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

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Abstract

I study the relation between price changes and the interaction of individual investors and financial institutions. Using the complete records of all trading in Finland over a nine-year period, I find that prices move consistently when individuals trade with institutions. Specifically, at daily, weekly, or monthly horizons, prices increase when individual investors sell shares to institutions, and decrease when individuals buy shares from institutions. Prices do not move consistently when individuals trade with other individuals or when institutions trade with other institutions. However, when price movements are caused by trading among individuals, they are quickly reversed. Moreover, these reversals occur because institutions trade with individuals to push prices toward previous levels. The results suggest that prices move in response to institutional trading, and individuals supply liquidity to institutions.

Keywords: Institutional investors; Individual investors; Liquidity provision; Price impact
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Models of market microstructure posit the existence 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 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, p. 531) defines noise trading as "trading on noise as if it were information." The literature provides considerable evidence that individual investors play this role.[2,3] For example, individual investors make remarkably poor investment decisions. In the data used in this paper, stocks heavily bought by individuals *underperform* stocks heavily sold by 6.8% over the subsequent year. In sharp contrast, stocks heavily bought by institutions outperform stocks heavily sold by 9.0% (see Table 1). There are two possible explanations for these results, which have been previously documented in other data. One, offered by Barber, Odean, and Zhu (2006) and Hvidkjaer (2006), is that individual investors push prices away from fundamentals; the subsequent reversal to fundamental value leads to the documented poor performance. The second, supported by Kaniel, Saar, and Titman (2006) and Campbell, Ramadorai, and Schwartz (2007), 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.

In this paper, I use the complete daily trading records for all trading in Finland over a nine-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

[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.

[3] Throughout this paper, I use the terms "individual" and "household" investors interchangeably. In all cases, I am referring to individual traders, and not institutional investors or professional traders.

institutions, but also *within* each group. I document that institutions are about half as likely to trade with individuals as they are to trade with other institutions. This is particularly interesting given the herding that has been documented among both individuals (Odean 1998) and institutions (Wermers 1999), which would mean that trading between groups is very common—if all institutions are buying, they cannot buy from other institutions. Second, I show that prices move consistently when institutions trade with individuals. In particular, when individuals 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, institutions move prices and individuals supply liquidity to meet the trading needs of institutions. I confirm these results at daily, weekly, and monthly horizons, and with vector autoregressions. Third, I show that if prices do move as a result of trading among individuals, they are more likely to revert than after trading between individuals and institutions or between two institutions. This price reversion is consistent with individuals being uninformed. Moreover, I show that these price reversions occur because institutions subsequently trade with individuals in a direction that moves prices back toward previous levels.

My data include the complete daily trading records of all households, financial institutions and other entities that trade stocks on the Helsinki stock exchange between 1995 and 2003. 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, nonfinancial corporation, government agency, nonprofit organization, or foreigner. Therefore, there is no need to estimate an investor classification as there is in datasets available for the U.S. Second, whereas data available in the U.S. are either available quarterly or from proprietary datasets 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 the estimation technique developed by Campbell, Ramadorai, and Schwartz (2007). Third, the data cover a nine-year period for the entire Finnish stock market. The sample includes 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. Barber, Odean, and Zhu (2006) and Hvidkjaer (2006) 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 quantities of trades and classify this as the trading of individuals. Barber, Odean, and Zhu show that this order-imbalance is correlated with the order-imbalance among a sample of investors at a discount brokerage firm. A potential problem with this approach is that either individuals or institutions could be initiating these small trades. The identification strategy employed by these authors, however, relies on the assumption that individuals initiate these trades. This could raise concerns about the generality of the results found in these papers. Indeed, in contrast to these results, Kaniel, Saar, and Titman (2006), Campbell, Ramadorai, and Schwartz (2007), and Linnainmaa (2007) all find that individual investors supply liquidity to meet institutional demand for immediacy.[4]

The remainder of the paper is organized as follows. Section 1 develops the hypotheses to be tested in the paper. In Section 2, I motivate my classification method and show how it is implemented. I present my results in Section 3. Section 4 concludes.

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,

[4]The large literature examining the performance of institutional investors also highlights the importance of using high-frequency data. Increases in institutional ownership are associated with price increases at a quarterly or annual frequency (Nofsinger and Sias 1999, Cai and Zheng 2004). However, it is difficult to tell from quarterly data whether institutional trading within the quarter leads, lags, or is contemporaneous with returns. This makes it difficult to determine causality, particularly since fund managers follow momentum strategies (Carhart 1997, Daniel, Grinblatt, Titman, and Wermers 1997, Wermers 1999). Sias, Starks, and Titman (2006) develop a technique to extract the covariance of returns and institutional trading at a monthly or weekly level from quarterly data. They find that institutional trading leads returns. Griffin, Harris, and Topaloglu (2003), examine daily trading in 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.

or by institutions selling overvalued stocks to individuals. To differentiate between these alternatives, I develop and test a number of hypotheses.

While researchers typically think of liquidity provision as submitting a limit order that gives others the option to trade, Kaniel, Saar, and Titman (2006) 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 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 caused by 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.[5] Grinblatt and Han (2005) show that momentum in stock returns can be caused by disposition-prone investors behaving this way.

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 northeast and southwest 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.[6] 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.

[5]The disposition effect is the well-documented reluctance of investors to sell stocks below their purchase price. The behavior was first described by Shefrin and Statman (1985). See Seru, Shumway, and Stoffman (2007) and references therein.

[6]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.

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

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. In particular,

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 3.5.

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 dataset 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 type of investor owns shares.

The data cover daily trading in all Finnish stocks over a nine-year period. Grinblatt and Keloharju (2000, 2001a, 2001b) use a subset of the same data, comprising the first two years of my sample period. Summary statistics for the data are presented in Table 2. The data include the transactions of nearly 1.3 million individuals and firms, beginning in January, 1995 and ending in December, 2003. For accounts that existed prior to 1995, opening account balances are also included, making it possible to reconstruct the total portfolio holdings of an account on each day. While the dataset includes exchange-traded options and certain irregular equity securities, I focus on trading in ordinary shares. After excluding trading in very thinly-traded securities,[7] there are more than 37.5 million trades in the data, including 10.7 million trades by 583,518 unique household accounts. The remaining trades are placed by financial institutions, corporations, and to a much smaller degree, government agencies and certain other organizations. Because all trading is recorded in the data, it is possible to construct measures of trader interaction that are not feasible with datasets that include small samples of the population.

Trading in Finland is conducted on the Helsinki Stock Exchange, beginning with an opening call from 9:45 to 10:00 a.m., and ending with a closing call from 6:20 to 6:30 p.m. Continuous trading during regular hours is 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. 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. Identification of trading by other foreigners is discussed below.)

I augment the transactions data with return data from the Thomson Datastream database. I take returns excluding dividends but accounting for share splits. I exclude dividends because my focus is on price impact, and I am therefore interested in a stock's price change, not the total holding-period return.

2.2 Complications

There are a number of complications that arise when working with these data. First, transactions are not time-stamped, so it is not possible to determine the order in which trades took place within a day. Second, while each transaction is identified as either a buy or a sell, the absence of quote data makes it impossible to identify which side initiated

[7] I exclude securities with fewer than 25,000 trades, or about ten trades per day during the sample period. This leaves 116 stocks. The additional requirement that daily returns data are available on Datastream reduces the sample to 106 stocks.

the trade, as is typically done with the quote-based algorithm of Lee and Ready (1991). Nevertheless, if prices consistently move in the same direction as an investor's trading, this investor must be initiating trades; an investor who sells shares into a rising market cannot be setting prices. To be more precise, since every transaction requires both a buyer and a seller, there is a sense in which both the buyer and the seller are setting prices. However, it is commonly understood in the literature that the initiator of a trade causes the price change; indeed, this is the identifying assumption of the Lee-Ready algorithm.

Third, the investor group classification is not always correct because of the existence of so-called "nominee" accounts. I outline my approach in dealing with these accounts in Section 2.2.1. A related issue is that financial institutions that act as market-makers are not separately identified in the data. In Section 2.2.2, I discuss the method I use to separate these accounts from my analysis.

Fourth, there is 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: one purchase and one sale. However, some trades are comprised of shares purchased or shares sold by more than one account, and in these situations there can be more than two records per trade. For example, if 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 reported in the data. This necessitates using a technique to identify the amount of trading that occurs between groups, which I discuss in Section 2.2.3.

2.2.1 Nominee accounts

Unlike investors domiciled in Finland, foreign investors are not required to register with the CSD. Instead, they may trade in an account that is registered in the name of a "nominee" financial institution. As a result, trading by foreign individuals can appear to be trading by the nominee institution. This is also true of American Depository Receipts (ADRs), which many Finnish firms have. For example, if an individual in the U.S. trades shares of Nokia's ADR on the NYSE, it will be classified in the CSD data as a trade by the institution that serves as a nominee for the ADR.

Since the focus of this paper is on examining the differences in the price impact of trading among groups of investors, it is important to deal with this misclassification in some way. Note, however, that this misclassification makes it *more* difficult to find differences in the price impact of trading by different groups, because the misclassification causes a "mixing" of the group members. Nevertheless, I adopt the following approach to identify accounts that are likely to be nominee or ADR accounts. First, I require an institution to own at least ten percent of the total shares outstanding before considering it to be acting as a nominee. Then, for each stock and day, I calculate the number of trades and quantity of shares traded by each institution as a percent of all trading in that stock/day. I then count the number of days in a month in which the institution accounts for more than ten percent of both the number of trades placed and the quantity of shares traded. Finally, I classify as a nominee any institution with ten or more such days in a month. While the specifics of this procedure are somewhat arbitrary, it generally identifies only a few accounts that serve as nominees for each security, which is expected. Moreover, the results in this paper are not sensitive to using a variety of alternative parameters of the classification procedure.

2.2.2 Market-makers

For the main analysis in this paper, I focus on individuals and institutions that trade for information or liquidity reasons. Therefore, it is necessary to identify certain institutions and individuals that trade particularly actively, effectively acting as market-makers by both buying and selling a given stock on a particular day. While the motivation for such trading may differ, this type of trading may be broadly classified as market-making. (Linnainmaa (2007) explores the behavior of individual day traders in this market.) Traders who act as market-makers are unlikely to be trading based on fundamental or long-term information, and I therefore exclude this set of traders from my analysis.

To identify market-makers, I simply check whether an account purchased and sold shares in the same company on the same day. Occasionally, there are cases where an account buys and sells shares, but the amounts traded are different by orders of magnitude. For example, an account may purchase 5000 shares and sell 5 shares of one stock. It is unclear why this would occur, but it is probably not correct to call this trader a market-maker. Therefore, I require the amount purchased to be between 10 and 90 percent of the total amount traded by an account for it to be classified as a market-maker on that day. (The results are not sensitive to this restriction.) If an account is classified as a market-maker on at least five trading days in a particular month, I treat it as a market-maker for the entire month. The results in the paper are unchanged if I exclude only accounts acting as market-makers on a day-by-day basis, or if I only allow financial institutions to be classified as market-makers. Note that market-makers are identified after the nominee accounts are identified, as discussed above in Section 2.2.1.

2.2.3 Identifying investor interaction

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 on one day for one stock 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 $450/2500 = 18\%$ (45 shares) were purchased from other members of Group A, $1800/2500 = 72\%$ (180 shares) were purchased from members of Group B, and so on. 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

This estimation strategy conditions on the actual amount of purchases and sales by each group; we are *not* assuming that investors from each group randomly choose to buy and sell. Instead, we are assuming that, given the actual number of shares sold by a group, the probability of selling to any other group that bought shares is proportional to the relative amount of shares purchased and sold by each group.

This procedure is an approximation technique. In the previous example, it is possible that members of Group A did not purchase any shares from other members of Group A, although the estimate is that 45 shares were traded within this group. However, the procedure can yield an exact identification of the amount of trading that occurred between two groups. In the example, as is frequently the case in the data, one group (B) accounts for much of the purchases and sales. 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. In fact, 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 happens. 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.[8] In my data, on average 28.2% (ranging from 3.4% to 60.3%) of a stock's trading volume is exactly identified in this manner.

An alternative method to determine how much trading occurs within and between groups involves establishing bounds on how much trading could have occurred. Referring again to the example, note that Group A investors could have traded no more than 250 shares with other Group A investors, since Group A only bought 250 shares in total. Similarly, intragroup trading in Group B could have been no more than 1800 shares. But since total purchasing by Groups A and C amounts to only 500 shares, Group B investors must also have sold no fewer than $1800 - 500 = 1300$ shares to other Group B investors. Therefore, intragroup trading for Group B must have been between 1300 and 1800 shares. Since any amount of trading within these bounds could be used as the estimated amount of trading, using the mean seems sensible. In the example, this value is quite close to the value estimated using the technique above—1550 vs. 1440, or 62% vs. 58% of total trading. When applied to my data, these two methods generally provide very similar estimates of trade interaction, so the results reported below are generated from the first approach, which is somewhat less complicated. The results are not substantively changed, however, by using the second method.

[8]Suppose that institutions purchased 800 shares and sold 1000 shares, and that individuals purchased 200 shares but sold no shares. The institutions must have sold 200 shares to the individuals and 800 shares to other institutions—there is no ambiguity here, and no estimation is required.

3 Results

I turn now to presenting the results of the paper. I begin by quantifying the amount of trading that occurs among investor groups. Institutions and individual investors account for a large proportion of total trading, and it is certainly possible that trading by either of these groups could have important prices effects. I then examine the relation between contemporaneous returns at a daily, weekly, or monthly horizon and inter- and intra-group trading quantities. Returns are higher when institutions buy shares from individuals, and lower when institutions sell shares to individuals, suggesting that institutions move prices. This indicates that, on average, institutions are informed and individuals are not. To allow returns and trading quantities to be mutually dependent, I also estimate a vector autoregression (VAR). The VAR allows me to estimate price impact functions for each of the groups in the data. Next, using transaction prices, I show that institutions buy stocks at higher prices than do individuals when returns are high, and sell at lower prices than do individuals when returns are low, which provides additional evidence at an intraday frequency that institutions set prices. I then show that price reversion is more prevalent when intragroup trading by individuals is high. Moreover, the price reversion is caused by the subsequent trading of institutions.

3.1 Investor interaction

Table 3 shows the amount of trading that is accounted for by each of the four largest groups of traders. The omitted groups are Government agencies, Nonprofit organizations, and Registered foreigners; for most stocks on most days, these groups account for a negligible amount of total trading. The total amount of trading may be calculated as a percent of the number of shares traded (presented in Row 1) or as a percent of the value of shares traded (Row 2). The combined trading of individuals, institutions, nominees, and other corporations accounts for approximately 95% of all trading. About 40% comes from institutions, and about 20% from individuals ("Households"). Individuals account for 20.6% of trading by number of shares traded, and 17.4% by value, indicating that individuals tend to trade more heavily in low-priced stocks.

Using the total proportion of trade from each group, it is possible to calculate the amount of trading we would expect to occur within and between each group. The results of this exercise, using the percent of trading by shares (Row 1) is reported in the table under the heading "Expected % of all trading." For example, since financial institutions account for 38.1% of all trading, 0.381^2 =14.5% of all trading should be between two institutions. Similarly, the amount of trading that would occur between institutions and individuals is $0.381 \times 0.206 \times 2 = 0.157$, where we multiply by two because either the institution can buy from the individual or the individual can buy from the institution.[9]

The lower panel of Table 3 shows the estimated amount of trading that occurred between and within groups, using the technique described above in Section 2.2.3. That is, in contrast to the "expected" percentage in the top panel, we now condition on the actual amount of buying and selling by each group on each day, rather than total trading volume alone. There are several notable differences between actual and expected trading. Institutions trade more with each other, and less with individuals, than expected. As well, individuals trade more with other individuals than 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 between groups should be quite common—if all individuals are buying, they cannot trade with each other. The results presented here show that the previous findings 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 only 9.3% of trading takes place between individuals and institutions. Alternatively, ignoring nonfinancial corporations and ADRs, we see that institutions are about half as likely to trade with individuals as they are to trade with other each other.

What explains the discrepancy between the actual and expected amount of trading among individuals? There are several possibilities, each of which could partially contribute to 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, as in the model of Easley and O'Hara (1987), informed investors might only trade when there has been an information event. If institutions tend to be informed, they will be less likely to trade when no information event has occurred, and any trading by individuals will tend to be with other individuals. Indeed,

[9] The table is lower-diagonal because it shows the expected amount of total trading—not separated into buying and selling. A matrix showing the expected proportion of buying and selling separately would be symmetric, with the off-diagonal elements equal to one-half of the reported off-diagonal elements.

Easley, Engle, O'Hara, and Wu (2002) 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 (2006), who document that individual investors are more likely to trade following events that get media attention.

It is worth noting at this point that the amount of trading coming from each group determines how much power I will have to find a relation between group trading and price changes. For example, if almost all trading came from institutions, then it would be difficult to find a relation between price changes and the trading of any group because returns (the left hand side variable in my regressions) would vary, but the proportion of trading from each group (the right hand side variable) would not. The percent of trading reported in Table 3 suggests that trading is sufficiently spread among different groups to provide adequate power for my tests.

The results in Table 3 are calculated using data aggregated from all stocks in the sample. In the Finnish market, a few stocks account for much of the trading volume and market capitalization. Notably, the largest stock, Nokia, makes up 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). On average, Nokia accounts for 57% of the value of daily trading (ranging from 3% to 95%). To confirm that the reported results apply to Finnish stocks in general and are not driven by Nokia or a few other large stocks, I first calculate a time-series average of the daily interaction estimates for each stock, and then examine cross-sectional statistics for these means. This procedure puts equal weight on each stock's average interaction estimates. These results are reported in Table 4. Across the 106 stocks in my sample, trading among institutions and among individuals accounts for an average of 14.7% and 19.3%, respectively, confirming that intragroup trading is important across stocks. Trading among individuals ranges from 0.1% to 60.6% of all trading; the smaller numbers come from large actively-traded stocks in which trading is dominated by institutions, while the larger numbers come from smaller, less-liquid stocks. It is interesting to note that the range for trading between institutions and individuals is much narrower, indicating that it is generally an important part of trade volume, although it never accounts for more than 14.8% of the total.

The data presented in this section show that individuals account for approximately one-fifth of trading in the Finnish stock market. This 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. In the next section, I examine which type of trading is most 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 returns and the proportion of trading within and between investor groups. In particular, I estimate the regression

$$R_{i,t} = \alpha + \beta R_{i,t-1} + \gamma_1 \text{Inst/Inst}_{i,t} + \gamma_2 \text{Inst/Ind}_{i,t} + \gamma_3 \text{Ind/Inst}_{i,t} + \gamma_4 \text{Ind/Ind}_{i,t} + \epsilon_{i,t}, \quad (1)$$

where the notation $\text{A/B}_{i,t}$ represents the proportion of trading that is accounted for by investors from Group A purchasing shares from investors in Group B. "Ind" and "Inst" denote individuals and institutions, respectively. For brevity, I focus in the remainder of the paper only on the trading of individuals and institutions.[10] Since not all investor groups are included in the regression, the A/B trade variables do not sum to one, and including an intercept does not result in perfect collinearity.

I begin by estimating the regression at a daily horizon, and later confirm that similar results obtain using weekly or monthly data. If trading between members of Group A and Group B (possibly the same group) leads to price changes, then contemporaneous returns will be positive or negative, and the estimated γ coefficient for the relevant combination of trade will be significant. If no group has a consistent effect on prices, then the four trade variables will be economically small and statistically insignificant. The lag return, $R_{i,t-1}$, is included to control for the known autocorrelation in daily returns.

I estimate regression (1) using the approach of Fama and MacBeth (1973) in two ways: averaging results from time-series regressions by stock or from cross-sectional regressions by date. 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)

[10] The main conclusions are not altered if I include the other investor groups. In particular, the price impact estimates for nonfinancial corporations and nominee accounts lie between those of individuals and institutions, and the estimated coefficients for individuals and institutions are basically unchanged if these additional groups are included.

with five lags, which corresponds to one week of trading.[11] The adjustment for autocorrelation is unnecessary for the cross-section of estimates obtained from the first approach. 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. Using a panel regression with clustered standard errors yields similar results, but could suffer from a bias due to the lagged dependent variable, so I do not report these estimates.

Coefficient estimates for regression (1) are presented in Table 5, and provide an interesting picture of how prices are affected by the interaction of individual and institutional investors in the market. Panel A reports results where the A/B trade variables are calculated as the proportion of total trade volume each day, and Panel B uses trade variables calculated as the proportion of daily turnover (shares traded divided by number of shares outstanding) each day. Results from the stock-by-stock regressions are denoted "FM by stock," and the day-by-day regressions are denoted "FM by date."

Consider first the "FM by stock" regressions in Panel A. When institutions trade with other institutions, there is no significant change in price. As discussed above in Section 2.2.3, a large portion of trading comes from institutions trading with other institutions and households trading with other households. To date, the literature has not been able to address the importance of price changes that occur during this trading. The results in Table 5 bear directly on this question. The estimated coefficient is 0.0092, with a t-statistic of 1.35. Of the 106 stock-by-stock regressions, the Inst/Inst coefficient is significantly negative in 8% of regressions and significantly positive in 11% of regressions, using a 5% significance level. Similarly, trading between individuals does not yield significant results, although 27% of stocks yield statistically negative coefficients. That is, there appears to be little in the way of price changes when trading takes place within each investor group.

In sharp contrast, when institutions purchase from individuals, prices increase. The estimated coefficient of 0.0316 is highly significant, and fully 61% of the regressions yield statistically positive results; none of the coefficients is statistically negative. And when individuals buy from institutions, prices fall: the coefficient of -0.0423 is again highly significant, and 72% of the cross-sectional regressions yield statistically positive coefficients, with none significantly negative. The cross-sectional average of the stock-level standard

[11] With 2184 daily observations, the rule of thumb noted by Greene (2005, p. 267) calls for $\lfloor \sqrt[4]{2184} \rfloor = 7$ lags, and the significance level of all results is unchanged by using the longer lag length.

deviation in the trade variables is reported in the table under the heading "C.S. Std. Dev." These values can be used to ascertain the economic significance of the coefficient estimates. A one standard deviation increase in the Inst/Ind variable (that is, institutions buying shares from individuals) increases daily returns by $0.316 \times 0.1151 = 0.0036$ or 36 basis points (bps). This is economically large relative to an average daily return of approximately 10 bps. Similarly, a one standard deviation increase in the Ind/Inst variable leads to a decrease in returns of $0.0423 \times 0.1145 = 48$ bps.

The day-by-day cross-sectional ("FM by date") regressions deliver similar results, suggesting that the result is not driven solely by either time-series or cross-sectional relations. The effect of trading between households in this specification is to reduce contemporaneous returns. This result is not robust, however, which can be seen by looking at the results in Panel B. Across both panels and both specifications, the result that is consistent is that prices increase when individuals sell shares to institutions, and prices decrease when individuals buy shares from individuals. This evidence strongly supports Hypothesis 1.

3.3 Vector autoregressions

Another approach to examining the relation between group trading and subsequent price changes is to estimate a vector autoregression (VAR) 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 $\mathbf{y}_{i,t} \equiv (\text{Ind/Ind}_{i,t}, \text{Inst/Inst}_{i,t}, \text{Ind/Inst}_{i,t}, \text{Inst/Ind}_{i,t}, R_{i,t})'$. As above, the notation $\text{A/B}_{i,t}$ denotes the proportion of trading in stock i on date t that comes from Group A purchasing shares from Group B, and "Ind" and "Inst" denote individuals and institutions, respectively. The reduced-form VAR for each stock, i, is

$$\mathbf{y}_{i,t} = \sum_{k=1}^{p} \mathbf{\Phi}_k \mathbf{y}_{i,t-k} + \boldsymbol{\epsilon}_{i,t}. \tag{2}$$

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 (2) by $\mathbf{A}_0$ gives the dynamic structural VAR

$$\mathbf{A}_0 \mathbf{y}_{i,t} = \sum_{i=1}^{p} \mathbf{A}_k \mathbf{y}_{i,t-k} + \boldsymbol{\eta}_{i,t}, \tag{3}$$

where $\mathbf{A}_k = \mathbf{A}_0 \mathbf{\Phi}_k$ 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:

$$\text{Ind/Ind}_{i,t} = \sum_{i=1}^{p} \mathbf{A}_{1k} \mathbf{y}_{t-1} + \eta_{i,1t}, \tag{4a}$$

$$\text{Inst/Inst}_{i,t} = \sum_{i=1}^{p} \mathbf{A}_{2k} \mathbf{y}_{t-1} - a_{21} \text{Ind/Ind}_{i,t} + \eta_{i,2t}, \tag{4b}$$

$$\text{Ind/Inst}_{i,t} = \sum_{i=1}^{p} \mathbf{A}_{3k} \mathbf{y}_{t-1} - a_{31} \text{Ind/Ind}_{i,t} - a_{32} \text{Inst/Inst}_{i,t} + \eta_{i,3t}, \tag{4c}$$

$$\text{Inst/Ind}_{i,t} = \sum_{i=1}^{p} \mathbf{A}_{4k} \mathbf{y}_{t-1} - a_{41} \text{Ind/Ind}_{i,t} - a_{42} \text{Inst/Inst}_{i,t} - a_{43} \text{Ind/Inst}_{i,t} + \eta_{i,4t}, \tag{4d}$$

and

$$R_{i,t} = \sum_{i=1}^{p} \mathbf{A}_{5k} \mathbf{y}_{t-1} - a_{51} \text{Ind/Ind}_{i,t} - a_{52} \text{Inst/Inst}_{i,t} - a_{53} \text{Ind/Inst}_{i,t} - a_{54} \text{Inst/Ind}_{i,t} + \eta_{i,5t}. \tag{4e}$$

Here a_{mn} denotes the (m, n)th element of $\mathbf{A}_0$, and $\mathbf{A}_{jk}$ denotes the jth row of $\mathbf{A}_k$. Since the order in which the variables appear in the $\mathbf{y}_{i,t}$ vector determines which variables are allowed to affect other variables contemporaneously, there is a strong theoretical reason to put returns last, but the order of the trade variables is less obvious. I therefore confirm that all the results below are unaffected by permuting the order of the trade variables.

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 (2) yields estimates of the $\mathbf{\Phi}_k$ 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 $\mathbf{A}_k$ coefficient matrices. This is repeated for each of the 106 stocks in the sample, and Table 6 summarizes the results from these regressions for $k = 0, 1, 2$. For brevity, higher-order lags and the constant term are not reported.

Controlling for complex serial correlations does not alter the results reported above. The contemporaneous effect ($k = 0$) on returns of the Ind/Inst and Inst/Ind variables are very close to those reported in the previous table. In this specification, there is also evidence that returns are negative when individuals trade with each other: the Ind/Ind variable is negative and significant. The magnitude of this effect is considerably smaller than the effect of intergroup trading.

Looking at $k = 1$, the negative autocorrelation in daily returns that is consistent with bid-ask bounce is quite prevalent in these data. The amount of within- and between-group trading is positively autocorrelated up to three lags. For example, at the first lag ($k = 1$), the autocorrelation coefficients range from 0.0964 for the Inst/Inst variable to 0.1493 for the Ind/Inst variable, and all are significant at the 1% level. This pattern holds for higher-order lags and for all of the variables except returns.

3.3.1 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. That is, I calculate the effect of a one standard deviation impulse to each of the elements of the orthogonalized shocks, $\boldsymbol{\eta}_{i,t}$, one at a time. For example, to see the effect on returns of a shock to Inst/Ind I use equations (4d) and (4e) 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 Inst/Ind (solid line), Inst/Inst (short dash), Ind/Ind (long dash), and Ind/Inst (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 Inst/Ind increases the contemporaneous return by 21 bps, and there is no evidence of subsequent reversion. Similarly, a one standard deviation innovation in Ind/Inst leads to a return of -28 bps, and there is no subsequent reversion. In sharp contrast, a one standard deviation innovation in Ind/Ind is associated with a return of -12 bps, but prices subsequently revert. 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 are informed traders demanding liquidity from individuals. This result is clearly not consistent with individual investors actively moving prices.

3.4 Alternate horizons

3.4.1 Weekly and monthly 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. Daily returns are contemporaneously higher when institutions purchase shares from individuals and lower when they sell shares to individuals. There is little or no price effect from intragroup trading by individuals or institutions. As in the daily results, the price impact of institutions is stronger when they sell to individuals than when they buy from individuals.

It is interesting to note that the magnitude of the effect on returns (in absolute terms) is greater when institutions sell to households than when institutions buy from households, especially at the monthly horizon. That is, institutions appear to have larger price impact when they sell to individuals than when they buy from individuals. Campbell, Ramadorai, and Schwartz (2007) find a similar asymmetry, and suggest that it could stem from the reluctance of institutions to use short sales.[12] This asymmetry is not apparent in the daily results presented earlier, perhaps because daily returns are small and can be affected by

[12]Their argument is as follows: if institutions wish to increase their exposure to a particular risk factor, they may buy stocks that load strongly on that factor. If their buying causes price increases in one stock, they can purchase shares of another stock that also loads on the factor, thereby reducing their overall price impact. However, if an institution wishes to decrease its exposure to a factor and is reluctant or unable to

institutions with small positions, but short-sale constraints then become binding at longer horizons.

3.4.2 Intraday results: Evidence from trading prices

A potential concern with the daily results presented above relates to the timing of trades within the day. It is possible that trading by individuals moves prices, and that institutions subsequently trade at those new prices, but that institutional trading does not actually affect 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 institutions did not cause the price change.

The strength and robustness of the results above suggest that this scenario is unlikely. When individuals purchase shares, same-day returns are typically lower than when they sell shares. Nevertheless, an additional test to rule out this possibility is in order. Unfortunately, the transactions in the dataset are not time-stamped, so it is not possible to examine 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 individuals purchase and sell shares, and the relation between these prices and contemporaneous returns.

To understand this test, suppose that on a particular day, a stock trades only at two prices, \$10 and \$11. Suppose further that both Groups A and B bought at \$10 and sold at \$11, but only A bought at \$11. If the closing price is \$11, it can only be because Group A moved the price; Group B did not purchase any shares at \$11, so they could not have caused the price to move up to that level. That is, since Group B bought at a lower price than did Group A—and prices increased—it is not possible for Group B 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 difference in the purchase or sale prices of individuals and institutions. 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,

use short sales, it can only sell stocks it currently owns. This forces the institution to sell more aggressively the stocks it owns, and could lead to larger price impact.

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.

This test also allows us to differentiate intraday price movements from close-to-open price movements. For example, suppose the opening price is above the previous day's close, but then remains flat during the day. If most trading just happened to come from institutions buying shares from individuals, the earlier regressions would find that institutions buy from individuals when prices increase—but the price change happened entirely when the market was closed. This intraday test, however, would find that individuals and institutions both bought at the same price on a day when returns increased.

Of course, stocks typically trade at more than two prices on one day, so I look instead at the average price at which institutions and individuals buy or sell shares. Specifically, I test the relation using Fama-MacBeth estimation of the regressions

$$\bar{b}^I_{i,t} - \bar{b}^H_{i,t} = \beta_1 \cdot \mathbf{1}_{\{R_{i,t}>0\}} + \beta_2 \cdot \mathbf{1}_{\{R_{i,t}<0\}} + \epsilon_{i,t} \tag{5}$$

and

$$\bar{s}^I_{i,t} - \bar{s}^H_{i,t} = \beta_1 \cdot \mathbf{1}_{\{R_{i,t}>0\}} + \beta_2 \cdot \mathbf{1}_{\{R_{i,t}<0\}} + \epsilon_{i,t}, \tag{6}$$

where $\bar{b}$ and $\bar{s}$ denote the average purchase and sale prices, respectively, for stock i on date t, and superscript I and H denote institutions and households, respectively. The indicator function, $\mathbf{1}_{\{\cdot\}}$, takes a value of one only when the condition in curly brackets is true; otherwise it is zero. Intercepts are excluded to prevent perfect collinearity. In a second set of regressions, I allow the purchase or sale price difference to vary with the magnitude of the return:

$$\bar{b}^I_{i,t} - \bar{b}^H_{i,t} = \alpha + \beta_1 \cdot \mathbf{1}_{\{R_{i,t}>0\}}|R_{i,t}| + \beta_2 \cdot \mathbf{1}_{\{R_{i,t}<0\}}|R_{i,t}| + \epsilon_{i,t} \tag{7}$$

and

$$\bar{s}^I_{i,t} - \bar{s}^H_{i,t} = \alpha + \beta_1 \cdot \mathbf{1}_{\{R_{i,t}>0\}}|R_{i,t}| + \beta_2 \cdot \mathbf{1}_{\{R_{i,t}<0\}}|R_{i,t}| + \epsilon_{i,t}. \tag{8}$$

Excluding intercepts in this second set of regressions is unnecessary. In each of these regressions, it is important to scale the prices so that the magnitude of the estimates may be compared across stocks, which is key to the Fama-MacBeth approach. Therefore, I scale the price difference by each stock's average trade price for that day. Scaling by the average closing price in the previous week yields similar results, as does using share-weighted prices instead of a simple average.

Estimates of regressions (5)–(8) are presented in Table 8. The results are not consistent with individuals moving prices. Focusing on Column 1, on days when returns are positive, institutions purchase shares at higher prices than individuals purchase shares, but on days when prices are negative, there is no statistical difference between the purchase prices. Economically, there is clearly a large difference between the coefficients on positive- and negative-return days (25 bps compared to 2 bps). Similarly, on days when returns are negative, institutions sell at lower prices than do individuals (Column 3). On the sell side, the economic magnitude of the difference is not as large as it is for purchase prices, but there is still a very large statistical difference. Columns 2 and 4 present results for similar regressions, but here we allow the effect size to vary with the level of returns. The statistical differences are even stronger in this specification. The economic magnitude of these estimates is not particularly large: when a stock has a positive return of 1%, institutions purchase shares at about 6.5 bps above individual purchase prices. Nevertheless, the magnitude of the difference between positive and negative return coefficients is both economically and statistically large.

These results convincingly show that prices move in response to institutional demand. Price changes cannot be attributed to the trading of individuals: when prices rise, institutions buy shares at higher prices than do individuals, and when prices fall, institutions sell shares at lower prices than do individuals. In either case, prices are clearly not being pushed up or down by individuals. Combined with the evidence presented in Section 3.2 for daily, weekly, and monthly horizons, these results provide strong support for Hypothesis 1.

3.5 Returns following trade

The second hypothesis to be tested is that price reversion is more likely following days when trading is dominated by intragroup individual trading. 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

$$\begin{aligned}R_{i,t} = \alpha + \beta_1 \text{Ind/Ind}_{i,t-1} R_{i,t-1} + \beta_2 \text{Inst/Inst}_{i,t-1} R_{i,t-1} \\ + \gamma_1 R_{i,t-1} + \gamma_2 \text{Ind/Ind}_{i,t-1} + \gamma_3 \text{Inst/Inst}_{i,t-1} \\ + \gamma_4 \text{Ind/Inst}_{i,t-1} + \gamma_5 \text{Inst/Ind}_{i,t-1} + \epsilon_{i,t}, \quad (9)\end{aligned}$$

for stock i on date t. "Inst" denotes financial institutions, and "Ind" denotes individual investors. Pairs of groups represent purchasing of shares by the first group from the second group. For example, "Ind/Inst" is the proportion of trading accounted for by individuals buying shares from institutions.[13]

If returns tend to revert after days when individuals trade with other individuals and returns are either high or low, β_1 should be negative. As shown in the results presented in Table 9, 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 not significantly different from zero in either set of regressions. Consistent with the VAR results presented above, the estimates in the last two lines of Table 9 show that days when individuals buy shares from institutions—which we previously found to be days when prices decline—are followed by further price declines. And when institutions buy shares from individuals—which are days when prices increase—prices tend to increase further on the following day. That is, prices revert less than usual when trading there is more intragroup trading; they revert more when individuals trade with other individuals or when institutions trade with other institutions. 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. In particular, it is possible that institutions react to the price movements caused by individuals by subsequently purchasing (selling) underpriced (overpriced) shares from individuals. To investigate this, I examine the relation between institutional trading with individuals on date t and intragroup trading by individuals on date $t-1$.

[13]In the remainder of the paper I use level of the trade variables and not the unexpected components from the VAR in section 3.3. All reported results remain unchanged if I instead use the residuals from each of the trade variable equations.

Specifically, I estimate the regressions

$$\begin{aligned}\text{Inst/Ind}_{i,t} = \alpha &+ \beta_1 \text{Ind/Ind}_{i,t-1} R_{i,t-1} + \beta_2 \text{Inst/Inst}_{i,t-1} R_{i,t-1} \\ &+ \gamma_1 R_{i,t-1} + \gamma_2 \text{Ind/Ind}_{i,t-1} + \gamma_3 \text{Inst/Inst}_{i,t-1} \\ &+ \gamma_4 \text{Ind/Inst}_{i,t-1} + \gamma_5 \text{Inst/Ind}_{i,t-1} + \epsilon_{i,t}, \end{aligned} \tag{10}$$

and

$$\begin{aligned}\text{Ind/Inst}_{i,t} = \alpha &+ \beta_1 \text{Ind/Ind}_{i,t-1} R_{i,t-1} + \beta_2 \text{Inst/Inst}_{i,t-1} R_{i,t-1} \\ &+ \gamma_1 R_{i,t-1} + \gamma_2 \text{Ind/Ind}_{i,t-1} + \gamma_3 \text{Inst/Inst}_{i,t-1} \\ &+ \gamma_4 \text{Ind/Inst}_{i,t-1} + \gamma_5 \text{Inst/Ind}_{i,t-1} + \epsilon_{i,t}, \end{aligned} \tag{11}$$

for stock i on date t. The dependent variable in regressions (10) and (11) is either $\text{Inst/Ind}_{i,t}$ or $\text{Ind/Inst}_{i,t}$—that is, the proportion of trading accounted for by institutions purchasing shares from individuals or the proportion accounted for by individuals purchasing shares from institutions.

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 individuals on date t and more likely to sell shares to individuals on date t. That is, we would expect β_1 to be negative in regression (10) and positive in regression (11). As shown in the estimation results presented in Table 10, this prediction is borne out by the data. Institutions are less likely to buy shares from individuals (Panel A) and more likely to sell shares to individuals (Panel B) if more trading on $t-1$ occurred between two individuals and prices increased. Combined with the results in Table 9, these results indicate that if prices are moved by individuals, institutions subsequently trade with individuals in a direction that leads prices to revert. This evidence provides strong support for Hypothesis 3.

4 Conclusion

This paper studies the relation between returns and trading by individual and institutional investors. I show that trading between individuals and institutions is relatively uncommon, but that these trades consistently lead to price changes. In contrast to the recent work of Barber, Odean, and Zhu (2006) and Hvidkjaer (2006), I find very little evidence of price effects from the trading of individual investors. In addition, I show that when prices change as a result of individual investors trading with other individuals, price reversion is more common than when they trade with institutions. Moreover, this reversion is caused by institutions subsequently trading with individuals in a direction that pushes prices back toward previous levels.

There are a number of reasons why it is important to understand what type of trading leads to price changes. First, if prices are determined primarily by traders with poor information or are contaminated by beliefs of investors suffering from behavioral biases, then features of the return series, such as volatility and covariance with macroeconomic variables like consumption may be spurious. This is of obvious importance to research in asset pricing, which seeks to explain relations among these variables. Second, a large literature seeks to understand the performance of mutual funds. Part of the challenge in assessing this performance is the difficulty of determining whether trading by mutual funds causes price movements. I find that the trading of mutual funds and other institutions moves prices, so findings of positive correlation between institutional trading and returns at low frequencies cannot be taken as evidence of good performance. However, my results do not rule out the possibility of further price movements allowing funds to earn profits.

In contrast to previous papers, the results presented here are calculated with daily data. At this relatively high frequency, it is apparent that price movements are generally caused by the trading demands of institutions. And if prices do move when individuals trade with each other, they quickly revert. This suggests that while there may be short-term price effects caused by individual investors, prices are unlikely to be affected by such distortions at longer horizons.

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Table 1: Stock Returns Following Trading by Institutions and Households

This table presents average returns to stocks in the year subsequent to trading by institutions and individuals, separated by the rank of each group's buying pressure. In June and December of each year, firms are assigned to one of three portfolios for each group based on the proportion of buy volume for that group, $B_{i,t}/(B_{i,t}+S_{i,t})$. The table reports the returns to these portfolios over the subsequent year. t-statistics are presented in parentheses. Statistical significance at the 10%, 5% and 1% levels is denoted by †, *, and **, respectively.

	Institutions	Households
Most sold	-0.0011	0.1175
	(-0.04)	(4.34)**
Most bought	0.0892	0.0492
	(3.12)**	(1.85)†

Table 2: Summary Statistics

This table provides summary statistics for the data. The sample period is 1995–2003. The "Nominees/ADRs" group is identified using the technique explained in Section 2.2.1. "Other" includes Government Agencies, Nonprofit Organizations, and Registered Foreigners. The number of accounts and total number of trades are shown in the first two columns, respectively. The remaining columns present averages for per-trade, per-day, or per-account data.

	Number of:		Average of:			
	Accounts	Trades (MM)	Shares per trade (000s)	Value per trade (000s)	Trades per day (000s)	Securities traded
Financial institutions	920	14.0	3.6	77.8	6.4	33
Households	583,518	10.7	1.2	7.3	4.9	4
Nominees / ADRs	47	7.4	4.2	65.5	3.4	169
Nonfinancial corporations	29,186	4.6	3.8	57.3	2.1	8
Other	12,269	0.8	1.6	30.8	0.4	2
All	625,940	37.5	2.9	47.8	3.4	43

Table 3: Trader Interaction

This table shows the amount of trading (in percent) that occurs in total and between the different investor groups. The expected amount of trading between groups is calculated assuming random interaction in proportion to the percent of total trades based on number of shares traded presented in the first row. The actual amount of trading is estimated using the technique discussed in the text. The total number of shares traded between each group is calculated for each stock/day during the period 1995–2003. The percentages do not sum to 100% because the trading of certain groups that account for very little total trading volume is omitted.

	Financial Institutions	Households	Nominees / ADRs	Nonfinancial Corporations
Percent of trading (by shares)	38.1	20.6	15.2	20.9
Percent of trading (by value)	40.9	17.4	16.1	20.5
Expected % of trading with:				
Financial institutions	14.5			
Households	15.7	4.2		
Nominees / ADRs	11.6	6.2	2.3	
Nonfinancial corporations	15.9	8.6	6.4	4.4
Estimated % of trading with:				
Financial institutions	20.6			
Households	9.3	9.1		
Nominees / ADRs	10.1	3.5	5.7	
Nonfinancial corporations	13.9	8.1	4.9	6.2

Table 4: Trader Interaction—Cross-Sectional Statistics

This table shows the average amount of trading (buying and selling, in percent) that occurs between the different investor groups. The amount of trading is estimated for each stock/day using the technique discussed in the text. The time-series average is then calculated for each stock, and the table reports cross-sectional statistics for those means ($N = 106$ stocks).

Group 1	Group 2	Mean	Std. Dev.	Min.	Max.
Financial institutions	Financial institutions	14.7	10.5	0.5	41.4
	Households	5.9	2.6	1.6	14.8
	Nominees / ADRs	4.0	3.8	0.0	14.4
	Nonfinancial corporations	5.2	2.6	0.3	13.2
Households	Households	19.3	17.1	0.1	60.6
	Nominees / ADRs	2.6	1.9	0.0	8.6
	Nonfinancial corporations	6.1	4.4	0.5	17.1
Nominees / ADRs	Nominees / ADRs	4.2	4.5	0.0	26.4
	Nonfinancial corporations	1.6	1.1	0.0	4.6
Nonfinancial corporations	Nonfinancial corporations	4.5	2.2	0.5	15.9

Table 5: Returns and Group Interaction—Daily

This table presents the results of the regression

$$R_{i,t} = \alpha + \beta R_{i,t-1} + \gamma_1 \text{Inst/Inst}_{i,t} + \gamma_2 \text{Inst/Ind}_{i,t} + \gamma_3 \text{Ind/Inst}_{i,t} + \gamma_4 \text{Ind/Ind}_{i,t} + \epsilon_{i,t},$$

where the notation A/B$_{i,t}$ represents the proportion of trading that is accounted for by investors from Group A purchasing shares from investors in Group B. "Ind" and "Inst" denote individuals and institutions, respectively. Panel A reports results where the A/B trade variables are calculated as the proportion of total trade volume each day, and Panel B uses trade variables calculated as the proportion of daily turnover (shares traded divided by number of shares outstanding) each day. The regression is estimated using the Fama-MacBeth ("FM") approach in two ways: averaging results from time-series regressions by stock or from cross-sectional regressions by date. *t*-statistics for the FM by date regressions are calculated using standard errors robust to heteroscedasticity and autocorrelation using the Newey and West (1987) adjustment with five lags. The columns labeled "Sig. at 5%" report the percentage of regressions in which the coefficient is significantly negative or positive at the 5% level. Cross-sectional and time-series average standard deviations of the independent variables are reported in the columns labeled "C.S. Std. Dev" and "T.S. Std. Dev," respectively. Statistical significance at the 10%, 5% and 1% levels is denoted by †, *, and **, respectively.

		FM by stock				C.S.	FM by date				T.S.
				Sig. at 5%					Sig. at 5%		
		Estimate	*t*-stat	Neg.	Pos.	Std. Dev	Estimate	*t*-stat	Neg.	Pos.	Std. Dev
						Panel A: Proportion of Daily Trading Volume					
Intercept		0.0022	3.72**	0%	44%		0.0011	3.16**	20%	26%	
$R_{i,t-1}$		-0.0634	-5.89**	52%	17%	0.0011	-0.0837	-11.46**	28%	11%	0.0009
Buyer:	*Seller:*										
Institutions	Institutions	0.0092	1.35	8%	11%	0.1481	0.0003	0.50	4%	4%	0.1691
	Households	0.0316	5.36**	0%	61%	0.1151	0.0189	16.09**	2%	11%	0.1180
Households	Institutions	-0.0423	-4.74**	72%	0%	0.1145	-0.0172	-12.70**	11%	3%	0.1130
	Households	-0.0025	-0.24	27%	0%	0.2002	-0.0023	-4.41**	9%	6%	0.2306
						Panel B: Proportion of Daily Turnover					
Intercept		-0.0020	-8.45**	42%	3%		-0.0008	-3.06**	24%	19%	
$R_{i,t-1}$		-0.0791	-8.86**	58%	7%	0.0011	-0.1338	-19.87**	36%	7%	0.0009
Buyer:	*Seller:*										
Institutions	Institutions	0.0026	4.57**	0%	42%	0.9767	0.0011	3.69**	4%	10%	0.7566
	Households	0.0481	4.29**	1%	76%	0.5838	0.0390	19.62**	2%	27%	0.3728
Households	Institutions	-0.0339	-3.24**	48%	5%	0.2920	-0.0167	-10.15**	20%	6%	0.2782
	Households	0.0479	2.54*	2%	69%	0.3204	0.0033	2.27*	14%	18%	0.4697
Number of observations				134196					134196		
Number of FM regressions				106 (stocks)					2184 (days)		

Table 6: Returns and Group Interaction—VAR Results

This table presents coefficient estimates from the dynamic structural VAR(10) in equation (3),

$$\mathbf{A}_0 \mathbf{y}_{i,t} = \sum_{k=1}^{10} \mathbf{A}_i \mathbf{y}_{i,t-k} + \boldsymbol{\eta}_t,$$

where $\mathbf{y}_{i,t} = (\text{Ind/Ind}_{i,t}, \text{Inst/Inst}_{i,t}, \text{Ind/Inst}_{i,t}, \text{Inst/Ind}_{i,t}, R_{i,t})'$. The notation $\text{A/B}_{i,t}$ denotes the proportion of trading in stock i on date t that comes from Group A purchasing shares from Group B, and "Ind" and "Inst" denote individuals and institutions, respectively. $\mathbf{A}_0$ is the lower diagonal matrix from the triangular factorization of the error covariance in the reduced-form VAR (equation (2)). Separate regressions are estimated for each of the 106 stocks in the sample. The table reports cross-sectional averages of coefficient estimates for $k = 0, 1, 2$. Standard errors, calculated from the cross-sectional distribution of the coefficient estimates, are reported in parentheses. For brevity, the constant terms and lags of order three and higher are omitted. Statistical significance at the 10%, 5% and 1% levels is denoted by †, *, and **, respectively.

	Elements of $\mathbf{y}_{i,t-k}$				
Equation	Ind/Ind	Inst/Inst	Ind/Inst	Inst/Ind	Return
			$k=0$		
Ind/Ind	–	–	–	–	–
Inst/Inst	-0.1303 (0.0355)**	–	–	–	–
Ind/Inst	0.0592 (0.0255)*	-0.0041 (0.0054)	–	–	–
Inst/Ind	0.0859 (0.0325)**	-0.0074 (0.0087)	-0.1091 (0.0057)**	–	–
Return	-0.0161 (0.0046)**	0.0059 (0.0041)	-0.0433 (0.0070)**	0.0344 (0.0064)**	–
			$k=1$		
Ind/Ind	0.1489 (0.0074)**	-0.0201 (0.0093)*	0.0064 (0.0073)	0.0002 (0.0069)	-0.0135 (0.0213)
Inst/Inst	0.0227 (0.0200)	0.0964 (0.0057)**	0.0415 (0.0089)**	0.0488 (0.0063)**	-0.0303 (0.0174)†
Ind/Inst	0.0061 (0.0077)	0.0181 (0.0060)**	0.1493 (0.0062)**	-0.0083 (0.0039)*	-0.0560 (0.0130)**
Inst/Ind	0.0113 (0.0067)†	0.0339 (0.0094)**	-0.0045 (0.0035)	0.1451 (0.0116)**	0.0231 (0.0131)†
Return	0.0047 (0.0057)	0.0044 (0.0026)†	0.0019 (0.0024)	-0.0048 (0.0020)**	-0.0680 (0.0107)**
			$k=2$		
Ind/Ind	0.0773 (0.0066)**	-0.0093 (0.0133)	0.0054 (0.0073)	0.0013 (0.0063)	0.0191 (0.0163)
Inst/Inst	-0.0157 (0.0242)	0.0521 (0.0044)**	0.0005 (0.0094)	0.0249 (0.0091)**	0.0107 (0.0157)
Ind/Inst	0.0119 (0.0051)**	0.0096 (0.0044)*	0.0760 (0.0057)**	-0.0103 (0.0037)**	-0.0516 (0.0132)**
Inst/Ind	0.0004 (0.0056)	0.0110 (0.0045)**	0.0056 (0.0039)	0.0696 (0.0050)**	0.0567 (0.0119)**
Return	0.0023 (0.0025)	0.0011 (0.0015)	0.0010 (0.0018)	-0.0006 (0.0030)	-0.0260 (0.0055)**

Table 7: Returns and Group Interaction—Weekly and Monthly

This table presents the results of the regression

$$R_{i,t} = \alpha + \beta R_{i,t-1} + \gamma_1 \text{Inst/Inst}_{i,t} + \gamma_2 \text{Inst/Ind}_{i,t} + \gamma_3 \text{Ind/Inst}_{i,t} + \gamma_4 \text{Ind/Ind}_{i,t} + \epsilon_{i,t},$$

where the notation $\text{A/B}_{i,t}$ represents the proportion of trading that is accounted for by investors from Group A purchasing shares from investors in Group B. "Ind" and "Inst" denote individuals and institutions, respectively. Panels A and B report results for regressions using data aggregated into weekly and monthly observations, respectively. The regression is estimated using the Fama-MacBeth ("FM") approach in two ways: averaging results from time-series regressions by stock (Columns 3 and 4), or from cross-sectional regressions by date (Columns 5 and 6). t-statistics for the FM by date regressions are calculated using standard errors robust to heteroscedasticity and autocorrelation using the Newey and West (1987) adjustment with five lags. Statistical significance at the 10%, 5% and 1% levels is denoted by †, *, and **, respectively.

		FM by stock		FM by date	
		Estimate	t-stat	Estimate	t-stat
		Panel A: Weekly Horizon			
Intercept		0.0057	5.43**	0.0056	2.77**
$R_{i,t-1}$		-0.0355	-3.82**	-0.0713	-5.61**
Buyer:	*Seller:*				
Financial institutions	Financial institutions	0.0320	1.14	0.0011	0.42
	Households	0.1882	3.87**	0.0630	8.37**
Households	Financial institutions	-0.2292	-5.59**	-0.0680	-11.07**
	Households	-0.0356	-0.42	-0.0103	-3.09**
Number of observations		33124		33124	
Number of FM regressions		106 (stocks)		456 (weeks)	
		Panel B: Monthly Horizon			
Intercept		0.0117	1.12	0.0290	2.63**
$R_{i,t-1}$		0.0001	0.01	-0.0103	-0.33
Buyer:	*Seller:*				
Financial institutions	Financial institutions	-0.0866	-1.13	-0.0197	-0.77
	Households	1.1009	5.01**	0.1689	3.12**
Households	Financial institutions	-1.7529	-2.97**	-0.2742	-8.52**
	Households	2.4445	1.73	-0.0295	-1.49
Number of observations		7680		7680	
Number of FM regressions		106 (stocks)		104 (months)	

Table 8: Returns and Group Interaction—Intraday Price Evidence

This table presents results from Fama-MacBeth regressions

$$\bar{b}^I_{i,t} - \bar{b}^H_{i,t} = \beta_1 \cdot \mathbf{1}_{\{R_{i,t}>0\}} + \beta_2 \cdot \mathbf{1}_{\{R_{i,t}<0\}} + \epsilon_{i,t}$$

and

$$\bar{s}^I_{i,t} - \bar{s}^H_{i,t} = \beta_1 \cdot \mathbf{1}_{\{R_{i,t}>0\}} + \beta_2 \cdot \mathbf{1}_{\{R_{i,t}<0\}} + \epsilon_{i,t},$$

where $\bar{b}$ and $\bar{s}$ denote the average purchase and sale prices, respectively, for stock i on date t, and superscript I and H denote institutions and households, respectively. The indicator function, $\mathbf{1}_{\{\cdot\}}$, takes a value of one only when the condition in curly brackets is true; otherwise it is zero. Results for these specifications are presented in Columns (1) and (3), respectively. Columns (2) and (4) show results for an alternative specification in which the price difference is allowed to vary with the magnitude of the return, $|R_{i,t}|$. For each stock and day, the average price at which individuals purchase (sell) shares is subtracted from the average price at which institutions purchase (sell) shares. This difference is used as one observation in a time-series regression for each stock. The table reports the mean coefficients estimates, with t-statistics (in parentheses) derived from the cross-sectional distribution of coefficient estimates. Statistical significance at the 10%, 5% and 1% levels is denoted by †, *, and **, respectively.

	Dependent Variable			
	$\bar{b}^I_{i,t} - \bar{b}^H_{i,t}$		$\bar{s}^I_{i,t} - \bar{s}^H_{i,t}$	
	(1)	(2)	(3)	(4)
$\mathbf{1}_{\{R_{i,t}>0\}}$	0.0025		-0.0011	
	(6.46)**		(-1.77)†	
$\mathbf{1}_{\{R_{i,t}<0\}}$	0.0002		-0.0016	
	(0.68)		(-6.24)**	
$\mathbf{1}_{\{R_{i,t}>0\}} \times \lvert R_{i,t}\rvert$		0.0649		-0.0005
		(11.67)**		(-0.09)
$\mathbf{1}_{\{R_{i,t}<0\}} \times \lvert R_{i,t}\rvert$		0.0026		-0.0718
		(0.37)		(-10.66)**
Number of observations	127501	127501	127501	127501
Number of regressions (stocks)	106	106	106	106

Table 9: Returns Following Trade

This table presents results for the regression

$$R_{i,t} = \alpha + \beta_1 \cdot \text{Ind/Ind}_{i,t-1} R_{i,t-1} + \beta_2 \cdot \text{Inst/Inst}_{i,t-1} R_{i,t-1} + \gamma \cdot \text{Controls} + \epsilon_{i,t},$$

for stock i on date t. "Inst" denotes financial institutions, and "Ind" denotes individual investors. Pairs of groups represent purchasing of shares by the first group from the second group. For example, "Ind/Inst" is the proportion of trading accounted for by individuals buying shares from financial institutions. The regression is estimated using the Fama-MacBeth ("FM") approach in two ways: averaging results from time-series regressions by stock (Columns 2 and 3), or from cross-sectional regressions by date (Columns 4 and 5). t-statistics for the FM by date regressions are calculated using standard errors robust to heteroscedasticity and autocorrelation using the Newey and West (1987) adjustment with five lags. Statistical significance at the 10%, 5% and 1% levels is denoted by †, *, and **, respectively.

	FM by stock		FM by date	
	Estimate	t-stat	Estimate	t-stat
$\text{Ind/Ind}_{i,t-1} \times R_{i,t-1}$	-0.2534	-4.09**	-0.1840	-3.50**
$\text{Inst/Inst}_{i,t-1} \times R_{i,t-1}$	0.0103	0.36	0.0443	1.26
Controls:				
Intercept	0.0011	5.41**	0.0009	2.52*
$R_{i,t-1}$	-0.0281	-2.63**	-0.0559	-6.62**
$\text{Ind/Ind}_{i,t-1}$	-0.0012	-1.31	-0.0009	-1.19
$\text{Inst/Inst}_{i,t-1}$	0.0006	1.18	0.0004	0.72
$\text{Ind/Inst}_{i,t-1}$	-0.0018	-2.55*	-0.0033	-5.84**
$\text{Inst/Ind}_{i,t-1}$	0.0022	3.09**	0.0013	2.37*
Number of observations	151324		151324	
Number FM of regressions	106 (stocks)		2184 (days)	

Table 10: Institutions' Response to Individual Trading

This table presents results for the regressions

$$\text{Inst/Ind}_{i,t} = \alpha + \beta_1 \cdot \text{Ind/Ind}_{i,t-1} R_{i,t-1} + \beta_2 \cdot \text{Inst/Inst}_{i,t-1} R_{i,t-1} + \gamma \cdot \text{Controls} + \epsilon_{i,t}$$

and

$$\text{Ind/Inst}_{i,t} = \alpha + \beta_1 \cdot \text{Ind/Ind}_{i,t-1} R_{i,t-1} + \beta_2 \cdot \text{Inst/Inst}_{i,t-1} R_{i,t-1} + \gamma \cdot \text{Controls} + \epsilon_{i,t},$$

for stock i on date t. "Inst" denotes financial institutions, and "Ind" denotes individual investors. Pairs of groups represent purchasing of shares by the first group from the second group. For example, "Ind/Inst" is the proportion of trading accounted for by individuals buying shares from financial institutions. The dependent variable in Panel A is the proportion of trading that comes from individuals purchasing shares from institutions (Ind/Inst$_{i,t}$), and in Panel B it is the proportion of trading that comes from institutions purchasing shares from individuals (Inst/Ind$_{i,t}$). The regression is estimated using the Fama-MacBeth ("FM") approach in two ways: averaging results from time-series regressions by stock (Columns 2 and 3), or from cross-sectional regressions by date (Columns 4 and 5). t-statistics for the FM by date regressions are calculated using standard errors robust to heteroscedasticity and autocorrelation using the Newey and West (1987) adjustment with five lags. Statistical significance at the 10%, 5% and 1% levels is denoted by †, *, and **, respectively.

	FM by stock		FM by date	
	Estimate	t-stat	Estimate	t-stat
Panel A: Dependent Variable=Inst/Ind$_{i,t}$				
Ind/Ind$_{i,t-1} \times R_{i,t-1}$	-0.6939	-3.12**	-1.7931	-4.02**
Inst/Inst$_{i,t-1} \times R_{i,t-1}$	0.1050	1.20	-0.0723	-0.43
Controls:				
Intercept	0.1240	21.45**	0.1020	48.13**
$R_{i,t-1}$	0.0557	1.67†	0.1645	2.34*
Ind/Ind$_{i,t-1}$	0.0239	2.81**	0.0519	7.10**
Inst/Inst$_{i,t-1}$	0.0016	0.44	-0.0241	-7.28**
Ind/Inst$_{i,t-1}$	-0.0643	-11.14**	-0.0180	-3.88**
Inst/Ind$_{i,t-1}$	0.2180	22.09**	0.2780	47.83**
Panel B: Dependent Variable=Ind/Inst$_{i,t}$				
Ind/Ind$_{i,t-1} \times R_{i,t-1}$	0.3886	2.03*	0.9371	2.42*
Inst/Inst$_{i,t-1} \times R_{i,t-1}$	-0.1958	-2.38*	-0.1951	-1.54
Controls:				
Intercept	0.1186	19.21**	0.0847	42.22**
$R_{i,t-1}$	0.0308	0.89	-0.0116	-0.20
Ind/Ind$_{i,t-1}$	0.0416	5.55**	0.0984	14.26**
Inst/Inst$_{i,t-1}$	0.0106	2.88**	-0.0150	-4.57**
Ind/Inst$_{i,t-1}$	0.2452	24.36**	0.3032	61.63**
Inst/Ind$_{i,t-1}$	-0.0483	-10.48**	0.0005	0.13
Number of observations	151324		151324	
Number FM of regression	106 (stocks)		2184 (days)	

Figure 1: Stylized Timeline of Price Path Around Trade

This 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.

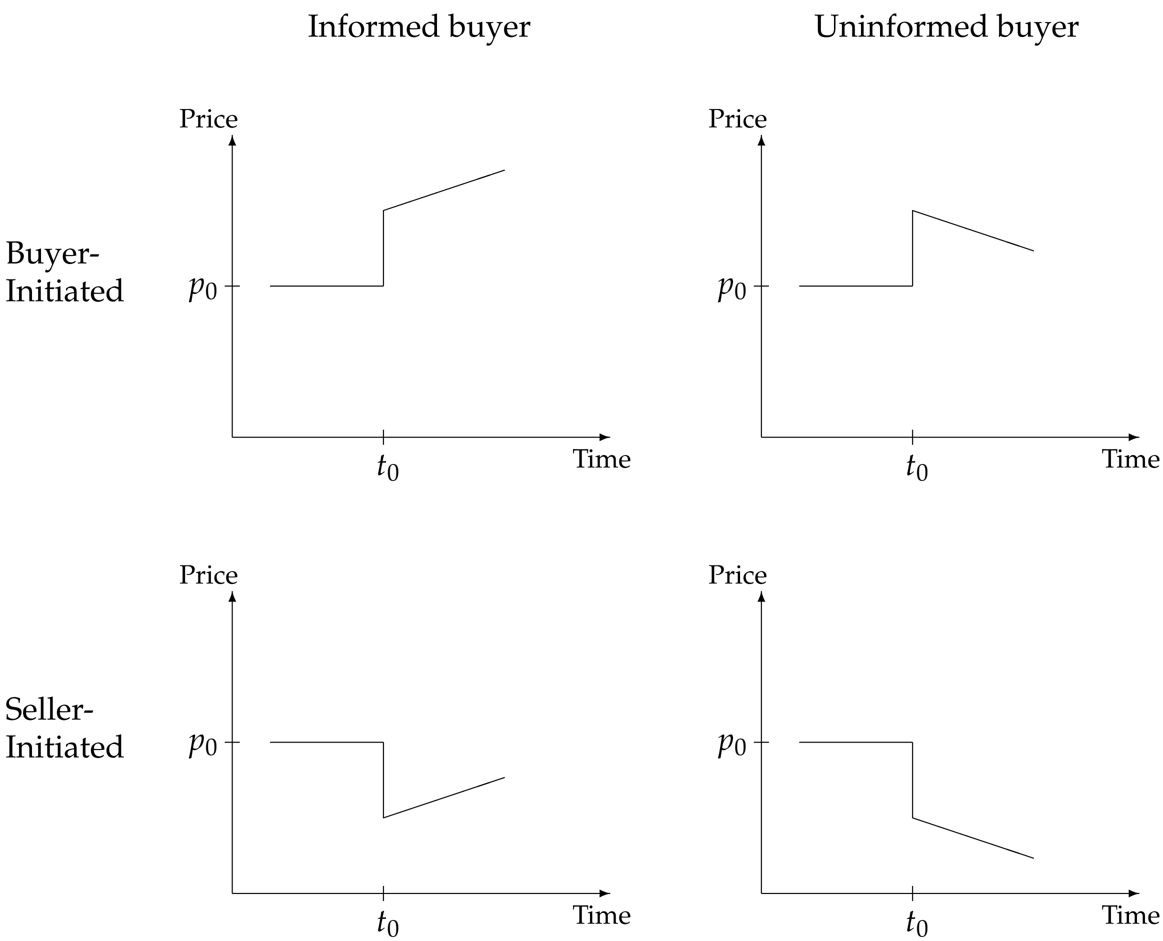

Figure 2: Cumulative Price Impact Functions

This figure plots the accumulated orthogonalized impulse response function for the structural dynamic VAR in equation (3),

$$\mathbf{A}_0\mathbf{y}_{i,t} = \sum_{k=1}^{10} \mathbf{A}_i\mathbf{y}_{i,t-k} + \boldsymbol{\eta}_t,$$

where $\mathbf{y} = (\text{Ind/Ind, Inst/Inst, Ind/Inst, Inst/Ind, Return})'$ and $\mathbf{A}_0$ is the lower diagonal matrix from the triangular factorization of the error covariance in the reduced-form VAR (equation (2)). The graphs show the cumulative effect on returns (in basis points) of a one standard deviation shock ($\eta_{i,t}$) separately to each of the trade variables. Inst/Ind (solid) is the proportion of trading accounted for by institutions purchasing shares from individuals; Ind/Ind (long dash) represents trading between two individuals; Inst/Inst (short dash) represents trading between two institutions; and Ind/Inst (dash-dot) represents individuals purchasing shares from institutions.