estimation of lagged variables, as all time-t variables are allowed to depend on all lags of all variables. Since we are primarily interested in this analysis to understand how returns move with the trade variables, it is not important to study how each trade variable is contemporaneously related to other trade variables. Because of this focus on the return equation, the ordering of the trade variables is not important so I choose one ordering, but confirm in untabulated results that all the reported results are unaffected by permuting the order of the trade variables in $\mathbf{y}_{i,t}$. That the ordering of the trade variables is empirically not important is not a surprising finding, as the trade variables are all negatively correlated contemporaneously and it is not important to the return equation whether we allow, say, I/I_t to depend on H/H_t or the other way around.

Methods to estimate VARs in panel data are not well-developed. Therefore, in the spirit of Fama and MacBeth (1973), I separately estimate the dynamic structural VAR for each stock and then take cross-sectional means of coefficient estimates. Statistical significance is determined from the cross-sectional standard errors of these means. I choose ten lags ($p = 10$) by examining the Akaike Information Criterion for the VAR. While a lower-order VAR fits well for some stocks, I fit the same model to all stocks to ease comparison of results. Estimating a model with five lags yields results that are substantially the same as those reported here. Estimation of (3) yields estimates of the $\mathbf{\Phi}_k$ and $\mathbf{\Theta}$ matrices, and triangular factorization of the estimated error covariance matrix gives an estimate of $\mathbf{A}_0$, which is then used to calculate estimates of the $\mathbf{A}_k$ and $\mathbf{C}_k$ coefficient matrices. This is repeated for each of the 111 stocks in the sample, and Table 6 summarizes the results from these regressions for $k = 0, \ldots, 5$. The controls are the return on the market and abnormal turnover, as in the previous regressions. For brevity, these controls, as well as lags of order greater than five and the constant term are not reported.

Controlling for complex serial correlations does not alter the results reported in the previous section. The contemporaneous effect ($k = 0$) on returns of the H/I and I/H variables are quite similar to those reported in Table 4, while estimates of the H/H and I/I coefficients are an order of magnitude smaller and insignificant. The other coefficients in the $k = 0$ panel are all negative, which is expected since trading between any two investor groups reduces the amount of other combinations of trading that can occur. The strongest effects are seen in the negative relation between I/I and H/H, and between I/H and H/I. That is, when lots of trading among households occurs, we are less likely to see trading among institutions. And when more trading is institutions buying from households, we are less likely to see institutions also selling to households.

Looking at higher order lags, the negative autocorrelation in daily returns that is consistent with bid-ask bounce is quite prevalent in these data, with significantly negative estimates at up to three lags. In the return equation, coefficient estimates on H/I and I/H have opposite signs than they do when $k = 0$, indicating some reversal of the effect of trading on contemporaneous returns, although the magnitude of these coefficients is significantly less than the initial effect. All of the trade variables are positively autocorrelated, as can be seen by the positive coefficients on the diagonal, even up to five lags, so confirming that the results hold in a VAR framework is useful.

3.4.1 Empirical price paths

The coefficient estimates from the VAR can be used to construct impulse response functions, which are the empirical analogue to the stylized price paths presented earlier in Figure 1. I calculate the effect of a one standard deviation impulse to each of the elements of the orthogonalized shocks, $\boldsymbol{\eta}_{i,t}$. For example, to see the effect on returns of a shock to I/H, I use equations (5d) and (5e) to estimate the increase in returns caused by a one standard deviation increase in $\eta_{i,4t}$.

Results from applying this procedure to the return equation of the VAR are presented in Figure 2. The figure plots the price impact function for the variables I/H (solid line), I/I (short dash), H/H (long dash), and H/I (dash-dot). Time is measured in trading days, so the ten lags that are plotted correspond to two weeks of trading. A one standard deviation innovation in I/H increases the contemporaneous return by 32 bps, and there is no evidence of subsequent reversion. Consistent with the results reported above, shocks to H/I have an even larger effect: a one standard deviation innovation leads to a return of -61 bps, again with no subsequent reversion. In sharp contrast, a one standard deviation innovation in H/H or I/I are associated with very little response (-5 bps and 1 bp, respectively), and any impact is statistically indistinguishable from zero almost immediately. Comparing these empirical price impact functions to the stylized examples in Figure 1 indicates that when institutions purchase shares from individuals or sell shares to individuals they look like informed traders demanding liquidity from individuals. This result is clearly not consistent with individual investors actively moving prices.

3.5 Longer horizon results

Table 7 presents results for estimation of regression (1) over different trading horizons. Panel A shows results when the trading percentage variable and returns are calculated over weekly horizons, and Panel B shows results calculated at a monthly horizon. At these longer horizons, the results remain consistent with what was found in the daily regression. Returns are contemporaneously higher when institutions purchase shares from individuals and lower when they sell shares to individuals. There is relatively little or no price effect from intragroup trading by individuals or institutions, especially at the monthly horizon. As in the daily results, the price impact of institutions is stronger when they sell to individuals than when they buy from individuals.

4 Conclusion

This paper studies the relation between trading by household and institutional investors, and stock returns. In contrast to related papers, the results presented here focus on the daily horizon. At this relatively high frequency, it is apparent that price movements are particularly associated with the trading demands of institutions, but not with those of households.

I show that trading among households, and among institutions, is quite common, but that this trading is not associated with significant price changes. Rather, it is when institutions trade with households that prices tend to move. In particular, prices consistently move in the direction of institutional trading: on average, when institutions buy from households, prices rise, and when they sell to households, prices fall.

In addition, I find that subsequent price reversion is more common following price changes that occur when individual investors trade with other individuals than when individuals trade with institutions. Moreover, this reversion coincides with institutions trading with individuals in a direction that would tend to push prices back toward previous levels—institutions buy following individual selling, and sell following individual buying.

While there may be short-term price effects caused by individual investors, my findings suggest that prices are unlikely to be affected by such distortions at longer horizons. Therefore the paper contributes to an active debate in the literature on whether and how trading by individuals and institutions alters returns. In particular, my results are consistent with those of Kaniel et al. (2008) and Kelley and Tetlock (2013), among others, that trading by individual investors does not lead to meaningful price distortions. However, future research could perhaps provide additional insight by asking why different settings and research designs have thus far delivered contradictory findings.

Appendix

Intraday results: Evidence from trading prices

A potential concern with the daily results presented in section 3.2 relates to the timing of trades within the day. Perhaps prices move due to trading by households, and then institutions subsequently trade at those new prices, but the institutional trading does not actually move prices. For example, suppose individuals trade in the morning at prices above the previous day's close, and when institutions see prices increasing they act as momentum traders and decide to buy shares. Their buying, however, could occur at prices that are not higher than the prices set by individual trading. In this situation, we would find that institutions purchase shares on days when prices rise, but we would be wrong to infer that institutions caused the price change.

The strength and robustness of the results suggest that this scenario is unlikely. Moreover, this story would imply, counterfactually, that the estimate of β_{HH} would be nonzero. Nevertheless, an additional test to rule out this possibility is in order. Unfortunately, the transactions in the data set are not time-stamped, so it is not possible to examine directly the order in which trades were placed and the path prices took within the day. However, we do observe trade prices for each transaction, so it is possible to compare the prices at which institutions and households purchase and sell shares, and the relation between those prices and contemporaneous returns.

To understand the test, suppose that on a particular day a stock trades only at two prices, L and H, with $L < H$. Suppose further that both household and institutional investors purchased shares at L, but only institutions bought at H. If the closing price is H, it can only be because institutions moved the price; households did not purchase any shares at H, so they could not have caused the price to move up to that level. That is, since households only bought at a lower price than did institutions—and prices increased—it is not possible for households to have caused prices to move. This suggests that we can test whether one group moves prices by examining the relation between returns and the prices at which households and institutions trade during the day.

The point of this exercise is not to determine trading profits within a day, since we are not comparing one group's purchase and sale prices; rather, we are looking at whether one group *purchased* stocks at *higher* prices than did another group on days when prices *rose*, or *sold* stocks at *lower* prices on days when prices *fell*. An intraday test also allows us to differentiate intraday price movements from close-to-open price movements. If the opening price is above the previous day's close and then remains flat during the day, and if most trading just happened to come from institutions buying shares from households, the previous regressions would show that institutions buy from individuals when prices increase—but the price change happened entirely when the market was closed. The intraday test in this section, however, can rule this out.

Table A1 presents the results of such a test. For each trading day of each stock, I calculate the proportion of trading at each price that comes from either institutions or households. Each proportion is adjusted by subtracting the unconditional average proportion of trading for each group (calculated quarterly for each stock), and then averaged within each stock across time. The table reports the cross-sectional means and t-statistics of these adjusted proportions broken down by high or low prices and whether returns are positive or negative. Panel A reports results for only those trades that occurred at the highest or lowest trade price of the day, while Panel B includes all trades in the top or bottom quartile of trade prices for each stock-day.

The intraday results confirm that prices move in response to institutional trading. Consider first the results of Panel A. On days with *positive* returns, institutions buy 8.5% more than usual (and sell 4.9% less than usual) at the *highest* price of the day. In contrast, households undertake significantly less buying—and more selling—at the highest price of the day. Negative-return days deliver a mirror-image result: institutions sell 7.7% more than usual and buy 4.7% less than usual at the lowest price of the day, while households sell 6.8% less than usual and buy 4.1% more than usual at the lowest price.

Results in Panel B, which expands the set of prices examined, provide a similar picture. Again, it is worth noting that the very large t-statistics are not driven by a large sample size; these are cross-sectional statistics calculated from the 111 firms in the sample, and the small standard errors reflect the fact that these results are found in virtually every stock in the sample.

In summary, the intraday test shows that on days when prices rise, institutions are more likely to be buyers—and less likely to be sellers—at the *highest* prices of the day, while on days when prices fall they are more likely to sell—and less likely to buy—at the *lowest* prices of the day. Household trading generally follows the opposite pattern. This is entirely consistent with prices being moved by institutional trading, and therefore provides additional strong support for Hypothesis 1.

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Table 1: Summary Statistics

The table presents summary statistics for the sample. Panel A describes the firms in the data. Size denotes the quarter-end market capitalization. "Val/day" denotes the value of shares traded per day. (Prices prior to 1999 are converted to Euros at the official exchange rate.) "Num Accts" is the number of unique accounts that trade a stock each day. "Shareholders" is the number of unique shareholders in a security at the end of each quarter. There are 111 firms in the sample, but the sum across size tertiles is larger because some firms move between tertiles over time and N is the number of unique firms that are ever in each tertile. Panel B describes the account-level data. Data are from January, 1995 to June, 2009.

Panel A: Firm statistics

	N	Average of: Size (€MM)	Trades/day	Val/day (€MM)	Num Accts	Shareholders
All firms	111	2100	134	2.9	71	20233
Smallest tertile	72	151	40	0.3	34	10053
Middle tertile	76	509	89	0.9	62	15445
Largest tertile	59	3954	250	5.8	118	32281
Nokia (class A)	1	58136	2229	138.2	625	84723

Panel B: Account statistics

	Number of:		Average of:		
	Accounts	Trades (MM)	Shares per trade (000s)	Value per trade (000s)	Securities traded
Households	711,933	22.9	0.7	7.9	4.6
Financial institutions	950	17.2	3.5	60.0	23.9
Nonfinancial corporations	36,263	9.0	2.8	45.0	7.4
Government and nonprofit	6,731	1.0	5.8	84.5	6.9
Foreign organizations	5,915	6.9	1.9	29.5	3.8
All	761,792	57.0	2.1	33.5	4.8

Table 2: Proportion of exactly-identified trading

The table presents summary statistics for the proportion of trading in which the buyer and seller can be exactly identified using the method discussed in the text. Each observation represents the trading in one stock on one day. Panel A presents results as a proportion of the number of trades, while in Panel B it is as a proportion of the number of shares traded. In each panel, the first row presents data averaged across all firm-days. The next three rows present results broken down by firm size tertile at the end of the previous quarter. The final row shows results for the cross-sectional distribution of firm-level averages.

			Percentiles				
	N	Mean	1%	10%	50%	90%	99%
Panel A: Proportion of Trades							
All	224415	0.801	0.222	0.440	0.891	1.000	1.000
Size tertiles:							
Small	78560	0.879	0.226	0.548	1.000	1.000	1.000
Medium	74310	0.826	0.229	0.494	0.931	1.000	1.000
Large	71545	0.691	0.214	0.364	0.713	1.000	1.000
Avg. by firm	111	0.816	0.426	0.647	0.851	0.954	0.980
Panel B: Proportion of Trading Volume							
All	224415	0.865	0.159	0.590	0.960	1.000	1.000
Size tertiles:							
Small	78560	0.909	0.139	0.658	1.000	1.000	1.000
Medium	74310	0.873	0.121	0.582	0.982	1.000	1.000
Large	71545	0.807	0.247	0.564	0.852	1.000	1.000
Avg. by firm	111	0.873	0.639	0.781	0.881	0.961	0.985

Table 3: Interaction

The table shows how much trading is accounted for by households and institutions, and how much trading occurs within and between each group. The volume of shares traded by each group is calculated each day for each stock, and then a time series average calculated for each stock. The cross-sectional average of this quantity (across stocks or size tertiles) is reported in Panel A. Panel B presents the amount of actual interaction, and the expected amount of interaction from a "back of the envelope" calculation, both of which are described in the main text. Standard errors are reported in parentheses.

Panel A: Percentage of trading

	Households	Institutions
All firms	0.331	0.437
	(0.019)	(0.020)
Smallest tertile	0.450	0.288
	(0.016)	(0.018)
Largest tertile	0.165	0.618
	(0.018)	(0.027)

Panel B: Interaction

	Actual		Expected	
	Households	Institutions	Households	Institutions
All firms				
Households	0.228		0.150	
	(0.015)		(0.014)	
Institutions	0.251	0.140	0.208	0.236
	(0.007)	(0.012)	(0.007)	(0.019)
Smallest tertile				
Households	0.319		0.228	
	(0.017)		(0.017)	
Institutions	0.236	0.056	0.224	0.098
	(0.008)	(0.006)	(0.008)	(0.010)
Largest tertile				
Households	0.098		0.046	
	(0.011)		(0.011)	
Institutions	0.256	0.239	0.156	0.423
	(0.012)	(0.021)	(0.009)	(0.026)

Table 4: Fama-MacBeth Regressions

The table presents the results of Fama-Macbeth ("FM") estimates of regressions of the form

$$R_{it} = \alpha_i + \beta_{HH,i} H/H_{i,t} + \beta_{HI,i} H/I_{i,t} + \beta_{IH,i} I/H_{i,t} + \beta_{II,i} I/I_{i,t} + \sum_{k=1}^{3} \beta_{R,k} R_{i,t-k} + \sum_{k=0}^{3} \gamma_k R^M_{t-k} + \sum_{k=0}^{3} \delta_k ABNTO_{i,t-k} + \epsilon_{i,t},$$

where the notation $H/I_{i,t}$ denotes the fraction of trading in stock i on date t that is accounted for by households buying from institutions, $I/H_{i,t}$ is the proportion from institutions buying from households, etc. Control variables (not tabulated) include lags of: R_i, the daily return on stock i; R^M, the return on the value-weighted market portfolio; and $ABNTO_i$, the stock's abnormal turnover, which is calculated as the daily turnover (shares traded divided by shares outstanding) divided by its 40-day trailing average. The left panel shows the cross-sectional mean of time series regressions by firm, while the right panel shows the time-series mean of cross-sectional regressions by date. (To avoid perfect collinearity, R^M_t and its lags are not included in the cross-sectional regressions.) "Std. Est" denotes the average standardized estimate (the estimate multiplied by the ratio of the standard deviation of the dependent variable to the standard deviation of the regressor). The final two columns of each panel show the percentage of regressions in which a coefficient is significantly negative or positive at the 1% level. In Panel A, the trade variables H/H, I/I, H/I, and I/H are calculated as a proportion of the number of trades, while in Panel B they are calculated as a proportion of the number of shares traded. Panel C reports results of the same regression as in Panel B, but with the dependent variable replaced with the absolute value of the stock return. In this regression, control variables involving a return are also replaced by their respective absolute values. Significance at 5% and 1% levels is denoted by * and **, respectively.

	FM by stock ($N = 111$)					FM by date ($N = 3543$)				
				Sig. at 1%					Sig. at 1%	
	Estimate	t-stat	Std. Est	Neg.	Pos.	Estimate	t-stat	Std. Est	Neg.	Pos.
Panel A: Proportion of trades										
H/H	0.0036	1.86	-0.0037	6%	4%	-0.0017**	-3.87	-0.0207	3%	1%
I/I	0.0000	0.00	-0.0100	6%	1%	-0.0031**	-7.14	-0.0247	3%	1%
H/I	-0.0378**	-12.06	-0.1570	87%	0%	-0.0263**	-36.57	-0.1429	13%	1%
I/H	0.0280**	11.10	0.1126	0%	79%	0.0239**	40.79	0.1264	0%	10%
Panel B: Proportion of trade volume										
H/H	0.0057	1.10	-0.0082	6%	2%	-0.0029	-1.80	-0.0146	3%	2%
I/I	-0.0008	-0.86	-0.0079	2%	0%	-0.0014**	-4.57	-0.0142	2%	1%
H/I	-0.0370**	-8.76	-0.1242	85%	0%	-0.0205**	-17.80	-0.1057	10%	1%
I/H	0.0296**	7.59	0.0921	0%	65%	0.0199**	30.39	0.0974	1%	9%
Panel C: Proportion of trade volume, dependent variable = $\|R_{it}\|$										
H/H	0.0009	0.58	0.0049	2%	6%	-0.0014**	-2.99	0.0026	3%	3%
I/I	-0.0011	-1.63	-0.0012	8%	7%	-0.0003	-0.73	-0.0005	4%	5%
H/I	0.0067**	4.86	0.0259	1%	26%	0.0044**	5.71	0.0326	5%	7%
I/H	0.0052**	3.00	0.0191	2%	20%	0.0036**	5.06	0.0284	4%	6%

Table 5: Response to Household Trading

The table presents the results of Fama-Macbeth estimates of the regression

$$y_{i,t} = \alpha_i + \beta_1(H/H_{i,t-1} \times R_{i,t-1}) + \beta_2(I/I_{i,t-1} \times R_{i,t-1}) + \text{ Controls } + \epsilon_{i,t},$$

where the notation H/I denotes the fraction of trading accounted for by households buying from institutions, etc. Control variables (untabulated) include all of the controls from Table 4 as well as one lag of each of the trade variables (H/H, I/I, H/I and I/H). Each panel presents results from a different set of regressions. "Std. Est" denotes the average standardized estimate (the estimate multiplied by the ratio of the standard deviation of the dependent variable to the standard deviation of the regressor). Significance at 5% and 1% levels is denoted by * and **, respectively.

	FM by stock ($N = 111$)			FM by date ($N = 3543$)		
	Estimate	t-stat	Std. Est	Estimate	t-stat	Std. Est
Panel A: Dependent variable = $R_{i,t}$						
$H/H_{i,t-1} \times R_{i,t-1}$	-0.1906**	-3.07	-0.0327	-0.0934**	-4.28	-0.0494
$I/I_{i,t-1} \times R_{i,t-1}$	0.0115	0.58	-0.0057	0.1045**	8.52	0.0391
Panel B: Dependent variable = $H/I_{i,t}$						
$H/H_{i,t-1} \times R_{i,t-1}$	1.2670**	4.45	0.0315	0.2303*	2.11	0.0092
$I/I_{i,t-1} \times R_{i,t-1}$	0.0517	0.52	0.0171	0.0551	0.92	0.0051
Panel C: Dependent variable = $I/H_{i,t}$						
$H/H_{i,t-1} \times R_{i,t-1}$	-1.1627**	-3.75	-0.0271	-0.3731**	-3.14	-0.0150
$I/I_{i,t-1} \times R_{i,t-1}$	-0.0899	-1.07	-0.0223	-0.0622	-0.97	-0.0024

Table 6: Returns and Group Interaction—VAR Results

This table presents coefficient estimates from the dynamic structural VAR(10) in equation (4),

$$\mathbf{A}_0\mathbf{y}_{i,t} = \sum_{k=1}^{10} \mathbf{A}_k\mathbf{y}_{i,t-k} + \sum_{k=0}^{5} \mathbf{C}_k\mathbf{x}_{i,t-k} + \boldsymbol{\eta}_{i,t},$$

where $\mathbf{y}_{i,t} = (H/H_{i,t}, I/I_{i,t}, H/I_{i,t}, I/H_{i,t}, R_{i,t})'$. The notation $H/I_{i,t}$ denotes the fraction of trading in stock i on date t that is accounted for by households buying from institutions, etc. The exogenous variables, $\mathbf{x}$, include the value-weighted market return and the abnormal turnover (daily turnover scaled by its trailing 40-day moving average). $\mathbf{A}_0$ is the lower diagonal matrix from the triangular factorization of the error covariance in the reduced-form VAR (equation (3)). Separate regressions are estimated for each of the 111 stocks in the sample. The table reports cross-sectional averages of the $\mathbf{A}_k$ coefficient estimates for $k = 0, \ldots, 5$. t-statistics, calculated from the cross-sectional distribution of the coefficient estimates, are reported in parentheses. For brevity, the constant terms and lags of order six and higher are omitted. Statistical significance at the 5% and 1% levels is denoted by * and **, respectively.

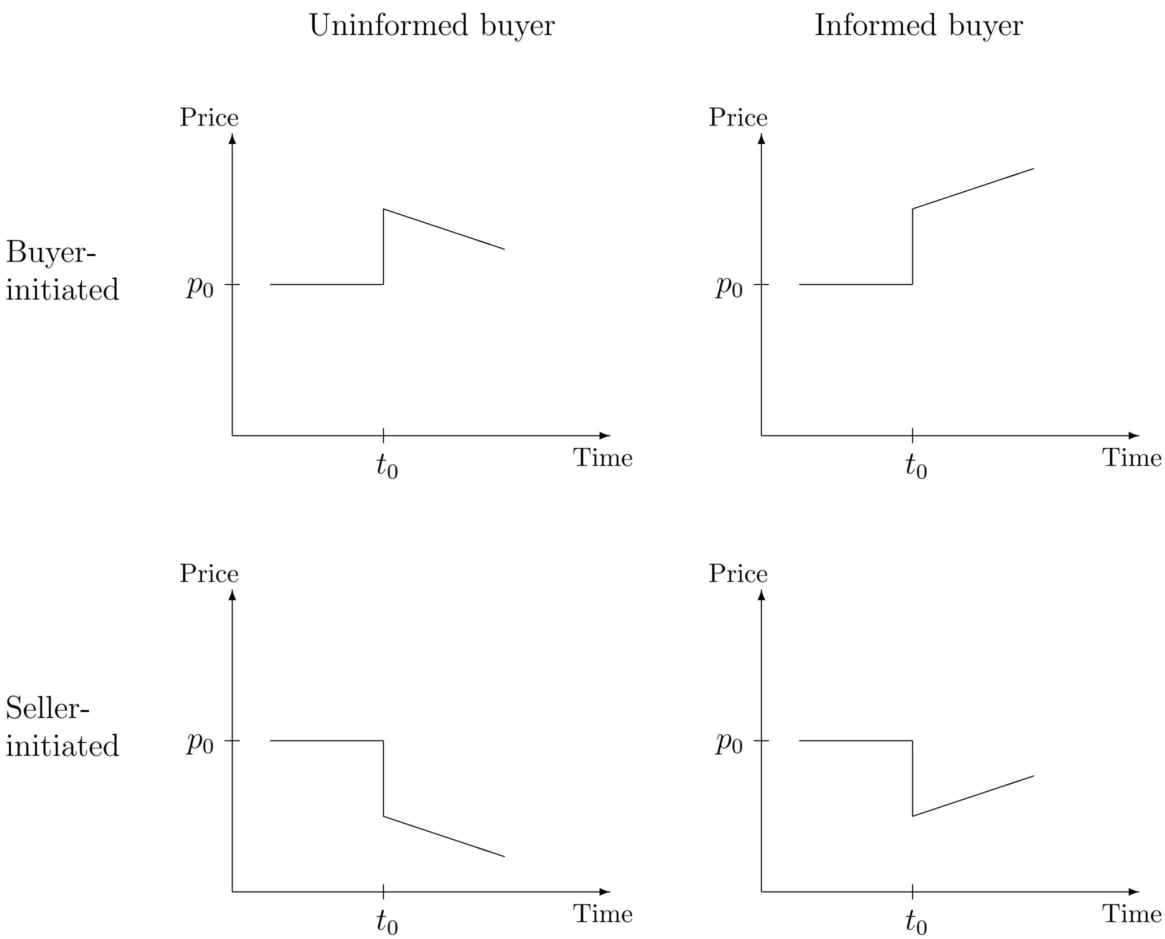
Equation	Elements of $\mathbf{y}_{i,t-k}$					Elements of $\mathbf{y}_{i,t-k}$				
	House/House	Inst/Inst	House/Inst	Inst/House	Return	House/House	Inst/Inst	House/Inst	Inst/House	Return
	$k=0$					$k=3$				
House/House	–	–	–	–	–	0.0568**	-0.0287**	0.0013	0.0024	-0.0057
						(12.04)	(-3.56)	(0.30)	(0.47)	(-0.24)
Inst/Inst	-0.4496**	–	–	–	–	0.0060	0.0627**	0.0060	0.0078*	-0.0084
	(-7.78)					(1.38)	(15.91)	(1.24)	(2.13)	(-0.62)
House/Inst	-0.0725**	-0.0522**	–	–	–	0.0146**	0.0198**	0.0700**	-0.0011	-0.0471**
	(-3.25)	(-3.84)				(3.05)	(4.45)	(16.84)	(-0.35)	(-2.88)
Inst/House	-0.1306**	-0.0855**	-0.3615**	–	–	0.0168**	0.0144**	0.0259**	0.0619**	0.0230
	(-4.32)	(-5.44)	(-25.47)			(4.66)	(3.07)	(7.16)	(16.93)	(1.44)
Return	-0.0017	-0.0012	-0.0518**	0.0371**	–	0.0003	0.0016	0.0044**	-0.0031**	-0.0210**
	(-1.37)	(-0.90)	(-12.17)	(11.95)		(0.33)	(1.24)	(4.89)	(-4.05)	(-5.41)
	$k=1$					$k=4$				
House/House	0.1754**	-0.0450**	0.0149*	-0.0093	0.0601*	0.0467**	-0.0115	0.0128**	0.0047	-0.0208
	(27.13)	(-5.17)	(2.12)	(-1.39)	(2.32)	(11.13)	(-1.80)	(2.82)	(1.08)	(-0.96)
Inst/Inst	0.0555**	0.2054**	0.0237**	0.0268**	-0.0059	0.0070	0.0474**	0.0013	0.0068*	0.0211
	(5.97)	(28.83)	(4.12)	(6.20)	(-0.37)	(1.09)	(13.49)	(0.31)	(2.09)	(1.21)
House/Inst	0.0373**	0.0410**	0.2384**	-0.0316**	-0.1121**	0.0110*	0.0026	0.0481**	-0.0048	-0.0296
	(7.86)	(7.31)	(37.84)	(-10.52)	(-5.18)	(2.06)	(0.45)	(13.51)	(-1.14)	(-1.85)
Inst/House	0.0351**	0.0549**	0.0529**	0.2151**	0.0171	0.0095*	0.0077	0.0123**	0.0476**	0.0101
	(4.65)	(10.05)	(11.24)	(32.17)	(1.04)	(2.55)	(1.54)	(3.45)	(12.49)	(0.75)
Return	0.0006	-0.0012	0.0106**	-0.0088**	-0.0816**	-0.0010	-0.0016	0.0048**	-0.0031**	-0.0032
	(0.45)	(-0.78)	(6.65)	(-6.01)	(-10.06)	(-0.85)	(-1.49)	(5.41)	(-3.96)	(-0.91)
	$k=2$					$k=5$				
House/House	0.0842**	-0.0276**	0.0066	-0.0029	0.0138	0.0433**	-0.0154*	-0.0001	-0.0058	-0.0134
	(17.97)	(-3.89)	(1.39)	(-0.56)	(0.63)	(10.33)	(-2.13)	(-0.03)	(-1.26)	(-0.51)
Inst/Inst	0.0397**	0.0919**	0.0083*	0.0114*	-0.0018	0.0142	0.0413**	0.0004	0.0058	0.0029
	(5.64)	(19.84)	(1.97)	(2.18)	(-0.15)	(1.94)	(10.54)	(0.12)	(1.77)	(0.20)
House/Inst	0.0113*	0.0212**	0.1092**	-0.0101**	-0.0708**	0.0113*	0.0045	0.0421**	-0.0007	-0.0337*
	(2.05)	(5.25)	(30.73)	(-3.73)	(-3.89)	(2.21)	(0.98)	(10.48)	(-0.22)	(-2.37)
Inst/House	0.0131**	0.0258**	0.0277**	0.0996**	0.0316*	0.0066	0.0065	0.0143**	0.0422**	0.0336*
	(2.92)	(4.97)	(6.96)	(18.72)	(2.31)	(1.27)	(1.57)	(4.64)	(11.07)	(2.48)
Return	0.0017	-0.0017	0.0048**	-0.0039**	-0.0317**	-0.0011	0.0000	0.0045**	0.0006	-0.0041
	(1.63)	(-1.35)	(4.80)	(-5.76)	(-7.24)	(-0.95)	(-0.04)	(4.58)	(0.48)	(-1.29)

Table 7: Returns and Group Interaction—Weekly and Monthly

The table presents results for the same Fama-Macbeth regressions presented in Table 4, but using data at a weekly horizon (Panel A) or monthly horizon (Panel B). The same set of controls is included in each regression (untabulated). "Std. Est" denotes the average standardized estimate (the estimate multiplied by the ratio of the standard deviation of the dependent variable to the standard deviation of the regressor). The final two columns of each panel show the percentage of regressions in which the coefficient is significantly negative or positive at the 1% level. Significance at 5% and 1% levels is denoted by * and **, respectively.

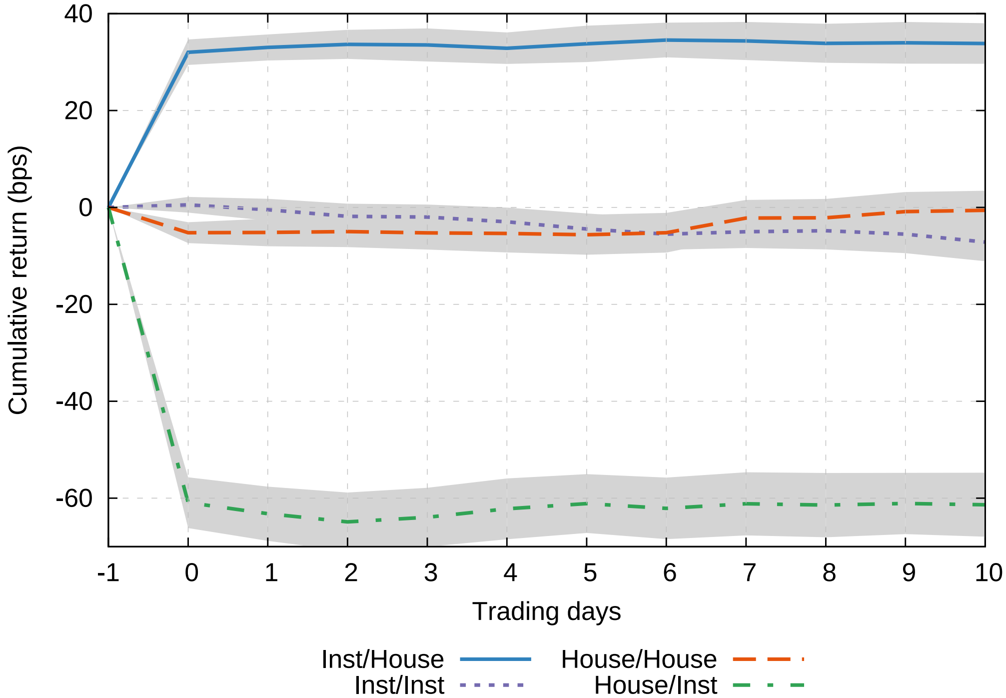
	FM by stock (N=111)					FM by date (N=741 weeks; N=168 months)				
				Sig. at 1%					Sig. at 1%	
	Estimate	t-stat	Std. Est	Neg.	Pos.	Estimate	t-stat	Std. Est	Neg.	Pos.
					Panel A: Weekly Data					
H/H	0.0268**	3.14	0.0024	5%	3%	-0.0069**	-3.00	-0.0404	4%	1%
I/I	-0.0020	-0.30	-0.0159	5%	2%	-0.0085**	-3.93	-0.0362	2%	2%
H/I	-0.1287**	-12.67	-0.2052	64%	0%	-0.0886**	-25.60	-0.1786	19%	0%
I/H	0.0816**	11.33	0.1066	1%	41%	0.0636**	21.11	0.1281	0%	10%
					Panel B: Monthly Data					
H/H	0.1088	1.61	-0.0065	4%	0%	-0.0142	-0.97	-0.0525	8%	3%
I/I	-0.0709	-0.78	-0.0257	7%	1%	-0.0270*	-2.26	-0.0513	5%	1%
H/I	-0.3906**	-8.46	-0.2175	29%	0%	-0.2834**	-14.60	-0.2242	27%	0%
I/H	0.3116**	7.15	0.1719	1%	23%	0.1983**	8.88	0.1424	0%	12%

Figure 1: Stylized Timeline of Price Path Around Trade



Thee figure shows alternative price paths following a trade. The trade takes place at time t_0. In the top two figures, the trade is initiated by the buyer, and the price immediately increases. In the bottom two figures, the trade is initiated by the seller, and the price immediately decreases. If the trade initiator is uninformed, prices subsequently revert. If the trade initiator is informed, there is no such reversion.

Figure 2: Cumulative Price Impact Functions



The figure plots the accumulated orthogonalized impulse response function for the structural dynamic VAR in equation (4),

$$\mathbf{A}_0\mathbf{y}_{i,t} = \sum_{k=1}^{10}\mathbf{A}_k\mathbf{y}_{i,t-k} + \sum_{k=0}^{5}\mathbf{C}_k\mathbf{x}_{i,t-k} + \boldsymbol{\eta}_{i,t},$$

where $\mathbf{y}_{i,t} = (H/H_{i,t}, I/I_{i,t}, H/I_{i,t}, I/H_{i,t}, R_{i,t})'$. The notation $H/I_{i,t}$ denotes the fraction of trading in stock i on date t that is accounted for by households buying from institutions, etc. The exogenous variables, $\mathbf{x}$, include the value-weighted market return and the abnormal turnover (daily turnover scaled by its trailing 40-day moving average). $\mathbf{A}_0$ is the lower diagonal matrix from the triangular factorization of the error covariance in the reduced-form VAR (equation (3)). Separate regressions are estimated for each of the 111 stocks in the sample, and the cross-sectional distribution of estimates is used to form confidence intervals (as in the Fama-Macbeth regression approach). The graph shows the cumulative effect on returns (in basis points) of a one standard deviation shock ($\eta_{i,t}$) separately to each of the trade variables.

Table A1: Returns and Group Interaction—Intraday Evidence

The table presents analysis of the intraday relation between returns and trading by institutions and households. For each trading day of each stock, I calculate the the proportion of trading at each price accounted for by each investor group. Each proportion is adjusted by subtracting the unconditional average proportion of trading for each group, and then averaged within each stock across time. The table reports the cross-sectional mean and t-statistic of this adjusted proportion broken down by high or low prices and on positive or negative return days. Panel A reports results for trades in the top or bottom 25% of trade prices each day, while Panel B includes only those trades that occurred at the highest or lowest trade price of the day.

Return	Price	Institutions		Households	
		Buy	Sell	Buy	Sell
Panel A: Highest/lowest price of day					
Positive	High	0.085**	-0.049**	-0.088**	0.034**
		(19.03)	(-15.00)	(-20.68)	(10.06)
	Low	-0.016**	-0.018**	0.005	0.031**
		(-4.74)	(-5.60)	(1.39)	(9.05)
Negative	High	-0.023**	-0.008*	0.043**	0.002
		(-7.81)	(-2.49)	(14.06)	(0.75)
	Low	-0.047**	0.077**	0.041**	-0.068**
		(-13.69)	(18.29)	(11.28)	(-17.57)
Panel B: Top/bottom 25% of prices					
Positive	High	0.082**	-0.050**	-0.085**	0.040**
		(24.37)	(-19.44)	(-26.07)	(14.48)
	Low	0.000	-0.029**	-0.009**	0.035**
		(0.03)	(-12.36)	(-3.86)	(13.76)
Negative	High	-0.027**	0.011**	0.042**	-0.013**
		(-10.35)	(4.12)	(14.47)	(-5.45)
	Low	-0.054**	0.070**	0.052**	-0.063**
		(-21.01)	(21.33)	(20.17)	(-21.76)

Table A2: Stock-by-stock regressions

The table presents the stock-by-stock results for the regressions summarized in Table 4. All of the same controls are included, but are untabulated for brevity. N is the number of trade days. Stocks are reported sorted by average market capitalization.

Company	N	H/H		I/I		H/I		I/H	
		Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
Nokia (class A)	3501	0.025	1.43	0.005*	2.39	-0.046**	-8.27	0.051**	9.55
Sonera	1060	0.045	1.94	-0.023*	-2.32	-0.193**	-10.21	0.029*	2.33
Nordea Bank	2324	0.014*	2.56	0.000	0.01	-0.071**	-12.50	0.030**	8.06
Nokia (class K)	968	0.000	0.00	-0.002	-0.60	-0.003	-0.27	0.010**	2.73
Fortum	2604	0.000	0.06	0.003	0.83	-0.063**	-10.86	0.034**	7.47
Neste	618	-0.002	-0.67	-0.002	-0.51	-0.011*	-2.04	0.009**	2.83
Sampo	2965	-0.001	-0.12	-0.002	-0.67	-0.045**	-8.24	0.043**	6.38
Kone	1023	0.093	1.54	-0.005	-0.86	-0.106**	-7.71	0.081**	5.60
UPM-Kymmene	3259	-0.005	-0.35	0.005	1.84	-0.056**	-9.11	0.059**	10.41
Stora Enso (class A)	3256	0.031*	2.06	0.004	1.63	-0.063**	-8.95	0.082**	10.50
Neste Oil	1019	0.038	0.93	0.003	0.50	-0.120**	-10.24	0.118**	8.08
Rautaruukki	3522	0.006	1.36	0.001	0.52	-0.051**	-13.46	0.039**	10.45
Metso	2493	0.006	0.37	-0.011**	-2.76	-0.091**	-11.93	0.053**	6.92
Helsingin Puhelin	550	-0.031*	-1.97	-0.027*	-2.39	-0.055*	-2.57	0.036**	2.76
Elisa	2358	-0.011	-0.79	0.002	0.40	-0.139**	-10.82	0.031**	4.61
Wartsila (class A)	3523	0.009*	2.09	0.000	-0.23	-0.024**	-7.98	0.027**	7.94
Tieto	3461	-0.007	-1.20	0.001	0.25	-0.074**	-10.86	0.062**	9.44
Outokumpu	3518	0.009	1.15	0.002	1.16	-0.045**	-10.85	0.050**	10.87
Merita (class A)	1212	-0.002	-0.28	-0.014**	-3.17	-0.031**	-3.33	0.019**	3.83
Nokian Tyres	3030	-0.011**	-3.32	-0.005*	-2.02	-0.025**	-7.28	0.033**	7.40
Sanoma	2518	-0.001	-0.41	-0.002	-0.97	-0.017**	-4.62	0.032**	6.55
Stora Enso (class R)	3012	0.009**	3.11	0.002	1.03	-0.018**	-7.13	0.018**	8.95
Kesko (class B)	3527	0.011**	2.98	0.004**	2.61	-0.034**	-12.14	0.030**	9.44
YIT	3102	-0.002	-0.95	0.000	-0.28	-0.020**	-7.23	0.022**	5.94
Comptel	2274	0.000	0.03	0.014*	2.13	-0.056**	-10.55	0.023**	5.47
Tamrock	703	-0.007	-1.50	0.004	0.33	-0.007	-1.20	0.035**	4.28
Pohjola Bank	3242	-0.001	-0.43	-0.001	-0.62	-0.021**	-7.93	0.016**	5.71
Cargotec	1001	0.056	1.37	0.000	0.00	-0.074**	-5.71	0.097**	6.74
F-Secure	2350	0.011*	2.27	0.000	0.08	-0.067**	-9.26	0.029**	5.53
Perlos	2163	0.006	1.12	-0.001	-0.20	-0.062**	-9.71	0.025**	4.36
Raisio	3419	0.008	1.90	-0.004	-1.09	-0.042**	-9.65	0.025**	6.84
Kemira	3513	0.003	0.94	-0.001	-0.68	-0.039**	-11.40	0.024**	8.12
Ramirent	1513	0.002	0.67	-0.002	-0.76	-0.020**	-5.19	0.042**	7.10
AvestaPolarit	402	-0.001	-0.13	0.003	0.72	-0.002	-0.45	0.028*	2.53
Uponor	3361	-0.005	-1.18	-0.001	-0.62	-0.034**	-10.02	0.038**	8.64
Outotec	655	0.154*	2.01	-0.015	-1.49	-0.201**	-8.73	0.171**	6.30
Pohjola (class B)	2754	-0.007	-1.49	-0.007**	-3.24	-0.012**	-4.56	0.019**	6.28
Orion (class B)	750	-0.023	-0.45	-0.006	-1.30	-0.059**	-4.12	0.096**	6.80
Elektrobit	2665	-0.007	-1.83	0.010	0.91	-0.049**	-8.17	0.015**	3.34
Konecranes	3067	-0.009	-1.14	-0.003	-1.71	-0.034**	-7.01	0.048**	8.29
Hartwall	1616	-0.002	-0.49	-0.007*	-2.44	-0.043**	-6.74	0.016**	3.71
Instrumentarium (class B)	1896	0.001	0.42	-0.002	-0.83	-0.022**	-4.99	0.015**	4.81
Fiskars	2726	-0.001	-0.83	0.001	0.20	-0.014**	-6.81	0.006**	2.78
Huhtamaki	3522	0.002	0.61	0.001	0.69	-0.032**	-9.27	0.024**	7.30
M-Real	3522	0.029**	3.24	-0.002	-0.95	-0.053**	-13.40	0.052**	11.04
Kesko (class A)	1705	-0.003	-1.27	0.002	0.43	-0.020**	-4.62	0.017**	4.65
Pohjola (class A)	1170	-0.006	-1.44	-0.005	-1.40	-0.015**	-3.31	0.012**	2.72
Amer Sports	3528	0.000	0.08	-0.001	-0.42	-0.042**	-10.33	0.025**	7.08
Talvivaaran Mining	28	0.022	0.22	0.195	0.64	-0.116	-1.17	-0.038	-0.34
Stonesoft	2314	-0.003	-0.96	-0.009	-0.83	-0.066**	-8.77	0.053**	7.97
Sponda	2575	-0.007**	-2.96	-0.002	-1.23	-0.024**	-7.68	0.014**	6.03
Geosentric	3426	0.017**	3.32	0.015	1.64	-0.029**	-4.59	0.067**	5.58
Wartsila (class B)	2739	-0.001	-0.67	-0.005*	-1.98	-0.018**	-6.59	0.010**	3.73
Finnair	3502	-0.001	-0.38	-0.001	-0.59	-0.026**	-11.89	0.022**	9.28
Merita (class B)	842	-0.010**	-2.85	0.001	0.13	-0.011	-1.90	0.003	0.80

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Company	N	H/H		I/I		H/I		I/H	
		Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
Finnlines	3388	0.005	0.95	-0.005**	-3.01	-0.022**	-7.34	0.020**	7.51
Orion (class A)	748	-0.001	-0.29	0.000	-0.04	-0.023**	-5.55	0.010*	2.52
Poyry	2031	0.002	0.80	0.001	0.36	-0.013**	-5.13	0.024**	6.61
Ahlstrom	801	-0.001	-0.26	0.002	0.46	-0.021**	-4.10	0.016**	3.09
Rauma	924	-0.001	-0.14	-0.008**	-2.72	-0.029**	-4.99	0.020**	3.43
Lassila & Tikanoja	1751	0.001	0.28	-0.004	-1.65	-0.015**	-5.36	0.028**	5.93
Conventum	307	0.010	1.12	0.001	0.05	-0.021	-1.29	0.021	1.47
Instrumentarium (class A)	1108	-0.011**	-2.71	-0.008*	-2.21	-0.024**	-3.72	0.005	1.56
Stockmann	3077	-0.006**	-3.38	-0.003	-1.13	-0.018**	-7.26	0.013**	6.08
Cultor (series I)	988	-0.002	-0.25	-0.005	-1.54	-0.022*	-2.17	0.014*	2.51
Lemminkainen	2477	-0.002	-1.10	-0.006**	-2.67	-0.013**	-5.77	0.008**	3.02
Sanitec	424	0.008	1.01	0.010	1.13	-0.080**	-6.64	-0.002	-0.43
Alma Media (series II)	927	0.004	0.42	-0.004	-1.34	-0.029**	-5.37	0.023**	3.40
Trainers House	2204	0.000	0.05	0.017	1.82	-0.041**	-6.51	0.021**	4.61
Partek	1790	-0.004	-1.42	-0.005	-1.46	-0.016**	-3.81	0.015**	5.12
Elcoteq	2803	0.003	0.52	-0.002	-0.52	-0.052**	-8.62	0.038**	7.10
Aspocomp	2096	0.004	0.96	0.000	-0.03	-0.022**	-4.84	0.023**	4.21
Vacon	1994	-0.002	-0.92	-0.002	-0.87	-0.023**	-8.07	0.015**	5.29
Kemira Growhow	815	-0.004	-0.67	-0.005	-1.13	-0.036**	-6.35	0.005	1.42
Aldata Solution	2316	0.000	0.14	0.005	0.63	-0.049**	-9.51	0.022**	5.33
Tamro	1945	-0.003	-1.13	-0.003	-1.06	-0.020**	-5.49	0.006**	2.88
Teleste	2396	0.002	0.81	-0.001	-0.17	-0.034**	-7.85	0.026**	5.87
Vaisala	2893	0.002	1.18	-0.002	-1.22	-0.015**	-7.90	0.016**	7.66
Glaston	1722	-0.003	-1.41	0.005	0.99	-0.018**	-5.40	0.009**	3.33
Alma Media (series I)	1263	-0.003	-0.61	-0.001	-0.30	-0.001	-0.36	0.015**	3.14
Oriola-KD (class B)	726	0.009	0.76	-0.005	-0.89	-0.031**	-3.45	0.038**	5.22
Eimo	1141	0.003	0.68	0.031*	2.09	-0.048**	-7.65	0.015**	2.62
Tecnomen	220	-0.004	-0.26	-0.016	-0.86	-0.056**	-2.84	0.096**	4.14
WM-Data Novo	1424	0.000	0.01	-0.008	-1.36	-0.031**	-5.50	0.020**	3.88
Cultor (series II)	969	0.023*	2.04	-0.002	-0.98	-0.030**	-4.12	0.022	1.70
Tekla	1543	0.002	0.77	-0.006	-1.64	-0.021**	-4.91	0.023**	4.64
Mandatum Pankki	498	-0.009*	-2.06	-0.010	-0.91	-0.014*	-2.34	0.010	1.36
Soon Communications	745	-0.008	-1.75	0.052	1.18	-0.055**	-2.99	0.017**	3.08
Tectia	1996	0.000	-0.04	0.004	0.15	-0.036**	-5.20	0.039**	5.77
SRV	480	-0.007	-1.38	-0.015	-1.52	-0.046**	-5.80	0.022*	2.35
Sievi Capital	1980	0.001	0.29	-0.010	-1.37	-0.012**	-2.92	0.019**	5.06
PKC Group	2626	0.000	0.14	-0.004	-1.16	-0.015**	-4.94	0.022**	5.49
Saunalahti	1257	0.011*	2.12	0.014	0.85	-0.040**	-3.82	0.024**	4.09
Basware	2045	-0.005*	-2.05	-0.008	-1.37	-0.016**	-4.16	0.006*	2.07
FIM Group	254	-0.005	-1.15	-0.003	-0.50	-0.021**	-2.88	0.009*	2.17
Visma Software	341	-0.001	-0.07	0.025	0.55	-0.032	-1.30	0.023	1.95
Capman	1970	0.002	0.80	-0.003	-0.81	-0.028**	-6.87	0.023**	6.60
Rapala VMC	1496	-0.002	-0.61	-0.002	-0.69	-0.010**	-3.73	0.009**	3.34
Biotie Therapies	1620	-0.007	-1.21	-0.042	-1.48	-0.038**	-4.89	0.026**	2.75
eQ	1775	-0.003	-1.43	0.010	1.08	-0.030**	-5.16	0.007**	2.68
Starckjohann	531	-0.004	-1.55	0.008	0.90	-0.012**	-2.64	-0.003	-0.66
Oriola-KD (class A)	677	-0.004	-0.96	-0.001	-0.21	-0.028**	-4.74	-0.001	-0.16
Digia	2051	0.000	0.06	-0.006	-0.83	-0.013**	-4.51	0.009*	2.53
Salcomp	661	-0.018**	-3.55	-0.002	-0.30	-0.027**	-4.12	0.009	1.22
Polar Real Estate	1656	-0.004	-1.72	-0.006	-0.74	-0.011*	-2.49	0.017**	3.48
Terveystalo Healthcare	499	0.012	1.77	-0.010	-0.17	-0.008	-1.03	0.077	1.52
Tecnotree	1973	0.000	0.05	-0.002	-0.26	-0.023**	-5.40	0.030**	6.09
Suominen	1617	-0.003	-1.25	0.010	1.41	-0.015**	-4.51	0.012*	2.53
Okmetic	1956	0.000	-0.08	0.016*	2.29	-0.013**	-3.54	0.021**	4.35
Revenio	1622	-0.009	-1.85	-0.081*	-2.34	-0.042**	-3.63	0.017	1.53
Affecto	956	-0.009**	-3.15	-0.014**	-3.33	-0.021**	-6.61	0.012**	2.81
Average		0.004		0.000		-0.038		0.028	
Cross-sectional t-statistic		1.86		0.00		-12.06		11.10	
Significantly pos/neg at 1%		4% / 6%		1% / 6%		0% / 87%		79% / 0%	