The Limit Order Effect*

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Abstract

The traders who place limit orders appear to react quickly and incorrectly to new information, and their trading decisions appear to depend on the pattern of past returns. This paper combines individual investors' trading records with limit order data to examine the importance of this effect. I find that limit order use is an important determinant of many behavioral patterns: the disposition effect (46%), contrarian trading strategies (24%–100%), and tendency to trade against firms' earnings announcements (100%). Limit order use reverses conclusions about individual investors' performance. It is the limit order traders who (*i*) appear to possess negative stock picking skills, who (*ii*) seem to misinterpret new information, and who (*iii*) lose money when trading high-attention stocks.

1 Introduction

Numerous studies conclude that individual investors' behavior is very sensitive to news and short-term returns. For example, Odean (1998) and Grinblatt and Keloharju (2000) find that individuals sell when prices rise and buy when prices fall. Hirshleifer, Myers, Myers, and Teoh (2003) show that individuals trade against earnings surprises, selling companies that release better-than-expected earnings and vice versa. Barber and Odean (2005) report that individuals trade on firms' news releases or significant stock price movements. Moreover, many studies find that individuals trade systematically in the wrong direction.[1] Collectively, the evidence suggests that individuals monitor the market closely but systematically misinterpret new information.

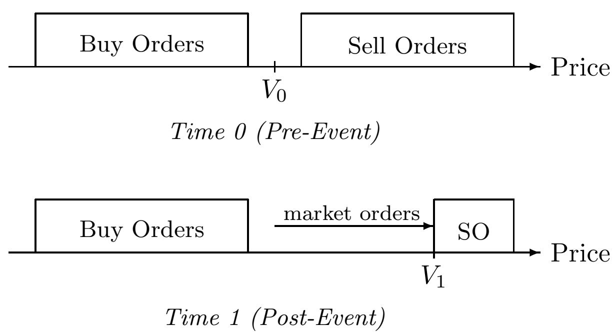

Figure 1: **Limit Orders Triggered by News**

This paper shows that individual investors' use of limit orders can explain *why* individuals seem to misinterpret new information. Figure 1 illustrates how limit orders affect inferences about investor behavior. Suppose there is no disagreement about a stock's fair value V_0, and that some investors place limit orders. Now, let the company unexpectedly upgrade its earnings guidance. Those who observe this announcement first react by submitting market

[1] For example, Odean (1999, pp. 1296) concludes: "What is more certain is that these [individual] investors do have useful information which they are somehow misinterpreting."

buy orders, triggering sell limit orders not withdrawn in time. All the sell limit orders in the book up to the new valuation V_1 execute and lose money. Thus, the arrival of news creates an appearance that (many) liquidity traders react to the news and lose money because of their poor decisions.

This paper uses a unique data set that combines investor trading records with limit order data to examine how significantly this limit order effect contributes to inferences about investor behavior and performance. I focus on the following:

1. **Misinterpreting New Information.** Hirshleifer, Myers, Myers, and Teoh (2003) find that "individuals... tend to make contrarian trades in opposition to the direction of earnings surprises." These contrarian and losing trades may be limit orders. Market order traders profit by cutting through the limit order book when new information arrives. This leaves limit order traders (passively) on the wrong side of the market.

2. **Disposition Effect.** Shefrin and Statman (1985) label investors' preference to realize gains too soon and losses too late "the disposition effect". Odean (1998), Shapira and Venezia (2001), Grinblatt and Keloharju (2001), Feng and Seasholes (2005), Dhar and Zhu (2006), and others show that individual investors more likely sell holdings with paper gains than those with paper losses. Limit order use may create such an appearance. For example, suppose an investor just bought ten stocks and needs to sell one of them. She may place a good-till-canceled sell limit order for each stock 10% above the current market price. When one of the orders executes, the stock that is sold will be the one with the highest capital gain—the unsold stocks must have unrealized returns less than 10%.

3. **Contrarian Behavior.** Heath, Huddart, and Lang (1999), Nofsinger and Sias (1999), Choe, Kho, and Stulz (1999), Grinblatt and Keloharju (2000), Grinblatt and Keloharju (2001), Richards (2004), and others conclude that individual investors follow contrarian trading strategies. Limit orders are always *contrarian* orders: they execute only when the stock price moves against the order. It may be that all active investors follow momentum strategies, forcing passive limit order investors into contrarian trades.

4. **Attention-Grabbing Behavior and Herding.** Barber and Odean (2005) and Seasholes and Wu (2005) report that individuals trade stocks that grab their attention—i.e., stocks that release news or experience significant price movements. Limit order traders appear to react to "attention" because more limit orders trigger when something happens in the market. Barber, Odean, and Zhu (2003) and Kumar and Lee (2006) report that (many) individual investors often trade in the same direction on the same day in the same stock. Prices sweeping through one side of the limit order book can create an appearance of herding.

5. **Underperformance of Attention-Grabbing Trades.** Barber and Odean (2005) document that individuals' trades in the high-attention stocks perform poorly: the stocks sold outperform the stocks purchased. Limit orders may be the cause: if it is new information that creates "attention", conditioning on "attention" is the same as conditioning on realizations of adverse selection risk.

6. **Negative Stock Picking Skills.** Barber and Odean (1999), Odean (1999), Grinblatt and Keloharju (2000), Barber, Lee, Liu, and Odean (2005), Grinblatt and Keloharju (2006), and others compare the returns of "buy" and "sell" portfolios to measure per-

Table 1: Summary of Findings

"Attributable to Limit Orders" column reports how much individual investors' limit order use contributes to various findings about investor behavior. Sections 3.1–3.5 show the technical details of the computations. Column "Table #" refers to the tables from which the numbers are taken.

Anomaly	Attributable to Limit Orders	Table #
Misinterpreting New Information	100.0%	3
Disposition Effect	45.6%	4
Contrarian Behavior		
t	100.0%	5
$t-1$	100.0%	5
$t-2$	52.8%	5
$t-3$	48.5%	5
$t-4$	49.5%	5
$[t-19, t-5]$	24.4%	5
$[t-39, t-20]$	24.6%	5
$[t-60, t-40]$	46.1%	5
Attention-Grabbing Behavior		
Sort by Same-Day Return	68.1%	7
Sort by Previous Day's Return	62.2%	7
Sort by Same-Day Abnormal Turnover	59.7%	7
Underperformance of Attention-Grabbing Trades	100.0%	9
Negative Stock Picking Skills	100.0%	10

formance. They report that individuals shift towards future losers and away from future winners. Adverse selection risk, faced by limit order traders, affects long term performance when private information is long-lived. An informed investor hides in the order-flow when trading against the uninformed investors (Kyle 1985). The uninformed investors find themselves on the wrong side of the market when the information is revealed.

Table 1 summarizes the key results. I find that limit orders contribute significantly to the anomalies about investor behavior. Limit orders' contribution ranges from a low of 24% (long term contrarian behavior) to 100% (short term contrarian behavior). Limit order use is an important determinant of investor performance. It is the passive limit order traders who (*i*) appear to possess negative stock picking skills, who (*ii*) seem to misinterpret new information, and who (*iii*) lose money when trading high-attention stocks. Market order traders, in contrast, earn positive returns when reacting to new information and when trading high-attention stocks. The limit order effect may be a simple yet powerful explanation for many findings about individual investors' behavior and performance.

Is it rational for investors to place limit orders? Handa and Schwartz (1996) conclude that a limit order is optimal when earning the spread offsets the adverse selection and non-execution risks: limit orders *per se* are not irrational.[2] However, even if investors place "irrational" limit orders, the nature and psychology of behavioral anomalies—e.g., individuals' tendency to misinterpret new information—are very different with limit orders as the root cause. If the anomalies emerge from prices sweeping through the limit order book, they do not reflect investors' irrational information processing. The high percentages in Table 1 suggest that to understand why individual investors behave the way they do, we must understand how they use limit orders. Behavioral biases may cause individuals to use such limit orders that propagate the anomalies—to express their biases. I study the consequences of limit orders and not why investors use limit orders. Although the "why" question is interesting, it is something I cannot address in this paper.

The rest of the paper is organized as follows. Section 2 discusses the data set. Section 3 examines the anomalies discussed above. Section 4 discusses the applicability of the limit order effect to other investors and markets, and tests a possible remedy. Section 5 concludes.

2 Data

This section discusses the rules of the Helsinki Exchanges and the Finnish market during the sample period from September 1998 to October 2001. I also discuss the data sets, categorize

[2] Linnainmaa (2006) concludes that limit orders alter inferences about investor behavior and performance in a limit order book model with fully rational agents.

order types, and explain how I match trading records with the limit order data.

2.1 Helsinki Exchanges

Trading on the Helsinki Exchanges (HEX) is divided into sessions. Each trading day starts at 10:10 a.m. with an opening call. Orders that are not executed at the opening remain on the book and form the basis for the continuous trading session. This trading session takes place between 10:30 a.m. and 5:30 p.m. in a fully automated limit order book. After-hours trading (5:30 – 5:45 p.m.) takes place after the continuous trading session and again the next morning (9:30 – 10:00 a.m.). Brokers can only report pre-negotiated trades in the after-hours session. (HEX changed its schedule twice during the sample period. On August 31, 2000, it extended the regular trading session to 6:00 p.m. and on April 10, 2001, it extended this session to 9:00 p.m.)

The HEX trading system displays the five best price levels of the limit order book on both sides. The public can view this book in a market-by-price form while financial institutions also receive market-by-order feed. A market-by-price book displays the amount of shares outstanding at the five best price levels on both sides of the market. A market-by-order book shows each order separately and also shows which broker submitted each order. HEX has no designated market makers or specialists. Investors trade by submitting limit orders. (The minimum tick size is EUR 0.01.) An investor who wants immediate execution must place the order at the best price level on the opposite side of the book. An investor who wants to buy or sell more shares than what is currently outstanding at the best price level must submit separate orders for each price level. If a limit order executes against a smaller order, the unfilled portion stays on the book as a new order. Time and price priority between limit orders is enforced. For example, if an investor submits a buy order at a price level that already has other buy orders outstanding, all the old orders must execute before the new order gains priority.

The total market value of the 158 companies on the Helsinki Exchanges was EUR 383 billion in the middle of the sample period (May 2000). I report several sample statistics for the 30 most actively traded stocks for future reference:

- A total of 14.2 million trades took place in these stocks. The most active stock is Nokia with 2.7 million trades.
- These stocks have an average realized spread of 0.44%. (Nokia's average spread is the lowest, 0.13%.)
- Three out of ten trades originate directly from individual investors. The proportion of trades originating from individual investors ranges from a low of 15% to a high of 72% in these 30 stocks. Individual investors' direct participation is higher for small and less actively traded stocks.

2.2 Investor Trading Records and Limit Order Data

I use two data sets in this study:

1. *The complete trading records and holdings information of all Finnish investors in all publicly traded Finnish stocks.* The Finnish Central Securities Depository registry (FCSD) provided this data for the period from January 1995 to November 2002. Each trade record includes a date-stamp, a stock identifier, and the price, volume, and an indicator for whether the transaction was a purchase or a sale. Each record also identifies the

investor type—a domestic institution, a domestic household, or a foreigner—and gives other demographic information. I classify all investors as either individuals or institutions for this study. Grinblatt and Keloharju (2000) provide greater details about this data set.

2. *The limit order data.* These data are the supervisory files from the HEX from September 18, 1998 to October 23, 2001. Each entry is a single order entered into the trading system, containing a unique order identifier, date- and time-stamps, a session code, a code for the brokerage firm submitting the order, a trade type indicator (i.e., whether the trade is a regular trade, a pre-negotiated trade, or an odd-lot trade), and the price and volume of the order. All entries also contain a set of codes for tracking the life of an order—an order can expire, be partly or completely filled, or modified. I use these data to reconstruct the limit order book for each second of every trading day for all the stocks.

2.2.1 Matching the Data Sets

I match the investor trading records against the limit order data using executed trades to get information on the type of the order that the investor used to execute the trade. Each trade record in the limit order data contains all the same information as the investor trading records *except* the investor identity. I use common elements to link the data sets.

There is no ambiguity in matching a trade that has a unique price-volume combination—e.g., if only one trade (in one stock-day) has a price of EUR 82 and a volume of 1,200 shares. (A trade is non-unique if multiple trades have the same price-volume combination.) There is no one-to-one link between the data sets for the remaining trades. However, even when multiple

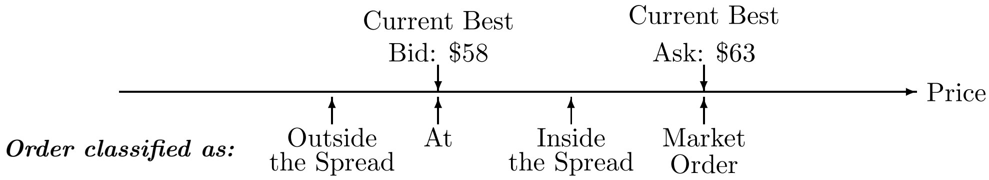

Figure 2: **Classifying a Buy Order**

trades have the same price-volume combination, it is possible to classify them unambiguously if all investors behind these trades used the same type of an order (e.g., everyone used market orders). Then, it does not matter if an investor's trading record is matched against "wrong" transaction. It is possible to determine unambiguously whether an investor used a market order or a limit order in 60.6% of all transactions ($N = 14,818,819$). I use these unambiguous trades in my empirical tests. My results are, however, qualitatively the same when I also include the potentially misclassified trades. This suggests that the measurement errors in my tests are orthogonal to the misclassifications.

2.2.2 Order Classification

I use the following categorization to classify every order entered into the trading system:

- *Market order.* An order placed at the best price level on the opposite side of the book to get immediate execution. (All orders on the HEX are technically limit orders; however, the market convention is to call these active orders "market orders".)

- *Inside the Spread Limit Order.* An order placed inside the current bid-ask spread.

- *At the Spread Limit Order.* An order placed at the best bid (for a buy order) or at the best ask (for a sell order).

- *Outside the Spread Limit Order.* An order placed outside the current bid-ask spread. This category also includes orders entered at a time when there are no other bids (for a

Table 2: Individuals' and Institutions' Use of Market and Limit Orders

This table shows how individual and institutional investors use market and limit orders. The sample consists of all uniquely matched trades in all the stocks traded on the Helsinki Exchanges between September 18, 2001 and October 23, 2001. The proportion of market orders is computed from the entire sample. The proportions for different types of limit orders are computed using data after July 10, 2000 because the earlier limit order book data is missing a time-stamp that indicates order withdrawals. This table reports the frequencies of different order types for executed trades. Limit orders classified as follows: (i) *inside* is an order placed inside the current bid-ask spread; (ii) *at* is an order placed at the bid-ask spread; (iii) *outside* is an order placed outside the current bid-ask spread, or entered when there are no other orders on the same side of the book, (iv) *pre-open* is an order entered into the system before trading starts; (v) *stale* is an order carried over from the previous trading day. Note that 'Inside' + . . . + 'Stale' = 100%. *Value-Weighted* column weights observations by the euro value of each trade. *Trade Size* is the average trade size in EUR 1,000s.

	Individual Investors ($N = 3,230,735$)			Institutional Investors ($N = 5,750,824$)		
Order Type	Equal-Weighted	Value-Weighted	Trade Size	Equal-Weighted	Value-Weighted	Trade Size
Market Orders	44.0%	41.3%	6.5	52.7%	50.3%	66.8
Limit Orders						
Inside	30.0	36.0	7.6	55.4	56.4	82.1
At	9.9	14.1	9.0	20.1	22.3	89.7
Outside	34.5	36.4	6.7	20.2	19.9	79.7
Pre-Open	19.6	9.1	3.0	3.6	1.1	25.5
Stale	5.9	4.4	4.8	0.8	0.2	22.2

buy order) or offers (for a sell order) in the book.

- *Pre-Open Limit Order.* A limit order entered before the continuous trading session begins. (The limit order book is not visible to the market participants at this time.)

- *Stale Limit Order.* An unfilled limit order carried over from the previous trading day. A limit order remains in the book until executed unless the investor specifies an expiration date.

Figure 2 shows an example of how a buy order is classified when best bid is currently \$58 and the best ask is \$63. An order with a limit price between \$58.01 and \$62.99 is classified as an inside-the-spread order.[3]

[3] The pre-July 10, 2000 limit order data is missing the time-stamp that reports when an unfilled order is withdrawn. This may lead to errors in limit order type classifications between categories "In", "At", and "Out"

Table 2 shows summary statistics for how individuals and institutions use different types of orders. It shows that individual investors use more limit orders than institutions (56% versus 47%). Individual investors' limit orders also differ substantially from institutions' limit orders. First, individuals often place their limit orders far away from the current bid-ask prices. Second, 25.5% of individuals' limit orders are submitted before trading begins or carried over from the previous trading day. Only 4.4% of institutions' limit orders are of this type. The rest of the paper, with the exception of Section 3.6, focuses on individual investors.

3 Empirical Tests of the Limit Order Effect

3.1 Misinterpreting New Information

Hirshleifer, Myers, Myers, and Teoh (2003) show that individuals trade against earnings surprises, selling companies that release better-than-expected earnings and vice versa. Stale limit orders may contribute to this finding: if individuals have limit orders in the book when the announcement arrives, only the ones "against" the news execute. This section uses data on earnings announcements released during regular trading hours to examine whether stale limit orders contribute to the "misinterpreting new information" results. Earnings announcements are ideal for this purpose: they provide a transient trading opportunity to those market participants who monitor the market closely. An investor who reacts to the information before her competitors can profit from all the limit orders between the current and post-announcement valuations. An earnings announcement also renders all pre-announcement limit orders *stale*.

I study trading around two types of earnings announcements: pre-scheduled announce-

because the exact state of the book is not known. Hence, the order-type specific results in Table 2 use data only for the second half of the data set. I use a coarser classification scheme in the rest of the paper: market orders, limit orders, and pre-open—including stale—limit orders.

ments (i.e., the company has pre-announced the date and time) and unscheduled announcements (i.e., the company complies with [the equivalent of] SEC's Form 8-K disclosure requirements). I use data on all earnings announcements during the sample period. The resulting sample consists of 586 pre-scheduled and 117 unscheduled earnings announcements. Each observation contains the date and time of the announcement.[4]

3.1.1 Methodology

I compute average trading gains for all individuals' executed orders around each announcement. Trading gains are defined as

$$\begin{aligned} r_{i,s,t} &= \begin{cases} \ln(c_{s,t+k}) - \ln(p_{i,s,t}) & \text{if a buy order} \\ \ln(p_{i,s,t}) - \ln(c_{s,t+k}) & \text{if a sell order} \end{cases} \qquad (1) \\ \text{where} \quad p_{i,s,t} &= \text{the trade price of trade } i \\ c_{s,t+k} &= \text{the closing price in stock } s \text{ on date } t+k. \end{aligned}$$

I study same-day, one-week, and two-week trading gains. I divide the period around each announcement into two-minute time intervals as well as into *before*, *during*, and *after* windows. *Before* contains all the same day trades executed before the announcement, *during* contains the trades executed during the first five minutes after the announcement, and *after* contains all the same day trades executed after these five minutes. I first compute value-weighted average

[4]The time-stamp is rounded downwards to the nearest minute. For example, if the time-stamp reads 12:03 p.m., the exact time of the announcement is $t \in [12{:}03{:}00, 12{:}03{:}59]$. An announcement is usually released both in English and in Finnish. I use the time-stamp from the announcement that arrives first. I do not classify announcements as positive or negative surprises or exclude announcements that cause no price movements.

trading gains conditional on order type for each period τ around announcement a,

$$r_{a,\tau} = \frac{1}{\sum_{i \in a,p} V_{i,s,t}} \sum_{i \in a,\tau} V_{i,s,t} r_{i,s,t}, \tag{2}$$

where $V_{i,s,t}$ is the value of trade i and τ is, e.g., the period from 10 minutes before the announcement to 8 minutes before the announcement. My measure of investor performance in period p is the cross-sectional average over these announcement-specific averages.

3.1.2 Results

Figure 3 shows that stale limit orders triggered after announcements perform very poorly. The trading gains are significantly negative for orders executed during the first eight minutes. For example, the cross-sectional average same-day return on orders executed during the $[0, 120s)$ interval is -2.1% with a t-stat of -2.7. Panel B shows that individuals lose *only* on their limit orders: their market orders have positive trading gains up to ten minutes after the announcement. (Limit orders entered after the announcement do not lose money. For example, the average same-day return for orders executed during the first five minutes is -0.05% with a t-stat of -0.08; not shown.)

Table 3 shows that the performance of stale limit orders worsens with the horizon. For example, the average one-week gain for the limit orders in the during-window is -2.9%. This increase corresponds to the post-earnings announcement drift. However, note that the standard errors also increase with the horizon—the *statistical* significance of the losses is almost unchanged. Hence, a strategy designed to exploit this effect would be risky. (An investor could use the data from the first minute after an announcement to observe the direction of the order-flow and then mimic this behavior. However, this strategy is linked to the post-

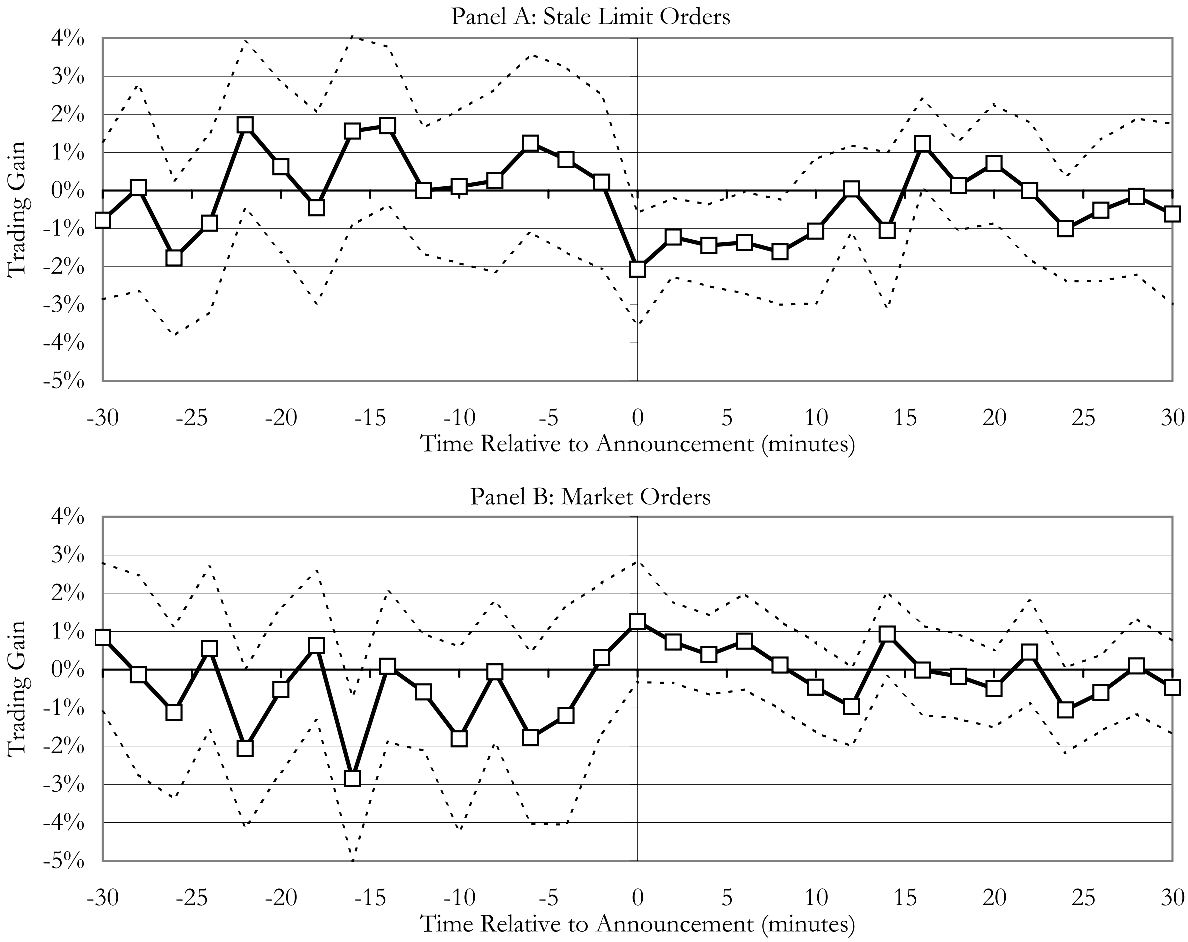

Figure 3: **Returns on Individual Investors' Market Order- and Stale Limit Order-Initiated Trades around Earnings Announcements.** This figure shows same-day trading gains for individuals' stale limit orders (Panel A) and market orders (Panel B) around earnings announcements. A stale limit order is an order entered into the book before the release of an announcement (time 0 on the x-axis). The sample consists of all 586 pre-scheduled earnings announcements released during the regular trading hours on the Helsinki Exchanges from September 18, 1998 to October 23, 2001. The value-weighted average trading gain is first computed separately for each order type/announcement/two-minute interval. This figure plots the cross-section averages of the first-stage averages. The dashed lines are the 95% confidence intervals.

earnings announcement drift (PEAD) because the first minute reaction is probably highly correlated with SUE. Thus, this strategy would capture the well-known PEAD result (Ball and Brown 1968). Moreover, the eight-minute persistence in the stale limit order losses may be an aggregation artifact: if the market reacts in Stock A between times 0 and 1, in Stock B between times 1 and 2, and in Stock C between times 2 and 3, the aggregated data shows a reaction between times 0 and 3.)

Table 3: Percent Returns on Individual Investors' Market Order- and Stale Limit Order-Initiated Trades around Earnings Announcements

This table reports trading gains for individuals' stale limit orders and market orders executed around earnings announcements. The sample consists of 586 pre-scheduled earnings announcements (Panel A) and 117 unscheduled earnings announcements (Panel B) released during the regular trading hours on the Helsinki Exchanges between September 18, 1998 to October 23, 2001. A stale limit order is an order entered into the book before the release of an announcement. *Before* contains trades executed before the announcement, *during* contains trades executed during the first five minutes after the announcement, and *after* contains trades executed after these five minutes. The value-weighted average trading gains are first computed for each announcement-interval. This table reports the means and standard errors of the announcement-specific averages. *Number of Trades* is the total number of trades across the N announcements.

Panel A: Trading Gains (%) around Scheduled Earnings Announcements

			Trading Gain Horizon					
	Number of		Same-Day		One Week		Two Weeks	
Period	Trades	N	Mean	s.e.	Mean	s.e.	Mean	s.e.
			Stale Limit Orders					
Before	9,108	392	0.53	0.20	0.67	0.34	0.44	0.41
During	2,526	210	−1.49	0.44	−2.82	0.81	−3.80	1.18
After	3,164	383	−0.31	0.19	−0.84	0.46	−1.41	0.76
			Market Orders					
Before	8,763	381	−0.22	0.26	−0.29	0.44	0.31	0.63
During	1,625	201	0.77	0.43	1.60	0.78	2.20	1.08
After	28,987	480	−0.16	0.10	−0.53	0.25	0.07	0.44
			Market Order − Limit Order Pairwise Difference					
Before	9,498	322	−0.87	0.43	−0.97	0.81	−0.11	1.16
During	2,461	146	3.24	1.12	5.86	1.98	7.82	2.90
After	13,617	338	0.09	0.28	0.18	0.74	1.65	1.35

Panel B: Trading Gains (%) around Unscheduled Earnings Announcements

			Trading Gain Horizon					
	Number of		Same-Day		One Week		Two Weeks	
Period	Trades	N	Mean	s.e.	Mean	s.e.	Mean	s.e.
			Stale Limit Orders					
Before	3,590	90	1.10	0.98	0.86	1.35	−0.04	1.40
During	1,342	72	−5.99	1.46	−9.69	2.25	−10.28	2.47
After	640	70	−1.27	0.84	−1.72	1.54	1.05	1.99
			Market Orders					
Before	3,344	85	−1.90	1.15	−1.32	1.43	−2.09	1.80
During	522	61	4.32	1.24	7.38	2.07	7.09	2.07
After	12,036	104	−0.14	0.33	0.20	0.78	−0.15	1.12
			Market Order − Limit Order Pairwise Difference					
Before	3,669	75	−2.59	1.93	−1.40	2.45	−1.54	2.58
During	1,357	52	11.84	3.18	19.27	5.03	18.77	5.31
After	3,717	62	1.30	0.96	3.44	1.78	−0.02	2.39

Stale limit orders lose even more when the earnings announcement is unexpected. For example, the same-day loss for stale limit orders triggered in the during-window is 6.0%. These losses increase to 9.7% with the one-week return horizon, although the statistical significance is again nearly unchanged. Market order traders' gains are significantly positive immediately after unscheduled earnings announcements. Those few market order traders—there are only 522 trades across 61 unexpected announcements—who react to the announcements earn 4.3% on the same day by sweeping through the limit order book.

These earnings announcement results contradict the perception that individuals systematically misinterpret new information. Investors who lose, lose because of their passivity—*active* investors make money. The poor timing of passive investors has to mirror the good timing of other investors. The mechanism that generates the stale limit order losses is important: it would not be possible to mechanically back out and reverse these individuals' trading strategies to make money. The importance of this mechanism may be enormous: earnings announcements are only a minor fraction of all news—it is largely the unobservable factors that drive stock price movements (Roll 1988).

3.1.3 Demographics of Stale Limit Order Investors

Who loses money with stale limit orders? Individuals with stale limit orders in the book during the first five minutes after the announcement are very different from the market order traders during the same interval. First, the average age of stale limit order traders is 50.2 while it is 43.1 years for the market order traders. Second, stale limit order traders have less investment experience, as measured by the number of earlier trades: 179.9 versus 591.8 trades. (These distributions are positively skewed. The medians are 108 and 254, respectively.) Third, stale limit order traders live in rural areas relative to market order traders. The average urban zip code index for stale limit order traders is 19.4% while it is 25.1% for market order trades.[5] (I

[5] All these differences are statistically significant. The pair-wise age difference is -7.38 years with a standard error of 3.41 years. The pair-wise difference in the number of trades is 434.52 with a standard error of 83.89 trades. Finally, the pair-wise difference in the zip code index is 5.18% with a standard error of 1.83%. These

compute this index for zip code i by dividing the number of investors living in zip code i by the number of investors living in the most densely populated zip code.)

These differences in demographics suggest that stale limit order traders may face higher monitoring costs. They may have decided that the cost of acquiring relevant information outweighs the expected loss from this type of adverse selection risk.

3.2 Disposition Effect

3.2.1 Methodology

I study how limit order use affects inferences about individual investors' sell versus hold decisions. I create a "sell versus hold" data set by collecting information about the stocks individual investors sell from their portfolios (individual investors' all holdings are visible in the FCSD registry). I generate separate observations for each investor's all holdings—i.e., not only for stocks that the investor sells but also for those he or she keeps—every day an investor sells at least one stock.

I run a logistic regression of a "sell" indicator variable—set to one if a holding is sold and to zero otherwise—against a capital gain indicator variable. This capital gain indicator variable is set to one if the sale price is higher than the FIFO price. (I use the same-day close as the benchmark price for unsold positions.) The slope coefficient on this variable measures the disposition effect: a positive estimates indicates that investors more often sell stocks with capital gains than those with capital losses.

I examine the limit order effect by categorizing all sell versus hold observations based on the type of the order the investor used to execute the actual sale. If the actual sale is completed

pair-wise differences are cross-sectional averages across the 162 earnings announcement-specific averages that have both market order- and stale limit order-initiated trades in the "during"-window.

with a market order, all the unsold holdings are also treated as market order-initiated trades. Are investors more likely to realize losses when they use market orders instead of limit orders?[6]

I estimate the logistic regression separately for each stock with more than 5,000 trades by individual investors (78 stocks) in the sample to account for heterogeneity across stocks. (Investors might keep stock X instead of stock Y because of some omitted variable.) This cross-sectional method also equal-weights the sample across stocks. This is an important consideration in a market with a small number of actively traded stocks. I estimate the stock-specific regressions in three samples for the sake of robustness:

1. *Full Sample*: includes all sell versus hold observations

2. *Small Trades*: I rank all "sell" and "hold" observations (across all investors) by the euro value of the actual sale. This sample includes the smallest quintile sales.

3. *Large Trades*: includes sales in the fifth trade size quintile.

I further split each sample by order type: all orders, market orders, limit orders, and pre-open limit orders.

3.2.2 Results

Table 4 shows that investors more likely sell stocks with capital gains than those with capital losses. The average capital gain-coefficient estimate across the full sample individual stock

[6] A logistic regression approach, unlike the alternative PGR/PLR (proportion of gains/losses realized) measure (Odean 1998 and others), allows us to control for other determinants of the sell versus hold decision. First, I include the first five powers of the length of the holding period (the number of days from the previous purchase divided by 100) to control for the relation between the holding period and the likelihood of a sale (Feng and Seasholes 2005). Second, I control for differences in the unconditional probability of observing an actual sale by including the number of stocks actually sold divided by the number of stocks in the portfolio as an explanatory variable. (For example, if an investor has only one stock in his or her portfolio, an actual sale would always be observed. I ignore such cases and require that investor has both "winners" and "losers" in her portfolio.) The regression I run is

$$\text{Actual Sale}_i = a_0 + b * \text{Capital Gain}_i + \mathbf{x}_i \mathbf{c} + \varepsilon_i \tag{3}$$

where $\mathbf{x}_i$ is a row vector of controls for observation i and $\mathbf{c}$ is a column vector of the coefficients.

Table 4: The Disposition Effect

This table reports estimates of disposition effect logistic regressions. The sample consists of "sell" and "hold" observations—a hold observation is generated every time an investor sells another stock from her portfolio. All observations must satisfy the following requirements: (1) The investor must have both winners and losers in her portfolio, (2) The investor must not sell all her holdings, (3) An unsold holding is included only if the investor does not purchase more shares of that stock on the same day, (4) The observation must have a valid FIFO price, and (5) An unsold holding must have an euro value as large as the euro value of the actual sale (i.e., the unsold holding could have been sold instead of the stock that was actually sold). The dependent variable is set to one if the stock is sold and to zero otherwise. The explanatory variables are: a capital gain indicator variable (the stock price is above the FIFO price), the first five powers of the length of the holding period, and the log-fraction of stocks sold from the portfolio on the day of the trade. The regression is estimated for the 78 stocks with at least 5,000 trades from individual investors between September 23, 1998 through October 23, 2001. This table reports the average coefficient estimates (Fama and MacBeth 1973) for the capital gain variable. The regressions are estimated separately for different order types: all orders, market orders, limit orders, and pre-open limit orders. *%-Chg* is the percentage difference in the capital gain coefficient estimates between "Market Orders" and "All Trades." The results are reported for three samples: a sample with all observations, a sample that contains trades in the smallest trade size quintile, and a sample that contains trades in the fifth trade size quintile.

		Capital Gain Coefficients				
Sample		All Orders	Market Orders	Limit Orders	Pre-Open Orders	%-Chg
Full Sample	Mean	0.902	0.491	1.179	1.248	−45.6%
	s.e.	0.040	0.038	0.042	0.048	
Small Trades Sample	Mean	0.783	0.303	1.061	1.067	−61.3%
	s.e.	0.052	0.056	0.054	0.060	
Large Trades Sample	Mean	0.883	0.589	1.154	1.496	−33.4%
	s.e.	0.056	0.069	0.059	0.131	

regressions is 0.90. These coefficient estimates are very different between the market order and limit order samples: the average coefficient is 0.49 for market orders and 1.18 for limit orders. Hence, limit orders contribute significantly to inferences about individual investors' disposition effect. The reduction in the disposition effect, after excluding limit order-initiated trades, is 46% for the full sample. Hence, almost half of the unconditional estimate of the disposition effect (i.e., of the "all orders" estimate) is due to limit orders. Table 4 also indicates that (*i*) (the appearance of) the disposition effect is stronger for pre-open limit orders and that (*ii*) limit orders contribute more to the disposition effect in the small trades sample than in the large trades sample.

A potential concern with the preceding analysis is that the choice between limit and market orders may not be independent of the (genuine) disposition effect: an investor placing a limit order 10% above the current stock price knows, ex ante, that she will be selling the stock with the highest capital gain if the order executes. Even so, this would be a very different type of disposition effect: the investor does not choose to sell a stock with the highest capital gain—the investor sells whichever stock first happens to appreciate enough. (This endogeneity concern is not as significant with the other behavioral anomalies I consider. For example, an individual who wants to trade attention-grabbing stocks could use stale limit orders. However, this strategy seems unattractive because of adverse selection risk.) Nevertheless, the possibility that investors use limit orders to satisfy behavioral-based preferences should be kept in mind when interpreting the results.

3.3 Contrarian Behavior

3.3.1 Methodology

This section modifies Grinblatt and Keloharju's (2001) method to study how lagged returns affect individual investors' buy versus sell decisions, and whether the effect is different for limit and market orders. I estimate a logistic regression in a sample that contains individual investors' all purchases and sales. The dependent variable is set to one for sales and to zero for purchases. The explanatory variables are 24 returns: eight are market returns over the previous three months[7] and the rest are stock-specific excess returns, $r_t^s - r_t^m$, where s is the stock and m is the market. Following Grinblatt and Keloharju (2001), positive and negative

[7] The regressions use the same return intervals as Grinblatt and Keloharju (2001) except that I leave out past returns that are more than three months old. (Grinblatt and Keloharju (2001) find insignificant coefficient estimates for these longer lags.) The return intervals used to explain day t trading behavior are: t, $t-1$, $t-2$, $t-3$, $t-4$, $[t-19, t-5]$, $[t-39, t-20]$, and $[t-60, t-40]$. Note that date t return, defined as the return from the previous day's close ($t-1$) to today's close, is partly forward-looking. Grinblatt and Keloharju (2001) use

stock-specific returns enter separately (8+8) to control for asymmetries between price increases and decreases. I again estimate the logistic regressions for each of the 78 stocks with more than 5,000 trades from individual investors and compute cross-sectional coefficient estimates.

3.3.2 Results

Table 5 reports the average coefficient estimates for the stock-specific excess return variables. The base results in the "All Orders" column replicate the Grinblatt and Keloharju (2001) result: individual investors employ contrarian trading strategies, buying shares when the same-day return is negative and selling when the return is positive. Individual investors' contrarian behavior weakens with the horizon. The coefficient decreases from 8.21 to 0.56 when the horizon increases from the same-day return to the two to three months horizon.

Limit order-initiated trades are significantly more contrarian-oriented than the market order-initiated trades. For example, the same-day return coefficient estimate is 20.1 for limit orders, and the limit order estimate is above the "All Orders" estimate at all horizons. The coefficient estimates for the pre-open limit orders sample are even larger than what they are for the overall limit order sample. Market order traders, on the other hand, are momentum traders with respect to the same-day and previous day's returns. A comparison of the market order estimates to the "All Orders" estimates shows that the return coefficients decrease significantly at all horizons: the reductions range from 24% to 100%. The trade size-specific

this definition. The regression I run is

$$\Pr(\text{Sale Dummy}^s_{i,t} = 1) = \mathbf{\Lambda}\Big(a_0 + b_1 \min(r^s_t - r^m_t, 0) + \ldots + b_8 \min(r^s_{[t-60,t-40]} - r^m_{[t-60,t-40]}, 0)$$
$$+ b_9 \max(r^s_t - r^m_t, 0) + \ldots + b_{16} \max(r^s_{[t-60,t-40]} - r^m_{[t-60,t-40]}, 0) + b_{17} r^m_t + \ldots + b_{24} r^m_{[t-60,t-40]} + \varepsilon_{i,t}\Big), \quad (4)$$

where s is the index for stock, i indexes the trades, t denotes day, m is the equally-weighted HEX market portfolio, and $\mathbf{\Lambda}(\cdot)$ is the logistic cumulative distribution function. I report averages of the positive and negative components (e.g., the average of b_1 and b_9) rather than individual coefficient for the sake of brevity.

Table 5: Contrarian Trading Strategies

This table estimates a logistic regression of individual investors' buy versus sell decision. The dependent variable is set to one for sales and to zero for purchases. The explanatory variables are 8 lagged market returns and 16 stock-specific excess returns. The stock-specific returns are decomposed into positive and negative components (8 + 8). The logistic regression is estimated for each of the 78 stocks that had at least 5,000 trades from individuals between September 23, 1998 and October 23, 2001. The regressions are estimated separately for different order types: all orders, market orders, limit orders, and pre-open limit orders. *%-Chg* is the percentage difference between the "Market Order Trades" and "All Trades" coefficient estimates. The regression is estimated in three samples: a sample with all observations, the smallest trade size quintile sample, and the largest trade size quintile sample. This table reports average return coefficients: each number in this table is an average over the 78 stock-specific regressions and across the positive and negative return components ($2 * 78 = 156$ coefficients).

		Order Type								
		All Orders		Market Orders		Limit Orders		Pre-Open Orders		
Sample	Return Variable	Mean	s.e.	Mean	s.e.	Mean	s.e.	Mean	s.e.	%-Chg
Full Sample	r_t	8.21	0.71	−5.13	0.75	20.11	1.28	33.91	1.82	−100.0%
	r_{t-1}	4.03	0.52	−0.10	0.51	7.84	0.77	13.03	1.03	−100.0%
	r_{t-2}	3.06	0.44	1.44	0.45	4.65	0.54	6.28	0.69	−52.8%
	r_{t-3}	3.11	0.41	1.60	0.43	4.54	0.51	5.64	0.74	−48.5%
	r_{t-4}	2.47	0.32	1.25	0.36	3.69	0.41	5.20	0.62	−49.5%
	$r_{[t-19,t-5]}$	1.59	0.23	1.20	0.24	1.93	0.23	2.42	0.29	−24.4%
	$r_{[t-39,t-20]}$	1.00	0.12	0.76	0.14	1.24	0.13	1.96	0.26	−24.6%
	$r_{[t-60,t-40]}$	0.56	0.11	0.30	0.13	0.77	0.12	0.98	0.18	−46.1%
Small Trades Sample	r_t	8.06	0.82	−5.99	0.90	21.41	1.43	30.84	2.22	−100.0%
	r_{t-1}	4.73	0.71	−0.75	0.73	10.48	1.40	14.36	1.44	−100.0%
	r_{t-2}	3.46	0.64	1.24	0.72	5.68	1.04	6.55	1.55	−64.1%
	r_{t-3}	3.44	0.58	1.77	0.65	5.22	1.13	5.87	1.20	−48.6%
	r_{t-4}	3.32	0.84	1.41	0.61	5.25	1.18	5.15	1.34	−57.5%
	$r_{[t-19,t-5]}$	2.35	0.48	1.52	0.37	2.71	0.54	2.58	0.48	−35.5%
	$r_{[t-39,t-20]}$	1.60	0.30	1.03	0.26	1.86	0.34	2.12	0.42	−35.7%
	$r_{[t-60,t-40]}$	0.99	0.24	0.85	0.24	1.30	0.35	1.02	0.51	−13.8%
Large Trades Sample	r_t	9.20	0.77	−3.11	0.86	20.14	1.34	48.71	3.36	−100.0%
	r_{t-1}	4.21	0.64	0.94	0.74	7.21	0.86	14.12	1.73	−77.7%
	r_{t-2}	3.31	0.52	1.63	0.76	4.94	0.63	7.22	1.29	−50.7%
	r_{t-3}	3.68	0.50	2.41	0.57	4.82	0.58	6.07	1.15	−34.4%
	r_{t-4}	3.03	0.40	2.34	0.49	3.89	0.50	7.02	1.32	−22.6%
	$r_{[t-19,t-5]}$	1.87	0.25	1.72	0.29	2.03	0.26	2.71	0.49	−8.4%
	$r_{[t-39,t-20]}$	1.20	0.14	0.95	0.18	1.48	0.16	2.58	0.43	−20.9%
	$r_{[t-60,t-40]}$	0.67	0.14	0.44	0.19	0.86	0.16	1.35	0.36	−34.5%

estimates show that small or large trades do not exclusively drive the results, although—similar to the disposition effect results—the limit order effect is stronger in the small trades sample.

A potential concern is that the data does not distinguish market orders from stop-loss orders. This could make the results too optimistic because stop-loss orders are mechanically momentum-oriented. However, I believe this effect is negligible. First, most Finnish brokers do not offer stop-loss orders, so their use is probably not widespread. Second, if stop-loss orders were pervasive, I would expect "market order traders" to respond to *negative* returns by selling. (Because shorting in Finland is very costly, individual investors would not use stop-loss orders contingent on positive returns.) Individual market order traders, however, exhibit stronger momentum behavior for *positive* returns. For example, the same-day estimate is -4.20 for the negative return component and -6.06 for the positive return component. (Table 5 does not report these individual estimates—it only reports their average, $\frac{(-4.20)+(-6.06)}{2} = -5.13$.)

3.4 Attention-Grabbing Behavior and Herding

Barber and Odean (2005) document that individual investors have a higher likelihood of trading on firms' news releases and significant stock price movements. Barber, Odean, and Zhu (2003) and Kumar and Lee (2006) report that many individual investors often trade in the same direction on the same day in the same stock. This section modifies Barber and Odean's (2005) methodology to measure how much limit order use contributes to individuals' attention-grabbing behavior and to the poor performance of these high attention trades. It also examines whether the triggering of limit orders contributes to individual investors' herding.

3.4.1 Attention Variables and the Execution of Stale Limit Orders

Methodology. I use three "attention" measures:

1. The close-to-close stock i return for the same trading day, $r_{i,t}$.

2. The close-to-close returns for the previous trading day, $r_{i,t-1}$.

3. The same-day abnormal turnover, computed as

$$V_{i,t}^{*} = \frac{V_{i,t}}{\frac{1}{252}\sum_{k=1}^{252} V_{i,t-k}} - 1 \tag{5}$$

where $V_{i,t}$ is stock i's day t turnover.

Barber and Odean (2005) use measures 2 and 3. I add measure 1 to examine a possible reverse-causality explanation for limit order investors' behavior.

Limit orders can contribute to the Barber and Odean (2005) results only if the attention variables are correlated with the execution of stale limit orders. I measure this correlation by regressing the proportion of executed outside the spread and pre-open limit orders—in stock i on date t—against the attention variables. (I enter the positive and negative parts of the attention variables separately to account for asymmetries.) I also run this regression with only the pre-open limit orders on the left-hand side.

Results. Table 6 shows that the attention variables correlate with the execution of "outside the spread" and "pre-open" limit orders: a higher proportion of these orders execute when the attention variables are more extreme. For example, if the same-day return is -10%, the predicted proportion of executed "outside the spread and pre-open" limit orders is 6.2% higher than what the proportion would be on a zero-return day. While the same-day return is the strongest predictor of the execution of "outside the spread" orders, previous day's return is the strongest predictor of the execution of "pre-open" orders. The turnover-sort results are economically weaker than the return-based results. The estimate indicates that the proportion of executed stale limit orders increases as the abnormal volume decreases. This may be endogenous: if the limit order book is sparser on low-volume days, more "stale" limit

Table 6: Attention Variables and the Execution of Stale Limit

This table reports estimates of six regressions that examine the relation between the attention variables and the execution of stale limit orders. Each observation is one trading day in one stock. The dependent variable in regressions (1)–(3) is the proportion of executed limit orders that were initially placed outside the spread or before the start of the trading day. The dependent variable in regressions (4)–(6) is the proportion of executed limit orders placed before the start of the trading day. The explanatory variables are stock i's same-day return, previous day's return, and the same-day abnormal turnover ($V^*_{i,t}$ from Eq. 5). All regressions control for stock fixed effects. The heteroscedasticity consistent standard errors (reported in parentheses) are clustered by stock.

Dependent Variable:	"Outside and Pre-Open" Orders			"Pre-Open" Orders		
Explanatory Variable	(1)	(2)	(3)	(4)	(5)	(6)
$\min(r_{i,t}, 0)$	−0.623			0.022		
	(0.048)			(0.037)		
$\max(r_{i,t}, 0)$	0.416			−0.113		
	(0.056)			(0.039)		
$\min(r_{i,t-1}, 0)$		0.061			0.306	
		(0.039)			(0.036)	
$\max(r_{i,t-1}, 0)$		−0.070			−0.296	
		(0.034)			(0.032)	
$\min(V^*_{i,t}, 0)$			−0.039			−0.072
			(0.004)			(0.003)
$\max(V^*_{i,t}, 0)$			0.000			0.000
			(0.000)			(0.000)
N	17,851	17,055	19,724	17,851	17,055	19,724
Adjusted R^2	19.1%	16.3%	18.3%	30.0%	27.8%	32.3%

orders are exposed to market orders.

3.4.2 Individual Investors' Attention-Grabbing Behavior

Methodology. I replicate Barber and Odean's (2005) attention-grabbing results by assigning all stocks into deciles each day based on the attention variables. I compute the buy-sell imbalance for partition p on date t as

$$\mathrm{BSI}_{pt} = \frac{B_{pt} - S_{pt}}{B_{pt} + S_{pt}}, \tag{6}$$

where B_{pt} is the number of purchases by individual investors in partition p on date t and S_{pt} is the number of sales. (Market-clearing—i.e., the number of buys = the number of sales—does not force these imbalances to zero because individual investors are but a subset of the market.) I compute imbalances separately for all orders, market orders, limit orders, and pre-open limit orders. I then examine how the imbalances vary across the attention variable deciles. (I use the number of purchases and sales in Eq. 6 instead of the euro values of purchases and sales to remain consistent with Barber and Odean (2005). A value-weighting scheme would emphasize wealthy individuals. My results are nearly identical (unreported) if B_{pt} and S_{pt} are replaced by the euro values of purchases and sales, respectively.)

I measure the limit order effect by decomposing the unconditional (i.e., "all orders") buy-sell imbalance to "market order" and "limit order" components. I run the following regression:

$$\mathrm{BSI}_{pt}^{\mathrm{all}} = a + b_1 \mathrm{BSI}_{pt}^{\mathrm{lim}} + b_2 \mathrm{BSI}_{pt}^{\mathrm{mkt}} + \varepsilon_{pt}, \tag{7}$$

where *all*, *lim*, and *mkt* indicate imbalances computed from all trades, limit order-initiated trades, and market order-initiated trades, respectively. The ratio

$$\frac{\text{Variation Explained by Limit Orders}}{\text{Variation Explained by Limit and Market Orders Together}} = \frac{\hat{b}_1^2 \mathrm{var}(\mathrm{BSI}_{pt}^{\mathrm{lim}})}{\hat{b}_1^2 \mathrm{var}(\mathrm{BSI}_{pt}^{\mathrm{lim}}) + \hat{b}_2^2 \mathrm{var}(\mathrm{BSI}_{pt}^{\mathrm{mkt}})} \tag{8}$$

is then the amount variation in the unconditional buy-sell imbalance that comes from the limit orders. (Eq. 8 can be stated in terms of R^2 increments. If we run the full regression in Eq. 7 as well as regressions with only one of the buy-sell imbalances as the explanatory variable, the ratio $\frac{R^2_{\mathrm{both}} - R^2_{\mathrm{mkt}}}{(R^2_{\mathrm{both}} - R^2_{\mathrm{mkt}}) + (R^2_{\mathrm{both}} - R^2_{\mathrm{lim}})}$ reduces to Eq. 8. Hence, Eq. 8 measures the incremental value of adding limit orders to a regression that already has market orders in it.)

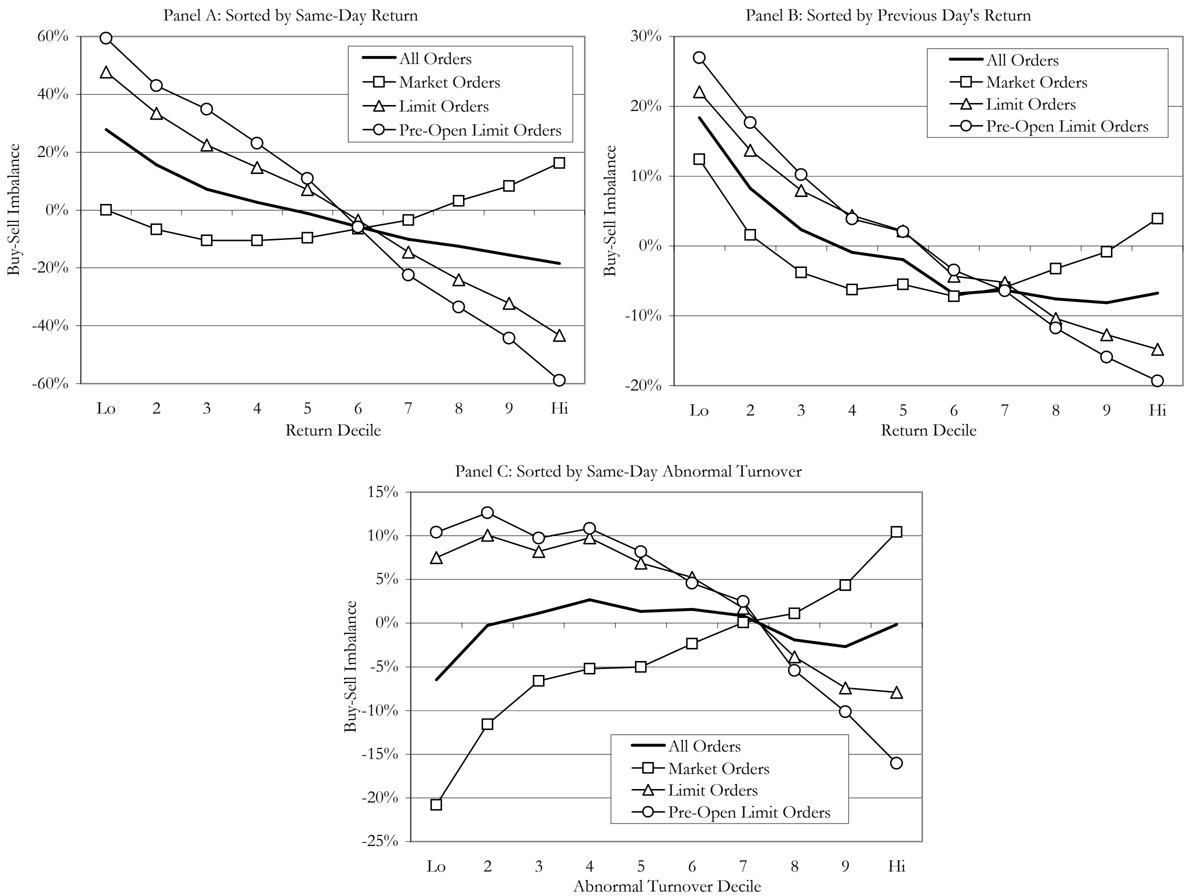

Figure 4: **Limit Orders and Attention-Grabbing Behavior.** This figure displays buy-sell imbalances for individual investors' market, limit, and pre-open limit order-initiated trades for deciles formed by the same-day return, previous day's return, and same-day abnormal turnover (see Eq. 5). The sample consists of all trades by individual investors between September 18, 1998 to October 23, 2001. All stocks with at least five trades are assigned into deciles each day. Buy-sell imbalances are computed for each day-decile-order type. The plots are time-series averages over 780 daily observations. All Newey-West ($k = 8$ lags) adjusted standard errors are between 1.0% and 2.7% (not drawn).

Results. Figure 4 shows that individual investors' unconditional buy-sell imbalances ("All Orders") vary significantly across the attention variable deciles. The behavior of the imbalances in the previous day's return sort is similar to the results in Barber and Odean (2005). The U-shape indicates that individual investors have a higher likelihood of purchasing stocks with very low or very high returns, relative to stocks with close-to-zero returns. The same-day abnormal turnover sort produces weaker results, although the direction is the same as in Barber and Odean (2005). For example, the buy-sell imbalance difference between the highest

Table 7: Percentage of Buy-Sell Imbalance Variance Explained by Limit Orders

This table reports how much limit orders contribute to the variation in individual investors' unconditional ("all orders") buy-sell imbalances. I regress unconditional buy-sell imbalance in partition p on date t against the market order- and limit order-specific buy-sell imbalances. I report how much limit order imbalances explain of the total variation in the unconditional imbalance (Eq. 7). The partitions p are deciles formed from same-day returns, previous day's returns, and same-day abnormal turnovers. The standard errors are bootstrapped by resampling the partition-day data 10,000 times. "Extreme deciles" are deciles 1 and 10 for the same-day's and previous day's return sorts, and decile 10 for the same-day's abnormal turnover sort.

	All Observations			Extreme Deciles		
Attention Variable	Mean	s.e.	N	Mean	s.e.	N
Same-Day Return	68.09	0.65	7,448	81.79	0.89	1,548
Previous Day's Return	62.17	0.80	7,453	67.42	1.49	1,548
Same-Day Abnormal Turnover	59.69	0.65	7,749	65.27	2.35	775

and the lowest decile is only 6.3%, while this spread is close to 40% in Barber and Odean (2005). (The small number of stocks and the concentration of trading on the HEX may cause this difference. It may also partly arise from that fact that the Barber and Odean (2005) sample is not representative: they find significantly positive imbalances for all investor groups (individuals and institutions) in the highest turnover decile. If the missing, offsetting trades come from individual investors, the "true" (i.e., population) slope is flatter.)

Figure 4 shows that limit order traders' buy-sell imbalances respond mechanically to the return sorts. The effect is the strongest when the sort is based on the same-day returns: the imbalance decreases from 47.7% in the lowest return decile to −43.3% in the highest return decile. Although market order traders also respond to the same-day return sort, their imbalances are modest compared to limit order traders' imbalances. Table 7 confirms this visual impression: limit orders contribute 68% of the variance in the total buy-sell imbalance (Eq. 8), and as much as 82% in deciles 1 and 10.

Market and limit order traders' buy-sell imbalances differ significantly from one another also in the previous day's return and the same-day abnormal turnover sorts. For example, although both market and limit order traders buy stocks that fell the day before, (i) market order traders' imbalances are less extreme and (ii) market order traders are net *buyers* in the highest return stocks while limit order traders are net *sellers*. The variance decomposition of Table 7 shows that limit orders generate 62% of the variation in the unconditional buy-sell imbalances when the returns are sorted by the previous day's return. The turnover sort shows that limit order traders are net buyers of thinly traded stocks while market order traders are net sellers. Limit orders generate 60% of the variation in the unconditional buy-sell imbalances. These decomposition results show that approximately two-thirds of what appears to be individual investors' attention-grabbing behavior does not reflect investors' active decisions—it mirrors the decisions of the market order traders who trade against them.

Reverse causality could explain these imbalance results: what if individual investors react to "attention" by submitting limit orders? The buy-sell imbalances for pre-open limit orders exclude this possibility. Because individuals entered these orders before trading started, their limit order decision could not have been conditional on the same-day return or turnover. Not only do pre-open limit orders act similarly to other limit orders, their imbalances are more extreme than those of other limit orders. Hence, individuals do not respond to "attention" by submitting limit orders—it is their old limit orders that trigger when "attention" sweeps through the limit order book.

3.4.3 Limit Order Traders' Passive Herding

Methodology. Do market order traders "push" limit order traders to one side of the market and create an appearance that limit order traders herd? I measure "passive herding" with a variant of the Lakonishok, Shleifer, and Vishny (1992) (LSV) herding measure. I measure how significantly market and limit order traders' buy-sell imbalances deviate from one another: do these traders coordinate *against* each other—consistent with "passive herding"—or do they choose their sides independently from one another? I define H_{it} as a measure of the distance between market and limit order traders' buy-sell imbalances:

$$H_{it} = \left| \left(\mathrm{BSI}_{it}^{\mathrm{mkt}} - \widehat{\mathrm{BSI}}_{t}^{\mathrm{mkt}} \right) - \left(\mathrm{BSI}_{it}^{\mathrm{lim}} - \widehat{\mathrm{BSI}}_{t}^{\mathrm{lim}} \right) \right| - \mathrm{E}\left[\left| \left(\mathrm{BSI}_{it}^{\mathrm{mkt}} - \widehat{\mathrm{BSI}}_{t}^{\mathrm{mkt}} \right) - \left(\mathrm{BSI}_{it}^{\mathrm{lim}} - \widehat{\mathrm{BSI}}_{t}^{\mathrm{lim}} \right) \right| \right], \quad (9)$$

where $\widehat{\mathrm{BSI}}_{t}^{\mathrm{mkt}}$ is the individual investors' average market order buy-sell imbalance on day t across stocks $i = 1, \ldots, N_t$, and $\widehat{\mathrm{BSI}}_{t}^{\mathrm{lim}}$ is defined similarly.

The first term is the absolute distance between the two trader classes, adjusting for the differences that are common across all day t observations. The second term in Eq. 9 is the expectation of the first term. This expectation assumes that market and limit order-initiated purchases have independent binomial distributions; e.g., the market order imbalance follows a binomial distribution with $B_{it}^{\mathrm{mkt}} + S_{it}^{\mathrm{mkt}}$ draws and the success probability is the average proportion of market order purchases across all day t observations. This second term makes the expectation of H_{it} zero under the null of no coordination between market and limit order traders. A positive H_{it} indicates that market and limit order traders are more often on the opposite sides of the market than if their imbalances were independent.

Results. The estimates of the distance measure (Eq. 9) in Table 8 show that market order traders "push" limit order traders, forcing them to herd on the opposite side of the market. The average daily distance between limit and market order traders' buy-sell imbalances is 32%. This means that, on average, limit and market order traders would have stock-specific

Table 8: Percentage Difference between Limit and Market Order Traders' Buy-Sell Imbalances

This table reports average differences between individual market order and limit order traders' buy-sell imbalances. These differences are adjusted by subtracting off the expected absolute difference (Eq. 9)—the expectation assumes that market and limit order traders do not coordinate against each other. A positive adjusted difference indicates that limit and market order traders are more often on the opposite sides of the market than they would be if they chose imbalances independently. The buy-sell imbalances are computed for market and limit order traders for each stock and at three frequencies: daily, monthly, and weekly. The sample is restricted to observations in which the investor held shares of the stock a day before the trade to avoid spurious coordination generate by short-sale constraints (see Wylie (2005) and Dorn, Huberman, and Sengmueller (2005)). The average differences are computed over stock-period observations. Standard errors are clustered by period.

Frequency	Mean	s.e.	N
Daily	32.02	0.47	45,003
Weekly	20.79	0.32	18,942
Monthly	17.14	0.57	5,973

imbalances of -16% and 16% (assuming that $\widehat{BSI}_t^{\text{mkt}} = \widehat{BSI}_t^{\text{lim}} = 0\%$). This estimate quantifies what is visible in Figure 4: when limit order traders are net buyers, market order traders are usually net sellers, and vice versa. This passive herding-mechanism persists over long time periods: even at the monthly frequency, the difference in the buy-sell imbalances is 17%. Hence, even such low frequency herding is not necessarily genuine coordination.

Limit and market order traders herd very differently. While market order traders herd actively—they choose their sides—limit order traders' herding is a spill-over: they must herd because the market clears. If we split the entire market—not just individual investors—into limit and market order traders, these groups' LSV (Lakonishok, Shleifer, and Vishny 1992) herding measures must be identical: $\text{BSI}^{\text{lim}} \equiv \text{BSI}^{\text{mkt}}$ for the entire market. How closely this identity holds for individual investors depends on the number of institutions our individuals-only sample "ignores". The R^2 from regressing individual limit order traders' imbalance against individual market order traders' imbalance is 12% in the entire sample and 55% in a sample where a stock has at most five trades per day.[8] Institutions' lower trading activity in

[8]The slope coefficient is -0.348 (s.e. $= 0.028$, $N = 75,181$) in the first regression and -0.722 (s.e. $= 0.011$,

thinly traded stocks increases the explanatory power in the latter sample: when institutions are all but absent, the "market clearing identity" binds individual investors stronger. In such situations, knowing market order traders' imbalance reveals a lot about limit order traders' imbalance, and vice versa.

3.4.4 Performance of Attention-Grabbing Trades

Methodology. I replicate Barber and Odean's (2005) methodology to measure the performance of attention-grabbing trades. I compute the value-weighted average one-month returns for purchases and sales separately for each order type-partition-day. The time-series difference between the returns on the purchases and sales portfolios is a measure of investor performance in the "high" and "low" attention stocks.

Results. The performance results in Table 9 show that limit order-initiated trades perform poorly in the highest return and abnormal volume deciles. This asymmetric response is similar to the one reported by Barber and Odean (2005): also their traders experience significant losses only when the previous day's return or abnormal turnover is in the top decile. (If the deciles were formed from *absolute* returns, the statistically significance would disappear because of this asymmetry.) The difference in the performance between limit and market order traders is statistically significant with both the equal- and value-weighted measures. For example, market order purchases outperform market order sales in the highest previous day's return decile by 0.99% whereas this spread is −0.50% for limit orders.

It is the triggering of limit orders that generates individual investors' losses in the high-attention stocks. These losses arise not because individuals respond to "attention" but because

$N = 17,979$) in the second. I cluster heteroscedasticity-consistent standard errors by stock.

Table 9: Percentage Performance of Attention-Grabbing Trades

This table reports the performance of individual investors' market and limit order trades for deciles sorted by previous day's return and same-day abnormal turnover (see Eq. 5). The sample consists of all trades by individual investors between September 18, 1998 to October 23, 2001 (775 daily observations). All stocks with at least five trades are assigned into deciles each day. The value-weighted average one-month returns are computed separately for purchases and sales for each order type-partition-day. This table reports the time-series averages of the daily differences between the buy and sell portfolio returns. Standard errors (Newey-West adjusted with $k = 8$ lags) are reported in parentheses. Rows *All*, *Market*, *Limit*, and *Pre-Open* denote samples containing (1) all trades, (2) market order-initiated trades, (3) limit order-initiated trades, (4) pre-open limit order-initiated trades. *Mkt-Lim* is the pairwise difference between market and limit order-initiated trades.

	Return/Abnormal Turnover Decile									
Order Type	Lo	2	3	4	5	6	7	8	9	Hi
	Sort by Previous Day's Return									
All	0.36	0.45	0.44	0.62	0.82	0.57	0.04	0.14	0.07	0.19
	(0.25)	(0.23)	(0.29)	(0.26)	(0.33)	(0.30)	(0.28)	(0.26)	(0.30)	(0.23)
Market	0.49	0.72	0.62	1.05	1.11	0.69	0.63	0.35	0.41	0.99
	(0.25)	(0.25)	(0.35)	(0.31)	(0.37)	(0.33)	(0.35)	(0.30)	(0.32)	(0.26)
Limit	0.27	0.23	0.19	0.48	0.57	0.36	−0.49	−0.08	−0.12	−0.50
	(0.33)	(0.30)	(0.36)	(0.30)	(0.39)	(0.34)	(0.31)	(0.35)	(0.35)	(0.29)
Pre-Open	0.19	0.54	0.06	−0.26	0.01	0.18	−0.46	−0.42	−1.02	−1.34
	(0.53)	(0.57)	(0.53)	(0.49)	(0.57)	(0.46)	(0.57)	(0.51)	(0.61)	(0.46)
Mkt-Lim	0.26	0.48	0.43	0.56	0.55	0.35	1.10	0.43	0.53	1.49
	(0.35)	(0.33)	(0.42)	(0.33)	(0.45)	(0.33)	(0.38)	(0.43)	(0.35)	(0.34)
	Sort by Same-Day Abnormal Turnover									
All	0.15	0.34	0.74	0.44	0.40	0.65	0.27	0.54	0.66	0.60
	(0.26)	(0.25)	(0.26)	(0.27)	(0.33)	(0.30)	(0.28)	(0.22)	(0.23)	(0.30)
Market	0.08	0.60	1.35	0.54	0.35	0.53	0.42	0.46	0.80	1.05
	(0.35)	(0.35)	(0.31)	(0.34)	(0.37)	(0.35)	(0.35)	(0.25)	(0.25)	(0.36)
Limit	0.17	−0.01	0.29	0.46	0.38	0.78	0.08	0.54	0.55	0.07
	(0.34)	(0.30)	(0.32)	(0.33)	(0.36)	(0.33)	(0.30)	(0.30)	(0.28)	(0.37)
Pre-Open	−0.13	0.22	−0.36	−0.36	−0.27	0.88	0.07	0.11	0.74	−1.21
	(0.54)	(0.47)	(0.49)	(0.55)	(0.52)	(0.50)	(0.45)	(0.45)	(0.47)	(0.58)
Mkt-Lim	−0.08	0.60	1.06	0.07	−0.04	−0.24	0.34	−0.09	0.24	0.96
	(0.49)	(0.43)	(0.37)	(0.39)	(0.36)	(0.35)	(0.34)	(0.33)	(0.31)	(0.43)

"attention" triggers individuals' limit orders. Although market order traders' imbalances also respond to return and volume sorts (Figure 4), this behavior is not costly—in fact, individual investors' market orders perform quite well in the high-attention stocks.

Could reverse-causality—i.e., individual investors respond to attention by submitting limit orders—generate the performance results? The performance of pre-open limit orders in the abnormal turnover sort precludes this possibility. Because investors entered these orders before trading started, their limit order decision could not have depended on the same-day abnormal turnover. The pre-open limit orders perform worse than other limit orders in the highest decile—the spread between purchases and sales is −1.21% in the top decile. These losses arise because "attention" clears part of the limit order book—not because individuals respond to attention by submitting limit orders.

3.5 Negative Stock Picking Skills

3.5.1 Methodology

I examine how limit order use affects an analysis of individual investors' stock picking skills. I compute equal- and value-weighted average K-day cumulative returns for all purchases and sales on date t as

$$R^{ew}_{t,t+K} = \frac{1}{N_t}\sum_{i=1}^{N_t}\left(\ln P_{s_i,t+K} - \ln P_{s_i,t}\right) \quad (10)$$

$$R^{vw}_{t,t+K} = \frac{1}{\sum_{i=1}^{N_t} V_i}\sum_{i=1}^{N_t} V_i\left(\ln P_{s_i,t+K} - \ln P_{s_i,t}\right) \quad (11)$$

where s_i is the stock traded in observation i, N_t is the number of day t purchases (or sales), V_i is the value of trade i, $P_{s_i,t+K}$ is the closing price on date $t+K$ and $P_{s_i,t}$ is the closing price on the day of the trade. (I use the same-day closing price instead of the actual trade prices for consistency with prior research.) I compute returns up to six months ($K = 130$) for all trades as well as for market order-, limit order-, and pre-open limit order-initiated trades. The time-series average difference between the average buy and sell returns is a measure of stock picking abilities. This "buy versus sell" methodology has been used by Barber and Odean (1999), Odean (1999), Grinblatt and Keloharju (2000), Barber, Lee, Liu, and Odean (2005),

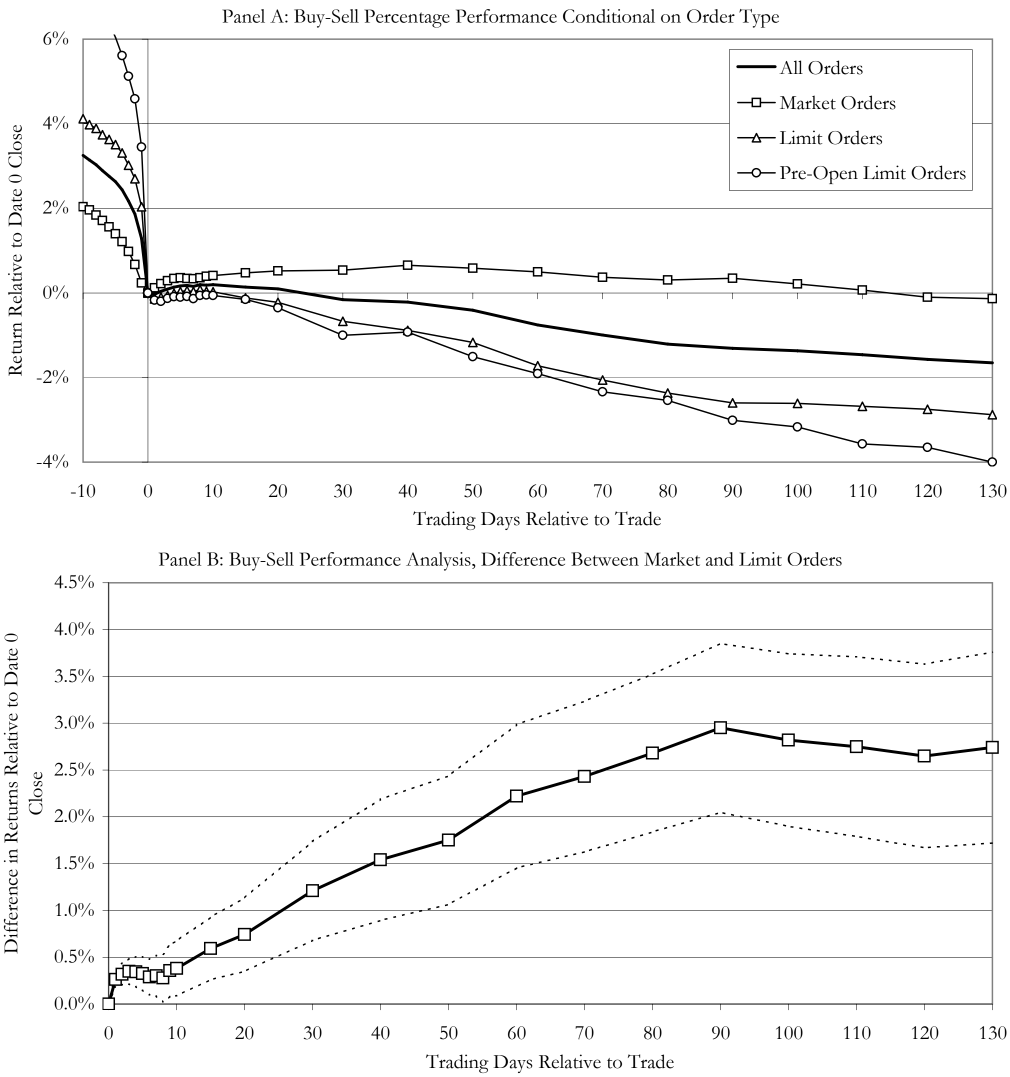

Figure 5: **An Analysis of Stock Picking Skills with the Buy Versus Sell Measure.** This figure shows results for individuals' stock picking skills by constructing "buy" and "sell" portfolios for each day between September 23, 1998 and October 23, 2001 (775 daily observations). The cumulative value-weighted return from the same-day close up to six months after the trade are computed for buy and sell portfolios each day (Eq. 11). Panel A plots the "buy minus sell" difference for all trades as well as for market order, limit order-, and pre-open limit order-initiated trades. A positive difference for $t > 0$ indicates that the stocks bought outperform the stocks sold. Panel B subtracts limit orders' buy-sell difference from market orders' buy-sell difference. The dashed lines denote 95% confidence intervals, with Newey-West ($k = 8$) adjusted standard errors.

Grinblatt and Keloharju (2006), and others.[9]

[9]Overlapping observations—e.g., computing average k-day returns and standard errors from *all* daily observations, $t = 1, \ldots, n$—do not cause problems: the day t buy-sell return measure weights individual stock returns by individual investors' day t trades. Hence, k-day returns for days t and $t + 1$ do *not* share $k - 1$ observations as would be the case if the portfolio weights were constant. A bias in standard errors requires serial correlation in individual investors' trades. I use Newey-West standard errors with $k = 8$ lags to account for such serial dependence.

Table 10: Buy Versus Sell Difference as a Measure of Stock Picking Skills

This figure shows results for individuals' stock picking skills by constructing "buy" and "sell" portfolios for each day from September 23, 1998 through October 23, 2001 (775 daily observations). The cumulative equal- (Eq. 10) and value-weighted (Eq. 11) returns from the same-day close up to six months later are computed for both portfolios each day. This table reports the time-series average "buy minus sell" differences conditional on the order type. A positive difference indicates that the stocks bought outperform the stocks sold. "Market-Limit Difference" is the pair-wise difference between the performance of market- and limit order-initiated trades. The Newey-West ($k = 8$) adjusted standard errors are reported in parentheses.

	Number of Trading Days after Trade					
Order Type	1	5	10	20	60	130
	Equal-Weighted Returns (%)					
All	−0.03	0.18	0.26	0.29	−0.37	−1.17
	(0.03)	(0.09)	(0.16)	(0.23)	(0.49)	(0.75)
Market Order	0.15	0.35	0.42	0.67	0.69	−0.22
	(0.04)	(0.11)	(0.19)	(0.28)	(0.55)	(0.79)
Limit Order	−0.17	0.03	0.11	−0.06	−1.27	−1.96
	(0.04)	(0.11)	(0.18)	(0.26)	(0.57)	(0.82)
Pre-Open Limit Order	−0.15	−0.03	0.02	−0.23	−1.70	−3.34
	(0.05)	(0.16)	(0.25)	(0.35)	(0.77)	(1.10)
Market-Limit Difference	0.32	0.32	0.31	0.73	1.97	1.74
	(0.05)	(0.12)	(0.18)	(0.28)	(0.56)	(0.66)
	Value-Weighted Returns (%)					
All	−0.03	0.17	0.20	0.10	−0.76	−1.65
	(0.03)	(0.09)	(0.16)	(0.21)	(0.47)	(0.70)
Market Order	0.12	0.36	0.41	0.52	0.50	−0.14
	(0.03)	(0.09)	(0.15)	(0.21)	(0.45)	(0.66)
Limit Order	−0.14	0.03	0.03	−0.22	−1.72	−2.88
	(0.04)	(0.11)	(0.19)	(0.24)	(0.54)	(0.79)
Pre-Open Limit Order	−0.17	−0.10	−0.06	−0.35	−1.91	−4.00
	(0.06)	(0.19)	(0.31)	(0.41)	(0.89)	(1.30)
Market-Limit Difference	0.26	0.33	0.38	0.74	2.22	2.74
	(0.04)	(0.09)	(0.15)	(0.20)	(0.39)	(0.52)

3.5.2 Results

The unconditional return difference ("All Orders") between purchase and sale portfolios in Figure 5 drifts down to −1.7% as the horizon lengthens: the stocks individual investors sell outperform the stocks they purchase. The drift in Figure 5 is similar to the negative drifts reported by Odean (1999) and others.

Figure 5 and Table 10 show that the subsequent performance of a trade depends critically on whether the individual used a market or a limit order. Market order-initiated trades outperform limit order-initiated trades, in particular as the horizon lengthens. The (value-weighted) average market order return difference is 0.50% (s.e. = 0.45%) after three months while the limit order return difference is −1.72% (s.e. = 0.54%). After six months, the market order buy-sell difference is indistinguishable from zero while the limit order difference is −2.88% (s.e. = 0.79%). Pre-open limit orders perform worse than the other limit order types: their six month loss is 4.0% while all other limit orders lose 2.4% (not shown). Thus, stale limit orders are an important component of the negative unconditional ("All Orders") drift.

The results show that individuals display poor "stock picking skills" only when someone trades against their limit orders. Market order traders do not exhibit systematically poor timing. (In fact, market orders earn significantly positive returns up to one month after the trade.) Hence, individual investors do not lose money because they actively make poor decisions—it is their passivity that generates the losses. Adverse selection is to blame: occasionally limit orders trigger not because of a liquidity-shock but because the other party has better information.

(The drifts in Figure 5 do not necessarily violate market efficiency. First, the drifts can arise from investors with long-lived private information trading against uninformed liquidity traders. For example, in a Kyle (1985) setup, price changes form a martingale—the drift can only be observed ex post. Second, the drifts may be an aggregation artifact. If private information becomes public at different times in different stocks, the aggregate returns will exhibit a drift even though all individual stock price reactions are instantaneous.)

3.6 Other Anomalies

Limit orders may also alter inferences about other anomalies that have been given behavioral interpretation. For example, a growing body of literature examines how trading experience affects investor behavior and performance. Seasholes and Wu (2005) find that more experienced investors overcome most of the disposition effect. Nicolosi, Peng, and Zhu (2004) find that more experienced investors display better stock picking abilities than the less experienced investors. If more experienced investors are less likely to place limit orders, we will see these correlations. The data supports the order use-experience relation: 25.4% of all limit orders placed by the least experienced investors—i.e., investors in the lowest "the number of earlier trades"-decile—are pre-open limit orders. This proportion is only 6.7% in the top decile.

This order use-experience correlation suggests that investor experience can affect inferences about investor behavior through two channels. First, investors may change their behavior or improve their stock picking skills as they gain experience. Second, investors may appear to reduce their behavioral biases or to improve their performance because the limit order effect weakens with experience. This second channel must be, however, interpreted with caution: the reason why the investor abandons pre-open limit orders must be exogenous to the behavioral pattern we measure. For example, if an individual switches away from pre-open limit orders to, e.g., counteract the disposition effect, the behavioral interpretation still holds—the reduction in the limit order effect is but a by-product.

4 Applicability of the Limit Order Effect to Other Investor Groups and Markets

4.1 Limit Order Effect and Institutional Investors

I have focused on individual investors because they have received the most attention in the literature. However, Grinblatt and Keloharju (2001), Shapira and Venezia (2001), and Coval and Shumway (2005) conclude that institutional investors also exhibit behavioral biases. To what extent does limit order use affect these inferences? Table 11 addresses this question by replicating the earnings announcement results (see Table 3 for individual investors) for institutional investors.

The results on institutions are very similar to the results on individuals. Institutions also lose significantly when a stale limit order triggers after an earnings announcement—in particular when the announcement is unexpected. For example, institutions' two-week loss for stale limit orders executed in the during-window after an expected announcement is 3.37%; individual investors lose 3.80% in the same situation. The losses following unexpected earnings announcements are 10.03% and 10.28%, respectively. Hence, limit order use affects inferences about institutions in the same way as it affects inferences about individuals. Thus, the limit order effect is not *specific* to individual investors: if an individual and an institution place same type of limit orders, the impact on their performance and behavior is the same.

However, because institutions differ markedly from individuals in their use of limit orders, stale limit orders do not affect institutions' "unconditional" results. For example, the stale limit orders-to-market orders ratio is 1.55 for individual investors in the during-window but only 0.37 for institutions. For unexpected announcements, these ratios are 2.57 and 0.31,

Table 11: Percent Returns on Institutional Investors' Market Order- and Stale Limit Order-Initiated Trades around Earnings Announcements

This table reports trading gains for institutions' stale limit orders and market orders executed around earnings announcements. The sample consists of 586 pre-scheduled earnings announcements (Panel A) and 117 unscheduled earnings announcements (Panel B) released during the regular trading hours on the Helsinki Exchanges between September 18, 1998 to October 23, 2001. A stale limit order is an order entered into the book before the release of an announcement. *Before* contains trades executed before the announcement, *during* contains trades executed during the first five minutes after the announcement, and *after* contains trades executed after these five minutes. The value-weighted average trading gains are first computed for each announcement-interval with at least two trades. This table reports the means and standard errors of the announcement-specific averages. *Number of Trades* is the total number of trades across the N announcements.

Panel A: Trading Gains (%) around Scheduled Earnings Announcements

			Trading Gain Horizon					
	Number of		Same-Day		One Week		Two Weeks	
Period	Trades	N	Mean	s.e.	Mean	s.e.	Mean	s.e.
Stale Limit Orders								
Before	18,582	328	0.45	0.25	0.60	0.46	0.09	0.63
During	1,951	193	−0.86	0.48	−2.32	0.81	−3.37	1.13
After	1,749	284	−0.26	0.24	−1.12	0.56	−0.94	0.80
Market Orders								
Before	17,952	323	−0.43	0.27	−0.76	0.47	−0.67	0.61
During	5,217	211	1.28	0.42	2.94	0.83	3.35	1.21
After	83,056	442	0.27	0.09	0.49	0.25	0.52	0.35
Market Order − Limit Order Pairwise Difference								
Before	20,052	257	−0.60	0.51	−0.57	0.93	0.28	1.34
During	4,207	156	2.37	1.03	6.33	1.83	8.43	2.70
After	37,395	239	0.64	0.36	1.90	0.88	1.76	1.32

Panel B: Trading Gains (%) around Unscheduled Earnings Announcements

			Trading Gain Horizon					
	Number of		Same-Day		One Week		Two Weeks	
Period	Trades	N	Mean	s.e.	Mean	s.e.	Mean	s.e.
Stale Limit Orders								
Before	9,234	80	0.36	1.21	0.36	1.52	1.23	1.96
During	747	60	−6.10	1.80	−9.45	2.73	−10.03	2.88
After	222	52	−1.81	0.97	−3.69	1.92	−1.30	2.31
Market Orders								
Before	9,317	78	−0.91	1.28	−0.75	1.69	0.78	1.94
During	2,443	77	4.96	1.12	7.56	1.67	8.42	1.82
After	29,041	101	0.30	0.21	0.42	0.67	−0.44	1.07
Market Order − Limit Order Pairwise Difference								
Before	10,254	69	−1.56	2.64	−1.60	3.26	−1.24	3.74
During	2,217	54	12.02	3.41	19.60	5.06	19.40	5.41
After	8,020	43	1.94	1.33	4.61	2.81	−1.35	3.77

respectively. Hence, stale limit orders play a minor role for institutions. Whereas institutions' active trades mask their passive trades, individual investors' passive trades mask their active decisions.

Institutions' order use differs from individuals' order use in three ways. First, individual investors use fewer limit orders to begin with (see Table 2). Second, institutions often place their limit orders near the opposite side of the book. These orders are more similar to market orders than to the far-from-the-spread limit orders often placed by individual investors. Third, institutions monitor their limit orders more closely. For example, institutions modify 14.8% ($N = 2,986,376$) of their limit orders (i.e., change the limit price or volume) at least once before they execute. This proportion is only 5.8% ($N = 1,682,739$) for individual investors. Hence, institutions can react to new information not only by submitting market orders but also by withdrawing their own limit orders out of the harm's way.

4.2 Limit Order Effect in the U.S. and Other Markets

Although I use Finnish data because of its unique attributes, there is a good reason to believe that the limit order effect is also important in the U.S. and other markets. First, limit orders are widely used also in the United States. For example, the Securities Exchange Act Release (Sep. 6, 1996) reports that "limit orders accounted for 50% of [the NYSE] customer trades of 100-500 shares and 66% of customer trades of 600-1000 shares." Lo, MacKinlay, and Zhang (2002) find that limit orders account for 45% of the total order flow on the NYSE. Second, Bae, Jang, and Park (2003) report that 14.4% of the U.S. limit orders (in the TORQ data) are good-till-canceled. The proportion of stale orders is 5.9% for individuals and 0.8% for institutions in my data.

Third, Dorn, Huberman, and Sengmueller (2005) show that limit orders cause spurious coordination among individuals using data from a German broker. (Their analysis is similar to my herding-analysis in Section 3.4.) This is direct evidence that the limit order effect exists also in another market. Moreover, others have concluded that the limit order effect is a probable explanation for their results although they lack direct evidence. For example, Richards (2004, pp. 31) concludes: "...the similarity between the [Korea Stock Exchange] data and [this study]...suggests that greater use of limit orders by households may be a fairly widespread phenomenon. It is therefore likely that order-submission effects are a substantial cause of the finding that domestic individual investors in Asian equity markets appear to be contrarian investors." Taken together, these results suggest that the limit order effect applies also in the U.S. and other markets.

My results offer some indirect evidence about the possible role of the limit order effect in the U.S. data sets. The unconditional ("all orders") results on individual investors' stock picking skills and attention-grabbing behavior are directly comparable to Odean (1999) and Barber and Odean (2005), respectively. For example, Odean (1999, pp. 1289) finds a buy-sell difference of (approximately) 1.5% six months after the trade date. I find a 1.7% difference in six months. These numbers would match if my individual investors used limit orders only as often as they use market orders—i.e., we get $50\% * -0.14\% + 50\% * -2.88\% = -1.5\%$ if we weight the market and limit order numbers in Panel B of Table 9. Similarly, the attention-grabbing results would line up if we weighted individuals moderately towards market orders. These quantitative matches suggest that the limit order effect *could* generate the U.S. results—just as it generates the Finnish results. It would require that limit order use is less widespread in the United States than what it is in Finland.

4.3 Countering the Limit Order Effect

A research that uncovers a trading anomaly should verify that limit order use is not to blame. It is difficult to counteract the limit order effect in data that do not differentiate between market and limit orders. Filter rules—i.e., excluding trades likely generated by stale limit orders—may, however, offer a partial remedy. For example, Lim (2006) controls for limit orders in her test of the "hedonic editing hypothesis"—i.e., that individuals prefer integrating losses and segregating gains (Thaler 1985)—by limiting her sample to sales that take place below the previous day's close.

I evaluate the effectiveness of this filter rule by replicating the disposition effect analysis (see Table 4 for the original analysis) for a filtered sample. I drop "sell" observations where the sale price is above the previous day's close and "hold" observations where today's closing price is above yesterday's closing price. This filtering rule works well: the number of limit order-initiated sales decreases from 60.3% ($N = 253,501$) to 37.6% ($N = 91,114$). In this new sample, the unconditional capital gain coefficient estimate is 0.570 while the market orders-only estimate is 0.396. Hence, the filter rule successfully eliminates part of the limit order effect: the difference between the two samples is down to 30.5% from the unfiltered difference of 45.6% computed in Table 4.

This type of filter rules should, however, be used cautiously for two reasons. First, the "out of sample" performance of such a rule is difficult to assess. For example, this countermeasure may fail when it is needed the most, similar to the shortcomings of the Lee and Ready (1991)-algorithm around earnings announcements (Odders-White 2000). Second, such a filter may be correlated with the research question itself: the trades that survive the filter may originate from investors very different from the overall population.

5 Conclusions

This paper analyzes how limit orders alter inferences about investor behavior. Because limit orders are mechanically contrarian and exposed to adverse selection risk, limit orders (*i*) are more likely to execute when there is an information event, (*ii*) generate losses when there is an information event, and (*iii*) create an appearance that the investor placing the order is reacting to news. For example, a limit order investor exhibits negative market timing when an informed trader triggers the order. A study that does not account for limit order investors' "passive reaction" to news runs the risk of confounding cause and effect.

I find that limit order use is an important determinant of numerous anomalies that have been given behavioral interpretations: the disposition effect (46%), contrarian behavior (24%–100%), and attention-grabbing behavior (62% with the previous day's return sort). Limit order use *reverses* inferences about investors' stock picking skills. Odean (1999) and others use negative performance results to emphasize the importance of behavioral biases. My results suggest that this underperformance is an artifact individual investors' passivity: they lose money when new information arrives because they do not withdraw their limit orders in time, and they lose in the long run because investors with long-lived private information trade against them. Individual investors do not possess *negative* stock picking skills—they lose because they are uninformed.

My results may be conservative because the "market orders" and "limit orders" distinction is not a perfect classification scheme. For example, even if an investor instructs her broker to sell at a limit price, the broker may use a market order to execute the trade after the stock price reaches the limit. (E.g., it may not be in the broker's best interests to display all liquidity in the book; Harris (1996).) Similarly, the investor could synthesize limit orders using market orders in a market that only accepts market orders. There would be no limit orders—but there might be a limit order effect. On the other hand, a limit order placed one tick away from the opposite side of the limit order book is almost a market order—and very different from days old limit orders.

I examine the *consequences* of limit orders and do not study *why* individuals use limit orders. Although uninformed investors must lose to informed investors, suboptimal limit price choices would increase these losses. The unobservability of investors' information sets and objectives complicates the optimality question. For example, an investor who is forced to sell something ignores the adverse selection risk: the objective is to maximize the sale price. Although this "why" question is interesting, it is not crucial for this study. I find that the anomalies arise because prices sweep through the limit order book. The traditional, behavioral interpretation is that individual investors react to new information. If stale limit orders generate the anomalies, any irrationality must at the very least precede the arrival of new information. The anomalies cannot be evidence of irrational information processing.

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