Do Limit Orders Alter Inferences about Investor Performance and Behavior?

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ABSTRACT

Individual investors lose money around earnings announcements, experience poor post-trade returns, exhibit the disposition effect, and make contrarian trades. Using simulations and trading records of all individual investors in Finland, I find that these trading patterns can be explained in large part by investors' use of limit orders. These patterns arise mechanically because limit orders are price-contingent and suffer from adverse selection. Reverse causality from behavioral biases to order choices does not appear to explain my findings. I propose a simple method for measuring a data set's susceptibility to this limit order effect.

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In this paper I show that the use of limit orders significantly alters inferences about individuals' trading intentions and investment abilities. This "limit order effect" arises because a limit order executes only if the price moves against the order. Further, limit orders alter inferences about investors' trading abilities due to limit orders' exposure to adverse selection risk.

I measure the significance of the limit order effect by re-examining four individual investor trading patterns, namely, individual investors' tendency to misinterpret new information, show poor stock-picking skills, exhibit the disposition effect, and make contrarian trades.

Using simulations I show that, even if investors decide randomly what to buy and sell, investors' reliance on limit orders creates the appearance that they follow specific trading rules. I simulate trades for both market order and limit order investors. Whereas market order traders' randomizing behavior carries over to the trading records, limit order traders exhibit each of the four trading patterns described above.

Next, using the trading records of all individual investors in Finland, I find that limit orders are also largely responsible for each of the four trading patterns in investor trading records. I run additional tests to examine whether the causality runs from order choices to these trading patterns or from the trading patterns to order choices. Investor-level regressions, which difference out the influence of investor traits on order choices, yield estimates comparable with the pooled-data estimates. I also examine the performance of individuals' unexecuted limit orders. If behavioral biases drive order choices, then unexecuted limit orders should reflect the same undesirable investor traits as executed limit orders. However, unlike the executed limit orders, a portfolio based on the unexecuted limit orders earns positive returns in the short run. These tests together with the simulations suggest that even though behavioral biases may affect order choices, reverse causality alone does not explain my results.

I propose a method for measuring a data set's susceptibility to this limit order effect. I show that the slope coefficient from a regression of a buy-versus-sell indicator variable on the same-day stock return is highly correlated with an investor's use of limit orders. Using this method I infer the extent of limit order use in the data from a large U.S. discount broker and find that some accounts appear to use limit orders extensively.

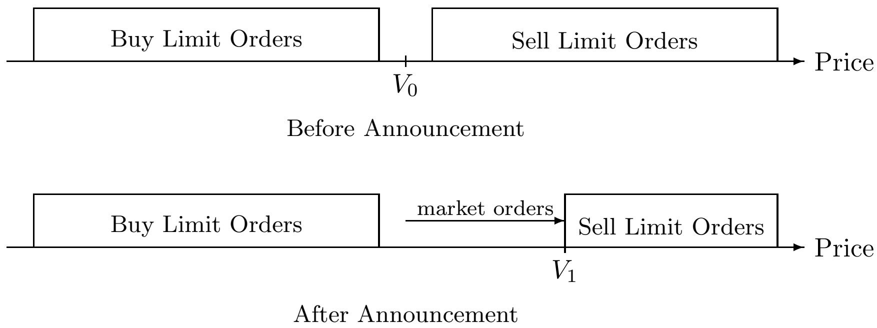
In additional analysis I study why individual investors use limit orders. I simulate data from Goettler, Parlour, and Rajan's (2009) dynamic limit order book model and compare individuals' order choices to the choices made by different types of traders in the model. I find that both the level of individuals' limit order use and the sensitivity of their order choices to the state of the market can be best explained if individuals are uninformed traders with no intrinsic motive to trade. Such traders enter the market to gain from the liquidity demand of impatient investors. I also compare individual investors' intraday returns on market orders and executed limit orders to examine the efficiency of individuals' order choices. This comparison indicates that the average individual investor would have been worse off if he had used more market orders to execute trades.

Many of the trading patterns I document are related to the market clearing constraints in financial markets. The behavior and returns of one investor group depend on the actions of other investors. If some investors earn excess profits, others must lose the same amount. If some investors follow momentum strategies, then others must follow contrarian strategies. My results suggest that the limit order book acts as a natural buffer that allows market order traders to trade as they please. Limit order traders appear to follow very specific trading patterns, although in reality these patterns may largely reflect market order traders' actions.

The paper is organized as follows. Section I discusses the background to my study, and Section II presents the data. Section III runs simulations that examine the implications of limit order use. Section IV measures the strength of the limit order effect in actual investor trading records, and Section V examines why individuals use limit orders. Finally, Section VI concludes.

I. The Limit Order Effect

The use of limit orders alters inferences about investor performance and behavior because limit orders are price-contingent and exposed to adverse selection risk. The following example illustrates this mechanism.



In the diagram above, a stock's fundamental value is V_0 and there is a limit order book that is built around this value. When the company announces positive news, the first investors to see the announcement profit from this information by submitting buy market orders. All sell limit orders with limit prices below the new valuation V_1 execute. Limit order investors thus appear to have monitored the market, reacted to the news, and lost money by misinterpreting new information.

In this study I examine the extent to which the use of limit orders alters inferences about the following trading patterns:

Misinterpretation of New Information. Individual investors sell stocks that announce positive news and buy stocks that announce negative news. Kaniel et al. (2008a) find that individual investors trade in the opposite direction to both pre-earnings announcement returns and the earnings surprise. Hirshleifer et al. (2008) show that although individual investors are net buyers after both positive and negative earnings surprises, the intensity of purchases increases as the news get worse: individuals are "net purchasers after bad earnings news, and rather weakly after good earnings news [. . . .]" Hirshleifer et al. (2008) also find that net buying by individuals in the five days following an extreme earnings surprise is a significant negative predictor of future abnormal returns.[1] These contrarian and losing trades may be limit orders. Limit buys execute more often when a company announces negative news and limit sells execute more often when a company announces positive news.

Poor Stock-picking Skills. The stocks that individual investors purchase underperform the stocks that they sell.[2] Odean (1999) finds that individuals' purchases underperform their sales by 3.3% one year after the trade. Grinblatt and Keloharju (2000) find a similar pattern in

Finnish data. This negative performance may reflect market clearing: if someone gains from trade, then someone else must lose the same amount. Harris (2003) notes that uninformed traders tend to lose even if they flip a coin to decide on which side to trade. If an uninformed investor submits a market order, he immediately loses an amount equal to half of the bid-ask spread. If the investor submits a limit order instead, he faces the adverse selection problem that lowers post-trade returns. Stock price momentum may also hurt the performance of limit order trades because executed limit orders are always contrarian trades.

The Disposition Effect. Individual investors sell winners and hold on to losers in a trading pattern known as the disposition effect.[3] The use of limit orders can create the appearance of the disposition effect even if investors are indifferent between selling winners and losers. If an investor places a sell limit order and the order executes, then the stock price must have gone up. This run-up makes it more likely that the stock that is sold is a winner. If the order does not execute, then the stock price must have either stayed the same or declined, increasing the probability that the unsold stock is a loser. Thus, the use of limit orders generates a trading pattern that is observationally equivalent to the disposition effect.

Contrarian Trading Strategies. Individual investors follow contrarian trading strategies in relation to past returns.[4] This effect is strongest at very short horizons, declining as the past return horizon lengthens. Griffin, Harris, and Topaloglu (2003) find a cumulative excess return of -0.37% for a 30-minute period before individuals buy intensively. Grinblatt and Keloharju (2000) find the strongest effect for same-day returns, the second-strongest effect for the previous day's returns, and so on. Individuals' use of limit orders may contribute to these contrarian trading patterns. An executed limit order is always contrarian because the stock price has to move against the order for it to execute.[5]

II. Data

I merge three data sets for this study:

- *Finnish Central Securities Depository (FCSD) registry.* These data contain the daily portfolios and trades of all Finnish household investors, Finnish institutions, and foreign institutions from January 1, 1995 through November 29, 2002. These records are exact duplicates of the official certificates of ownership and trades, and hence are very reliable. Details on this data set are reported in Grinblatt and Keloharju (2000).

- *Helsinki Stock Exchange (HEX) stock data.* I combine the daily stock prices from the HEX with the FCSD data to assess individual investors' performance. These data are from January 1, 1995 through December 31, 2003.

- *HEX microstructure data.* This record corresponds to the September 18, 1998 through October 23, 2001 period, and covers every order submitted to the fully electronic, consolidated limit order book of the Helsinki Stock Exchange. These are the original supervisory files, so they are complete and highly reliable. The data set tracks the life of each order submitted to the exchange, indicating when the order is executed, modified, or withdrawn.

Trading in the Helsinki Stock Exchange is effected by submitting marketable limit orders to a limit order book. Those orders that specify a price that matches the lowest ask price when buying or the highest bid when selling receive immediate execution. I call these orders "market orders" throughout this study.

I combine the FCSD registry with the HEX microstructure data to obtain information on investors' order choices. Each record in the microstructure data contains the same information as the investor trading records, except for the investor's identity. I use the common elements to merge the data sets.

I am able to unambiguously match all trades with unique price-volume combinations across the data sets. For example, if only one trade in stock A had a price of 59 for 350 shares on May 15, 2000, then I can directly combine the two data sets for this trade. There is no one-to-one link between the data sets for those trades that share the same price-volume combination. However, I can still combine the data sets for these trades if the trades are identical in all other dimensions, because then it does not matter which entries are matched against each other. Following this procedure, I can unambiguously classify 76.6% of individual investors' 5.6 million trades as originating from either a market or a limit order. I use these unambiguous trades in this study.

I use a probit model to identify individuals' unexecuted limit orders. I set the dependent variable to one for orders placed by individuals, and to zero for institutional investors. As the regressors I use the size of the order, the placement of the limit order relative to the bid-ask spread, and indicator variables for broker identities. Broker identities are powerful predictors of trader identities, because some brokers serve mostly individual investors while others cater only to institutional investors (Griffin, Harris, and Topaloglu (2003)). I first estimate this model separately for each stock by using data on executed trades for which I know the traders' identities. This probit model correctly identifies the trader for 85.4% of the executed orders. I then use the calibrated model to identify individuals' unexecuted limit orders.

In Finland, individual investors use limit orders extensively; fully 76.3% of individuals' orders are limit orders. The mix of market order trades and limit order trades is more even, however, because the fill rate for individuals' limit orders is only 34.2%, and hence 52.7% of individual investors' trades in my data originate from limit orders.

The microstructure data suggest that individuals may not always actively monitor their limit orders. First, individuals submit 22% of their limit orders before the trading session starts. Individuals place these limit orders without having any knowledge of the limit order book, because the book is not publicly available before the trading session starts. Second, individuals often leave their orders in the limit order book for several days. Although the microstructure data do not show expiration dates for limit orders, they do identify which limit orders are carried over from the previous trading day. The data show that 52% of the limit orders that appear in the limit order book in the morning of day t are limit orders carried over from day $t-1$. If limit order fill rates are uncorrelated with limit orders' initial expiration dates, then these figures suggest that individuals allow 25% of their limit orders to remain in effect for longer than one day.

III. Limit Order Effect in Simulations

A. Simulation Framework

I use simulations to study the implications of limit order use. I simulate investors who decide randomly what to buy and sell. Thus, these investors' intentions are not correlated with either market conditions or past and future stock returns.

I run the simulations side by side with the microstructure data from Finland. A simulated investor's limit order executes only if the actual stock price crosses the limit price. If a simulated investor submits a market order, I record the trade immediately at the best bid or ask price.

Each simulated investor enters the market each day with a probability p_{trade}. I set $p_{\text{trade}} = \frac{1.3}{252}$, so that the average investor enters the market 1.3 times a year. I draw the intraday arrival time from a uniform distribution over the trading hours. The probability that an investor submits a buy order is p^h_{buy}, where h is the number of stocks in his portfolio. I set $p^0_{\text{buy}} = 1$, $p^1_{\text{buy}} = \frac{5}{6}$, $p^2_{\text{buy}} = \frac{4}{6}$, $\ldots$, and $p^6_{\text{buy}} = 0$. Thus, each simulated investor's portfolio contains, on average, three stocks. I choose the trading activity and portfolio holdings parameters to match the features of the actual investor trading records. The average individual with trades in the FCSD data and with portfolio holdings one day before the limit order data begin trades 1.27 times a year and owns 2.64 stocks.

If a simulated investor submits a buy order, I choose the stock randomly from the entire universe of stocks. The probability that a stock is selected is proportional to the actual number of purchases by individual investors in the stock. I adjust these probabilities every time a new stock enters the sample or an old stock leaves it. If a simulated investor instead submits a sell order, I choose the stock randomly from the investor's portfolio, choosing each stock with equal probability. To eliminate the need to expend actual data to build investors' portfolios, I give each simulated investor three random stocks one day before the sample begins.

I run simulations for four trader types who use different order strategies. Market order traders always submit market orders. The "most-aggressive" limit order traders submit limit orders that undercut the best existing bid or ask by one cent. The "less-aggressive" limit order traders submit limit orders one-quarter of the way inside the actual limit order book. If the limit order book contains, say, eight buy limit orders when this trader enters the market, then I first sort the actual limit orders by price. I place the investor's limit order one cent behind the $(1/4) * 8 = 2^{\text{nd}}$ actual limit order in the book. The "least-aggressive" limit order traders submit limit orders three-quarters of the way inside the limit order book. If a less- or least-aggressive limit order trader faces a limit order book with fewer than four orders in it, then the trader places the order based on the historical average distance between the best bid (or ask) and the "one-quarter" or "three-quarters" order in the limit order book.

A simulated investor's order remains in the limit order book until it either executes or is withdrawn by the investor. Each unexecuted limit order is withdrawn at the end of the day with a probability of $p_{\text{withdraw}} = \frac{1}{5}$. Thus, the average unexecuted limit order remains in the book for one week.

As the simulations run, I keep track of investors' unexecuted limit orders, order executions, portfolio holdings, and purchase and sale prices. I adjust both purchase prices and the prices of unexecuted limit orders for stock splits and dividends. I run a group of 150,000 traders through the simulation at a time to ensure that the distributions of new buy orders and new sell orders are identical for each day, stock, and investor type. (I redraw random order assignments, following the rules described above, until these distributions coincide.) This equality requirement ensures that the average simulated trader's buy-versus-sell decision is perfectly independent of past and future returns in every simulation. I generate new blocks of investors until I have accumulated a sample of at least two million trades for each trader type.

B. Misinterpretation of New Information

Limit orders may be the reason why individual investors appear to misinterpret new information. Market order traders may react to new information by trading in the correct direction, and thus trade against the limit order traders. If the announcement contains negative information, then only buy limit orders execute after the announcement; alternatively, if the announcement contains positive information, only sell limit orders execute.

[Table I here.]

Table I reports average log-returns for simulated orders that execute around earnings announcements. I compute returns over three intervals: from the trade to the close on the announcement day, from the trade to the close one week after the announcement, and from the trade to the close two weeks after the announcement. I connect order executions to earnings announcements by dividing the trading day into three periods: the "before" period contains the orders that execute before the release of the announcement, the "during" period contains the orders that execute during the first five minutes following the announcement, and the "after" period contains the orders that execute after the first five minutes. I compute t-values from announcement-clustered residuals.

I examine earnings announcements that are released when the exchange is open. The causality from these earnings announcements to limit order execution is more clear than it would be for after-hours earnings announcements. Similar to the U.S.,[6] Finnish companies usually release earnings announcements when the exchange is closed. Of all the earnings announcements in the data, 62% are released after trading hours. I divide the sample into expected and unexpected earnings announcements. An announcement is expected if the company has previously announced the date on which the earnings announcement will be released.

Table I shows that limit order traders generally lose when their limit orders trigger after an announcement. The performance varies across different types of limit order traders and across expected and unexpected announcements. Even the most-aggressive limit order traders lose 3.5% on the day of an expected earnings announcement on those orders that execute within the first five minutes following an announcement. This loss is significantly higher, 12.6%, if the earnings announcement is unexpected. Limit order traders' losses are entirely due to orders that execute after the announcement arrives. By contrast, limit orders traders earn (often significantly) positive returns on those orders that execute before an expected earnings announcement arrives.

Limit order losses tend to increase in the length of the holding period. The most-aggressive traders' loss doubles from 3.5% to 7.4% for expected announcements as the period lengthens from one day to two weeks. The loss increases from 12.6% to 18.9% for unexpected announcements. This pattern is consistent with the presence of a post-earnings announcement drift.[7] Limit order traders buy stocks that depreciate on the announcement days and sell stocks that appreciate. The results in Brandt et al. (2007) suggest that such a return-based contrarian strategy loses money after the announcement because of the post-earnings announcement drift.

The losses on limit orders suggest that the picking-off risk can influence inferences about investors' abilities and trading intentions. The simulated traders' buying and selling intentions are uncorrelated with future returns by construction. It is only because limit orders trigger selectively around earnings announcements that limit order traders end up on the wrong side of the market. The selective execution of limit orders creates the impression that limit order traders misinterpret new information.

Market order traders also lose money on their trades, both before and after an announcement, because of the bid-ask spread. In contrast to the limit order losses, the losses on market orders remain stable as the holding period lengthens.

C. Simulated Traders' Stock-picking Skills

Limit order use may influence individuals' post-trade performance in two ways. The first mechanism is through adverse selection risk:[8] informed investors trade selectively against the limit order book. If a buy limit order executes at $10, then the price may later drift down to $9 as the informed trader's information works its way into prices. In contrast, if a sell limit order executes at $10, then the price may drift up to $11. While market order traders pay their trading costs (the bid-ask spread) up front, limit order traders pay their costs after the trade because the adverse selection problem lowers expected post-trade returns.

The second mechanism that may affect limit order performance is price momentum. Because a limit order executes only if the price moves against the order, executed limit orders are always contrarian trades. Gutierrez and Kelley (2008) find that extreme weekly returns are followed by a reversal that lasts up to a month. Stock prices then resume moving in the direction of the original extreme return.[9] This extreme-return result pertains to limit orders because limit order executions measure the severity of price movements. For example, a limit order placed outside the bid-ask spread executes only if there is a significant price movement. Gutierrez and Kelley's (2008) result then predicts that such an executed limit order experiences positive returns in the short run before starting to lose money.

I measure investors' stock-picking skills by constructing portfolios that mimic investors' purchases and sales. I net purchases and sales in the same stock on the same day within each investor category so that each stock enters either the buy or the sell portfolio, but not both (Barber et al. (2010)). I equal-weight trades within each portfolio. Table II reports the average returns for buy-minus-sell strategies.

[Table II here.]

I compute T-day returns as the average one-day returns on T strategies with different formation periods (Jegadeesh and Titman (1993)). On day t, I invest $\frac{1}{T}$ of the portfolio in a strategy that buys and sells stocks on day $t-1$; I invest another $\frac{1}{T}$ in a strategy that buys and sells stocks on day $t-2$; and so on until I invest the last $\frac{1}{T}$ in a strategy that buys and sells stocks on day $t-T$. This is a calendar-time strategy that rebalances a fraction $\frac{1}{T}$ of the portfolio each day. This approach avoids using overlapping returns.[10]

Table II shows that limit order executions predict future returns in the opposite direction. All of the long-run returns are negative and the statistical significance of the estimates for the two less-aggressive trader types are impressive. A buy-minus-sell portfolio that mimics the least-aggressive traders' trades loses 4% in three months and 7.2% in six months. The performance pattern is perfectly monotonic for the limit order traders after the one-week mark: the least-aggressive traders lose more than the less-aggressive traders, and the less-aggressive traders lose more than the most-aggressive traders.

The aggressive and the two less-aggressive limit order trader types experience different short-term returns. While the aggressive limit order traders see stock prices stay the same the day after the trade, the two less-aggressive trader types experience significant losses as stock prices move against them. This pattern indicates that when a limit order placed outside the bid-ask spread executes, the stock price usually moves further in the same direction the next day. After these initial losses, all limit order traders experience a favorable reversal that lasts at least a week.[11]

The long-run losses on executed limit orders are consistent with the hypothesis that either adverse selection risk or price momentum shows up in post-trade returns. Both the short- and long-run limit order return patterns resemble the weekly momentum return pattern (Gutierrez and Kelley (2008)). This similarity suggests that price momentum may be the primary driver of limit order losses. If executed limit orders' losses reflected adverse selection, then I would not expect to see a reversal in the post-trade returns.[12]

In contrast to limit order traders, market order traders' randomizing behavior carries over intact to the trading records. Because all market order traders' orders execute, their trades remain uncorrelated with future returns. The market order portfolio earns identically zero returns because the number of new buy orders in the simulations is always identical to the number of sell orders for each day, stock, and investor type. Although this equality also holds for limit order traders, not all of these traders' orders translate into trades.

D. Disposition Effect

The use of limit orders can create the appearance that investors exhibit the disposition effect pattern even if they are indifferent between selling winners and losers. I follow Grinblatt and Keloharju's (2001) method to measure the disposition effect. Each day that an investor sells a stock, I match the sale against all stocks in the investor's portfolio that are not sold on the same day. I run a logit regression in which the dependent variable takes the value of one if an investor sells a stock and the value of zero if the investor keeps the stock. The regressors are dummies for extreme capital losses ($> 30\%$) and for moderate capital losses ($< 30\%$). The omitted dummy is associated with either a capital gain or no price change. I estimate these regressions for the full sample and for two subsamples that split stocks based on their average daily trading activity. Table III reports on these estimates.[13]

[Table III here.]

The use of limit orders does not generate the disposition effect for traders who place their limit orders inside the bid-ask spread. However, when limit orders are placed at price levels observed in the actual limit order book, the effect is both economically and statistically very significant. The estimates for the least-aggressive traders indicate that when a stock has a moderate capital loss, the probability of a sale in a three-stock portfolio decreases from 0.33 to 0.22. An extreme capital loss lowers this probability further to 0.20. This limit order-induced disposition effect is stronger for low volume stocks. An extreme capital loss in a low volume stock more than halves the least-aggressive trader's sell probability from 0.33 to 0.15. An extreme capital loss in a high volume stock decreases the sale probability by over one-third from 0.33 to 0.21.

Although limit order traders place limit orders for randomly chosen holdings, a limit order executes only if there is a price run-up. This run-up creates the appearance of the disposition effect. The estimates for the less- and least-aggressive limit order traders indicate that the resultant effect is economically large for the type of limit orders that real investors use. These simulated traders always place their limit orders at price levels observed in the actual limit order book.

Although market order traders also sell a random holding from their portfolios, these traders' loss coefficient estimates are significantly positive because of the bid-ask spread. If a simulated trader submits a market order when the bid-ask spread is wide, then the probability that the sold stock is a loser increases sharply. The bid-ask spread does not systematically affect the unsold holdings because these holdings are marked to market at the closing stock prices, not at the bid price.

E. Contrarian Behavior

An executed limit order is always contrarian because the stock price has to move against the order for it to execute. I measure contrarian behavior by estimating a logit regression similar to the disposition effect regression. The dependent variable takes the value of one when an investor sells a stock and zero when he purchases a stock. I use the stock's own past returns as regressors, breaking the past three months of price changes into eight non-overlapping segments (Grinblatt and Keloharju (2001)).

Table IV shows that price-contingency of limit orders carries over to trading records and creates a declining pattern in the past-return coefficients. The most-aggressive limit order traders are very contrarian with respect to the same-day return. A 5% return on the day of the trade increases the probability of a sale from 0.5 to 0.57. The return coefficients are significant well beyond the same-day return for the two less aggressive limit order trader types. This pattern is particularly evident in the low volume sample, in which the effect is significant even for returns from one week ago to one month ago.

[Table IV here.]

The duration of the limit order-induced contrarian effect is related to the age of investors' limit orders. Although the average unexecuted limit order survives for a week, one-third of the orders survive at least a week, but less than 1% survives over a month. The coefficient estimates turn negative in some of the regressions for a related reason. If a sell limit order placed by the most-aggressive limit order trader executes on day t, the return on day t must have been positive. However, if the order was already entered on day $t-1$, the return on day $t-1$ must have been non-positive because otherwise such an aggressive order would have already executed on the same day. This survival mechanism leads to a negative relation between the sale probability on day t and lagged stock returns in some of the regressions.

Table IV indicates that limit order use can turn past returns into great predictors of investor behavior. The R^2 is about one-third for the less-aggressive traders and two-thirds for the least-aggressive traders. To appreciate the economic strength of this effect, suppose that the task is to predict whether the least-aggressive limit order trader buys or sells on day t, given that he trades a low volume stock. The slope coefficient for day $t-4$ indicates that if the stock price increases by 5% on that day, then the probability that the least-aggressive limit order trader sells on day t increases from 0.5 to 0.63. The estimates for market order traders are identically zero (and hence, omitted from Table IV) because, first, the number of new buy orders always equals the number of new sell orders, and, second, because market order traders' orders do not execute selectively.

IV. Limit Order Effect in Investor Trading Records

A. Misinterpretation of New Information

Table V reports on the performance of individual investors' orders executed around earnings announcements. I follow the same test procedure as with the simulated trading records.

[Table V here.]

The results are similar to the simulation-based results. The average same-day return for pre-announcement limit orders ("old limit orders") executed within the first five minutes is -2.7% for expected announcements and -7.1% for unexpected announcements. These losses increase as the holding period lengthens. The average losses are 6.2% and 9.2%, respectively, by the two-week mark. The greater limit order losses associated with unexpected announcements suggest that either individuals use limit orders more cautiously when they know an earnings announcement is imminent, or unexpected earnings announcements have greater influence on share prices. The long-run return estimates are noisier for unexpected announcements than for expected announcements due to smaller sample sizes.

Individuals who react to earnings announcements by submitting market orders earn positive returns. The average same-day return for market orders submitted within the first five minutes is 1.6% for expected announcements and 4.0% for unexpected announcements. These returns also increase in the length of the holding period. These positive returns are in sharp contrast to the simulations, in which market orders lose money because of the bid-ask spread. Both market orders and limit orders pay higher trading costs later in the trading day after the announcement. These losses are comparable in size to the losses seen in the simulations.

These results indicate that individuals do not lose money because they misinterpret new information, but rather because others take advantage of their limit orders. Since 69% of individual investors' post-announcement trades are limit order trades, the average individual investor loses money when an earnings announcement arrives. The average all-orders same-day loss is 2.1% ($t = -2.1$) for orders executed during the five-minute window. The fraction of limit order trades (in the during period) is higher for unexpected announcements (77%)

than for expected announcements (66%), supporting the hypothesis that individuals exert more caution in their order choices when they know to expect an announcement. Investors may have limit orders in the book around earnings announcements if they are unaware of an earnings announcement or if the cost of monitoring a limit order exceeds the expected loss due to an earnings announcement. I later show that the unconditional intraday return on an executed limit order is positive, indicating that even a small monitoring cost may induce investors to leave their limit orders unattended.

As a robustness test, I examine the returns on limit orders that executed following the terrorist attacks on September 11, 2001. When the South Tower of the World Trade Center was hit at 9:03 AM EDT, traders in Europe, who had been uncertain after the first attack against the North Tower at 8:46 AM EDT, ascertained that there had indeed been a terrorist attack. Traders observing the second attack reacted by submitting a flood of sell market orders, which led to an instant drop in share prices. Limit orders that executed between 9:03:00 and 9:05:59 AM EDT in the Helsinki Stock Exchange were down by a total of €3.1m by the end of the same trading day. This loss represented a one-day return of −8% to investors whose limit orders executed. These limit order traders lost money not because they misinterpreted new information, but because quicker investors picked off their limit orders.

If individuals were to misinterpret new information, then smart investors could earn abnormal profits by doing the exact opposite. However, because individuals lose money through picking-off risk, there is no mechanical trading rule that can be used to profit at these investors' expense.

B. Individual Investors' Stock-picking Skills

Table VI reports average post-trade returns for individual investors' market orders and executed limit orders. I follow the same procedure as with the simulated trading records. I evaluate performance for all trades, and for market order trades and limit order trades. Figure 1 plots cumulative portfolio returns, which are again based on buy-minus-sell calendar-time portfolios, for holding periods ranging from one day to six months.

[Table VI here.]

[Figure 1 here.]

The limit order results display three patterns that are similar to the simulation-based results. First, limit orders lose one day after the trade. The average stock price movement is 0.5% against executed limit orders. Second, limit orders regain some ground in the one-week period after execution. For example, the cumulative one-week return is positive at 0.2%. Third, limit orders resume losing money as the holding period lengthens beyond the one-month mark. By the three-month mark limit orders have lost 3.3%, and by the six-month mark they have lost 4.6%.

Individuals' market orders earn reliably positive returns up to the three-month holding period. The six-month estimates are also positive, but the increase in standard errors offsets the increase in the mean. These estimates suggest that individuals who use market orders may be trading on some useful information. Individual market order traders also often trade against individual limit order traders because of market clearing. In such cases, the return patterns for the two traders are identical, but with opposite signs.

Because individuals' market orders earn positive returns, a self-financing market orders-minus-limit orders portfolio earns statistically impressive positive returns at all horizons. The spread between market order and limit order trades is almost 1% the day after the trade. This difference increases to 8% in six months. However, the statistical significance of this spread decreases as the formation period lengthens beyond the three-month mark. These results suggest that individual investors do not lose money because they make misguided trading decisions. Only individuals' executed limit orders lose money.

The limit order return pattern in Figure 1 is again similar to Gutierrez and Kelley's (2008) price momentum pattern. This similarity suggests that limit orders probably lose money because a portfolio of executed limit orders is a particular contrarian strategy. This portfolio buys (sells) stocks that depreciate (appreciate) sharply. This is the opposite of the strategy in Gutierrez and Kelley (2008). If individuals lose money through this contrarian mechanism, then individuals' losses are due to this investment style, not because of poor stock picks.[14]

C. Evidence from Unexecuted Limit Orders

The poor post-trade performance of individuals' executed limit orders could be due to reverse causality. If some individuals systematically trade in the wrong direction and these same individuals use limit orders frequently, then limit order trades would exhibit poor post-trade performance.

I examine unexecuted limit orders to test for this possibility. If the causality runs from investor characteristics to order choices, then unexecuted limit orders should reflect the same undesirable investor traits as executed limit orders. The alternative hypothesis is that executed limit orders are special: stock prices moved against the executed orders but away from the unexecuted limit orders.

I identify unexecuted limit orders placed by individual investors by using the probit model described in Section II. I then form buy and sell portfolios from the unexecuted limit orders. I construct these portfolios just as I do for the executed limit orders.

Table VI shows that a portfolio based on unexecuted limit orders earns positive, not negative, short-run returns. The portfolio earns 0.8% one day after it is formed. This return increases up to the two-week mark before turning statistically insignificant. The return difference between the unexecuted limit order portfolio and the executed limit order portfolio is significant both economically and statistically.

The losses on limit orders are specific to orders that execute. Limit orders execute selectively, and it is this selection that predicts future returns. The unexecuted limit order portfolio earns positive returns because the imbalances for executed and unexecuted limit orders are negatively correlated. For example, if market order traders sweep through the buy side of the limit order book, the buy-sell imbalance is positive for executed limit orders and negative for unexecuted limit orders.

This analysis suggests that reverse causality from behavioral biases to order choices alone cannot explain my findings. One particular concern is that investors use limit orders to execute behavioral trades, but market orders to execute nonbehavioral trades. A comparison of executed and unexecuted limit orders is immune to this concern because this method uses information on only one type of orders, limit orders.

D. Disposition Effect

Table VII reports coefficients from logit regressions that measure the strength of the disposition effect. I follow the same test procedure as with the simulated trading records, estimating these regressions for the full sample and for two subsamples that split stocks based on their average daily trading activity.

[Table VII here.]

In all subsamples the estimates are consistent with the existence of the disposition effect. Although market order trades also exhibit the disposition effect, the effect is weaker than it is for limit order trades. The moderate loss coefficient is -1.14 for limit order sales but only -0.43 for market order sales. This difference is economically highly significant. For example, suppose that the base probability of selling a particular stock is 0.5. If this stock is a moderate loser to a market order trader, then the probability of a sale decreases by 0.1. For a limit order trader, the probability of a sale decreases by 0.26.

A comparison of the estimates between market order trades and limit order trades indicates that limit order use may be responsible for up to one-half of the disposition effect. Limit orders have a slightly larger effect in the low volume subsample. While a moderate loss in a lowvolume stock decreases the sell probability from 0.5 to 0.41 for market order sales, the corresponding change is from 0.5 to 0.22 for limit order sales.

Panel B of Table VII reports on investor-specific estimates that control for the possible reverse causality from the disposition effect to order choices. Here, I difference out fixed investor characteristics by studying individuals with both market order and limit order trades. I estimate the following linear probability model separately for each investor:

$$\begin{aligned}\text{Sell}_i \quad = \quad & \beta_0 + \beta_1 \text{ Moderate Loss}_i + \beta_2 \text{ Extreme Loss}_i + \gamma_0 \text{ Limit Order}_i \\ & + \gamma_1 \text{ Limit Order}_i * \text{Moderate Loss}_i + \gamma_2 \text{ Limit Order}_i * \text{Extreme Loss}_i + \\ & + \delta_1 \ \ln(\text{Number of Losers}_i + 1) + \delta_2 \ \ln(\text{Number of Winners}_i + 1) + \varepsilon_i,\end{aligned} \tag{1}$$

where Limit Order_i is a dummy variable that takes the value of one if sale i originates from a limit order. The last two regressors control for the portfolio's size and the winner-loser ratio. The coefficients γ_1 and γ_2 measure the difference in the disposition effect between limit order and market order trades. I also report estimates for an alternative model that combines the two loss variables into one variable. I can estimate this model for a larger sample of investors because it does not require investors to have all three types of positions (winners, moderate losers, and extreme losers) in their portfolios.

Panel B reports weighted average coefficients from these regressions. The weights are inversely proportional to the variances of the first-stage estimators (Ferson and Harvey (1999)). This approach pays less attention to individuals who have noisy first-stage estimates. I also report the fraction of positive coefficients for the individual-level regressions.

These individual-specific estimates suggest that reverse causality does not explain the disposition effect results. Limit order trades remain associated with higher disposition effect estimates. In the one-dummy model, the probability of a sale decreases by 0.04 when the investor uses a limit order rather than a market order. This difference is statistically highly significant.

The part of the disposition effect that is specific to market orders may be less harmful than the part that is specific to limit orders. The disposition effect is potentially harmful for two reasons. First, investors unnecessarily increase their tax bills if they realize more gains than losses. Second, the sold winners outperform losers by a significant margin the year after the transaction (Odean (1998)). However, because the negative post-trade returns are largely specific to limit orders, the non-limit order part of the disposition effect is costly only because of the tax consequences.

E. Contrarian Behavior

Table VIII reports coefficients from logit regressions that measure the strength of individuals' contrarian strategies. I follow the same test procedure as with the simulated trading records, estimating these regressions for the full sample and for two trading volume subsamples.

[Table VIII here.]

The estimates for the full sample show that individual investors follow contrarian strategies. Individuals buy stocks with negative past returns and sell stocks with positive past returns. This effect weakens over time. Although the all-trades estimate for the day $t-1$ return is 0.65, it is only approximately 0.1 for lagged returns older than one week.

The coefficient estimates for the past return variables are very sensitive to order choice, particularly for the low trading volume stocks. For low volume stocks the estimates for market orders are negative for past returns up to a month, while the estimates for limit orders are reliably positive. Thus, for low volume stocks, individuals' contrarian behavior can be traced back entirely to limit order trades.

Although limit orders are not as important beyond trading day $t-1$ for high volume stocks, the economic magnitude of the effect on day $t-1$ is still noteworthy. The day $t-1$ coefficient estimate is 1.1 for limit order trades and 0.3 for market order trades. If the base probability of a sale is 0.5 and the return on day $t-1$ is 10%, then the probability of a sale increases by 0.03 in the limit order sample and by 0.01 in the market order sample.

The most significant difference between market and limit order trades in Table VIII is the same-day return coefficient. The same-day return coefficient is significantly positive for limit order trades, but significantly negative for market order trades. Thus, individuals who submit market orders often trade in the direction of the same-day return.

Panel B reports estimates for investor-specific regressions. I estimate the following linear probability model separately for each investor who has both market order and limit order trades:

$$\begin{aligned} \text{Sell}_i &= \beta_0 + \beta_1\, r_{i,0} + \cdots + \beta_5\, r_{i,t-4} + \gamma_0 \text{ Limit Order}_i + \gamma_1 \text{ Limit Order}_i * r_{i,0} \\ &\quad + \cdots + \gamma_5 \text{ Limit Order}_i * r_{i,t-4} + \varepsilon_i, \end{aligned} \tag{2}$$

where Limit Order_i is a dummy variable that takes the value of one if trade i is a limit order trade. Coefficients γ_1 through γ_5 measure the difference in individual investors' contrarian behavior between limit order and market order trades. I include lagged return variables only up to $t-4$. Doing so enables me to estimate the model for a larger number of investors.

The estimates in Panel B suggest that reverse causality, from investors' trading strategies to order choices, does not explain the relation between the limit order use and contrarian behavior. Limit order trades remain associated with stronger contrarian behavior in these investor-specific regressions. The day $t-1$ coefficient is 2.5 times higher for an investor's limit order trades than for his market order trades. The day $t-2$ coefficient is 1.5 times higher and the day $t-3$ coefficient is over four times higher.

Both the pooled estimates and the individual-level estimates support the hypothesis that limit orders' price contingency carries over to investor trading records. Moreover, although market order traders remain contrarian with respect to some past returns, the post-trade return computations in Table VI suggest that this behavior is not associated with lower future returns.

F. Controlling for the Limit Order Effect in Other Data Sets

A regression of a buy-versus-sell indicator variable on the same-day stock return can be informative about the extent of investors' limit order use. Because of how limit orders work, limit order traders appear to trade against the same-day return. (Conversely, my data indicate that individuals who submit market orders often trade in the direction of the same-day return.) A significantly positively coefficient in a buy-versus-sell regression may indicate that an investor uses limit orders extensively.

I explore this idea by first estimating the following regression for each investor j who trades at least 10 times:

$$\text{Sell}_i^j = \beta_0^j + \beta_1^j \, r_{i,0} + \varepsilon_i^j, \tag{3}$$

where $r_{i,0}$ is the same-day stock return. The slope coefficient is significantly positive in 26% of the 33,230 regressions and significantly negative in 9% of the regressions. The average fraction of limit order trades is 65% for investors in the former group and 34% for those in the latter group.

Next, I regress the slope coefficient estimates from expression (3) against the fraction of limit order trades by investor j:

$$\hat{\beta}_1^j = \underbrace{\gamma_0}_{\substack{-1.42 \\ (-32.2)}} + \underbrace{\gamma_1}_{\substack{3.95 \\ (52.7)}} * \text{ Fraction of Limit Order Trades by Investor } j + \varepsilon_j. \qquad (4)$$

Heteroskedasticity-robust t-values appear in parentheses. I run the regression with the first-stage estimate as the dependent variable to avoid the errors-in-variables problem. I again use weights that are inversely proportional to the variances of the first-stage $\hat{\beta}_1^j$ estimates.

The relation between the first-stage slope estimate and the fraction of investors' limit order trades is both economically and statistically significant. A 10-percentage-point increase in limit order use increases the first-stage slope coefficient by 0.4.

The R^2 from expression (4) is 0.17. This high correlation suggests that the slope coefficient from expression (3) can be used as a control variable in further tests. Investors can be sorted into categories by using this variable, or investors with significantly positive slope coefficients can be excluded as a robustness test. Such procedures would help to establish that a newly discovered trading pattern is distinct from investors' use of limit orders.

I also estimate expression (3) for each account with at least 10 trades in the Barber and Odean (2001) data set from a large U.S. discount broker.[15] The average slope coefficient $\hat{\beta}_1^j$ across these 40,587 individual-level regressions is 0.78 with a t-value of 30.5. The slope coefficient estimate is significantly positive in 16% of the regressions and significantly negative in 8% of the regressions. These estimates suggest that some of the accounts may use limit orders extensively. I also find that the disposition effect estimates in these data are sensitive to same-day stock price movements. The direction of these results, which are detailed in the Internet Appendix, suggests that limit order use also amplifies the disposition effect estimates in the U.S. data.

V. Why Do Individuals Use Limit Orders?

A. Summary of Model-based Simulation Results

I summarize here the results from model-based simulations that examine why individual investors use limit orders. The Internet Appendix surveys the theory of order choice and provides a thorough discussion of these simulations.

I examine the order choices of both individual and institutional investors by comparing these investors' behavior to numerical solutions of the state-of-the-art dynamic limit order book model of Goettler, Parlour, and Rajan (2009). The financial asset in this model has both common and private components to its value. The private component of value generates an intrinsic motive for trade. Traders with low private values are traders who need to sell because of a negative liquidity shock. Also, because some traders want to trade for private reasons, other traders with no private value component (and no information) have an incentive to provide liquidity.

The model-based estimates indicate that information, patience, and private value component realizations affect not only unconditional limit order usage rates, but also each trader's sensitivity to the state of the market. For example, informed traders are more sensitive than uninformed traders to changes in market conditions and also use more market orders. Impatient traders and traders with extreme private value component realizations submit more market orders. Traders' sensitivity to market conditions, and in particular to those related to the bid-ask spread, increases significantly in the magnitude of the private value component.

In actual data both individuals and institutions respond to changes in market conditions in much the same way as the simulated traders. Investors are more likely to submit limit orders when the spread is wide or has just widened, when the bid-ask spread midpoint has moved away from the trader, and when the flow of market orders on the opposite side of the market has been high. A comparison of individual and institutional investors suggests that institutions are far more responsive to variation in the size of the bid-ask spread. By contrast, individuals and institutions respond quite similarly to changes in the other non-spread market conditions.

In simulations, traders who are uninformed, more patient, or whose private value component realizations are closer to zero use more limit orders. Of these three channels, the private value component has the strongest effect and variation in this dimension can generate a remarkably good match between the data and the simulations. If institutions tend to receive larger draws of the private value component, then differences in individual investors' and institutional investors' order usage rates and sensitivities to market conditions conform to the simulations. Variation in this dimension could explain, first, why individual investors use more limit orders in general and, second, why institutions are more sensitive to changes in the bid-ask spread.

The conclusion that the private component channel can explain institutions' and individuals' order choices is intriguing. The model does not need to bombard individual investors with extreme liquidity shocks to get them to trade. Instead, this result suggests that individual investors resemble uninformed traders with private value components close to zero. Such traders enter the market because they expect to gain from the liquidity demand of impatient investors with large private value component realizations. This characterization of individual investors is consistent with Kaniel, Saar, and Titman's (2008b) conclusion that individual investors provide liquidity to meet institutional demand for immediacy.

B. Intraday Returns on Individuals' and Institutions' Limit and Market Orders

Table IX reports on average intraday returns associated with market orders and executed limit orders. I compute average returns separately based on who submitted the limit order (i.e., an individual or institution) and who traded against the limit order with a market order. The first block reports on trades for which individual investors submit both types of orders. The second block reports on trades for which an individual investor submits the limit order and an institution submits the market order, and so on.

[Table IX here.]

I compute log-returns from the transaction price to the bid-ask spread midpoint at the end of the day. I reverse the signs for sell limit orders so that positive numbers indicate better performance. I compute t-values from stock-day-clustered residuals. Thus, these inferences are robust to correlations between similar orders on the same day in the same stock.

The returns in Table IX satisfy an important adding-up constraint: because there is a buyer and a seller in each trade, the average return is zero. Any deviation from zero indicates that there is a monetary transfer from one group of investors to another. Barber et al. (2010) examine a similar issue. They compute the total monetary transfer from one group of investors to another instead of just studying short-term trading costs.

Table IX shows that the average executed limit order earns 6.5 basis points on the day of the trade. The average market order loses the same amount. However, this average masks significant variation that depends on who placed the limit order and who submitted the market order. Executed limit orders perform better when they are hit by individual investors rather than by institutions. The difference in means, 36.1 bps compared to -3.8 bps, is economically impressive and statistically highly significant. This difference suggests that institutions' market orders are more informative than are individuals' market orders. This difference also holds for limit orders. Institutions' executed limit orders outperform individuals' executed limit orders no matter who is on the other side of the trade. Anand, Chakravarty, and Martell (2005) find a similar pattern in a U.S. data set.

Individual investors' executed limit orders outperform their market orders by a statistically and economically significant margin. While the average executed limit order earns 1.6 bps on the day of the trade, the average market order loses 36.1 bps. The main reason for this difference is the bid-ask spread. An executed limit order earns half of the bid-ask spread at the time of execution, but a market order pays this amount.

The performance differences in Table IX should be interpreted with caution. I only measure returns on executed orders, so there is no penalty for unexecuted limit orders. Nevertheless, I can conclude that individuals would have paid higher trading costs had they used more market orders. This conclusion is justified because investors submit more limit orders at times when bid-ask spreads are wide. Thus, replacing the average executed limit order with a market order would cost at least as much as the cost associated with the average market order.

The favorable intraday returns on executed limit orders go in the opposite direction from the long-run return results. Individuals are compensated up front for using limit orders. Although Table IX shows that the individual investors' average limit order loses significantly one day after the trade, this loss should be netted against the savings on the day of the trade. If I extend the return horizon in Table IX to the day after the trade, then the average return on a limit order falls from 1.6 bps to −16.3 bps while the average return on a market order increases from −36.1 bps to −26.3 bps.[16] The standard errors for these day-and-a-half average returns are 4.2 bps and 2.2 bps, respectively.[17] Hence, executed limit orders are ahead of the market orders, even at the end of the following day, by a statistically and economically significant 10 bps margin.

These intraday return results, together with the post-trade performance results, are similar to Kaniel, Saar, and Titman's (2008b) finding for a U.S. data set, which shows that individual investors are compensated for their liquidity provision services. After the stock prices move against limit orders one day after the trade, limit orders gain ground in the following weeks. Only at longer horizons are these gains offset as either adverse selection or momentum begins to move stock prices against limit orders. The positive returns that individuals earn on their executed limit orders are also consistent with my characterization of individuals, based on Goettler, Parlour, and Rajan's (2009) model, as uninformed traders with no intrinsic motive to trade.

Most studies on individual investors' performance ignore the same-day return to avoid any bid-ask spread effects. The results in Table IX suggest that because individuals often earn the bid-ask spread and because these initial profits are partially offset by lower returns in the days to come, performance studies should also include intraday returns.

VI. Conclusion

I find that because of the way limit orders work, investor trading records reflect mechanical effects that distort inferences about investors' intentions. Even if a limit order book is balanced between buy and sell limit orders, positive news causes more of the sell limit orders to execute, leaving an impression in the trading records that most investors wanted to sell their shares in response to good news.

Using trading records from Finland, I find that individuals lose money when their limit orders execute immediately after earnings announcements; that limit order trades lose money after the trade while market order trades do not; that approximately half of the disposition effect disappears if I exclude sales originating from limit orders; and that individuals' short-term contrarian behavior is mostly due to limit orders.

My results are probably not specific to Finland. Certainly, individuals in the U.S. also use limit orders frequently and some brokers nudge their customers towards using limit orders. Fidelity, for example, displays the following recommendation prominently on its order submission page: "Use caution with market orders as security prices can change sharply. Consider limit orders in volatile markets or with limited assets for transaction payment. . . ." The fraction of limit orders received by the largest five discount brokers ranges from 35% to 48% in the first quarter of 2006. Limit orders outnumber market orders on average by eight to five.[18] Individuals also set their orders to remain in effect for several days. Data from one large U.S. discount broker indicate that 23% of the time, individuals deviate from the same-day expiration (the default choice), letting their orders remain in effect at least until the next day. Individuals let 9% of their orders remain in effect for at least a month.

The market order-versus-limit order split understates the importance of the limit order effect when investors use market orders as substitutes for limit orders. For example, even if an investor instructs his broker to trade shares at some limit price, the broker may wait and submit a market order when the stock price reaches the limit price. Investors may avoid explicit limit orders to hide their trading interests (Bessembinder and Venkataraman (2004)). Also, if a broker charges a fee for unexecuted limit orders, then an investor may submit a market order when the stock price reaches his limit price. These price-contingent market orders can obscure the line between market orders and limit orders.

Many hedge funds use price-contingent trading strategies without always explicitly using limit orders. One popular strategy tries to identify stocks that experience large liquidity shocks just before the close. The hedge funds' algorithms then take positions in these stocks and unwind them the next morning to exploit small daily return reversals (French and Roll

(1986)). Given the hedge funds' large share of the daily volume in the U.S. equity markets (French (2008)), these price-contingent trading strategies may have interesting consequences. For example, since there is always someone else on the other side of these trades, the behavior and returns of these other investors depend on hedge funds' strategies.

Notes

[1]Ekholm (2006) and Ekholm and Pasternack (2007) find that Finnish individuals trade against the direction of new information. Vieru, Perttunen, and Schadewitz (2005) replicate the findings of Hirshleifer et al. (2008) using Finnish data.

[2]See, for example, Barber et al. (2010), Barber and Odean (2000, 2001), Grinblatt and Keloharju (2000, 2009), and Odean (1999).

[3]See, for example, Shefrin and Statman (1985) and Barberis and Xiong (2009). Shapira and Venezia (2001), Odean (1998), Grinblatt and Keloharju (2001), and Feng and Seasholes (2005) document the disposition effect pattern for Israeli traders, U.S. discount broker customers, Finnish households, and Taiwanese investors, respectively.

[4]See, for example, Heath, Huddart, and Lang (1999), Nofsinger and Sias (1999), Choe, Kho, and Stulz (1999), Grinblatt and Keloharju (2000, 2001), Griffin, Harris, and Topaloglu (2003, 2005), and Richards (2005). Goetzmann and Zhu (2005) suggest that individuals' contrarian behavior in a U.S. data set may be related to limit order use. Contrarian behavior largely disappears when these authors exclude trades with round- and half-dollar prices. Dorn, Huberman, and Sengmueller (2008) find that individuals' limit order use contributes to individual investors' tendency to "herd" on the same side of the market.

[5]In this paper I use the word "contrarian" to describe individuals' tendency to be net buyers in a stock as the stock price falls, and net sellers in a stock as the stock price rises. Thus, by this definition, individuals are contrarian investors. At the same time, however, individuals are more likely to buy stocks with positive past returns than those with negative past returns. Thus, if I were to infer individuals' beliefs and intents from such a cross-sectional analysis, it would be less obvious that individuals are contrarian investors. My results suggest that the selective execution of either buy or sell limit orders within a stock may explain why the within-a-stock analysis yields an answer different from the across-stocks analysis. I thank the associate editor for pointing out this distinction.

[6]See, for example, Doyle and Magilke (2009).

[7]See, for example, Ball and Brown (1968).

[8]See, for example, Bagehot (1971), Copeland and Galai (1983), Glosten and Milgrom (1985), and Glosten (1994).

[9]In the Internet Appendix, I show that the momentum pattern in weekly returns in Finland is similar to that in the U.S. The Internet Appendix is available online in the "Supplements and Datasets" section at http://www.afajof.org/supplements.asp.

[10]Barber and Lyon (1997) and Lyon, Barber, and Tsai (1999) discuss the problems inherent in long-run return measurements and tests. See also Barber et al. (2010).

[11]This short-term reversal pattern has been documented in a number of studies. See, for example, French and Roll (1986), Jegadeesh (1990), and Lehmann (1990).

[12]Wu (2007) suggests that the adverse selection and momentum explanations are not necessarily mutually exclusive. Uninformed traders in Wu's model passively accommodate buys (sells) by informed investors who receive a positive (negative) signal about a company's prospects. A fixed transaction cost creates the appearance of momentum in observed stock returns. Hence, adverse selection is intertwined with price momentum in Wu's model. I thank the referee for pointing out this connection.

[13]Feng and Seasholes (2005) show that the alternative approach, which compares the proportion of gains realized (PGR) to the proportion of losses realized (PLR), for testing for the disposition effect exhibits certain undesirable properties. For example, when this method is applied at the individual investor level, the number of stocks in an investor's portfolio is mechanically associated with the PGR and PLR numbers.

[14]Several studies contain similar results on individuals' post-trade performance. Kaniel, Saar, and Titman (2008b) find that individuals experience positive short-run returns by supplying liquidity to institutions. Barber, Odean, and Zhu (2009) find that individual investors' trade imbalances are positively correlated with the returns in the subsequent week (and up to a month) and negatively correlated with the returns from one month to 12 months. However, in contrast to my findings, Barber, Odean, and Zhu (2009) find a positive correlation between

individuals' trade imbalances and contemporaneous returns. Barber et al. (2010) find that individuals' passive trades in Taiwan earn positive returns in the short run, but that these trades begin losing ground around the one-month mark. However, their main finding is the opposite of mine. They find that almost all individual trading losses can be traced back to individuals' aggressive orders. Kaniel, Saar, and Titman (2008b) suggest that the dominance of individual investors in Taiwan may be the reason why their results (and mine) are different from those of Barber et al. (2010). Similar to the U.S., most of the daily volume in Finland, 85.4%, comes from non-household investors (Grinblatt and Keloharju (2000)). In contrast, 89.5% of the dollar on volume on the Taiwan Stock Exchange comes from individuals.

[15]These data contain trading records for 78,000 households from January 1991 through November 1996. See Barber and Odean (2001) for details.

[16]The changes in returns are smaller than the average one-day returns reported in Table VI. These two analyses are different in that I compute trading costs in event time (each trade is one observation), but Table VI reports on calendar-time portfolios (each day is one observation). The discrepancy between these two methods indicates that individuals' executed limit orders perform better at times of high trading activity.

[17]Because the day-and-a-half returns overlap in event time, I drop every other day from the sample and cluster residuals by order type, stock, and day in computing the standard errors.

[18]These figures are from the SEC Rule 606 reports. I thank the associate editor for these reports. The remaining "other orders" category includes, among others, stop orders, all-or-none orders, and market and limit orders that are instructed not to execute immediately ("not held"). I also received an internal report from one large U.S. discount broker. This report classifies all orders into just four categories (market orders, limit orders, stop market orders, and stop limit orders) and excludes business accounts. The fraction of limit orders in individuals' monthly order flow ranges from 70% to 74% from October 2004 through September 2005.

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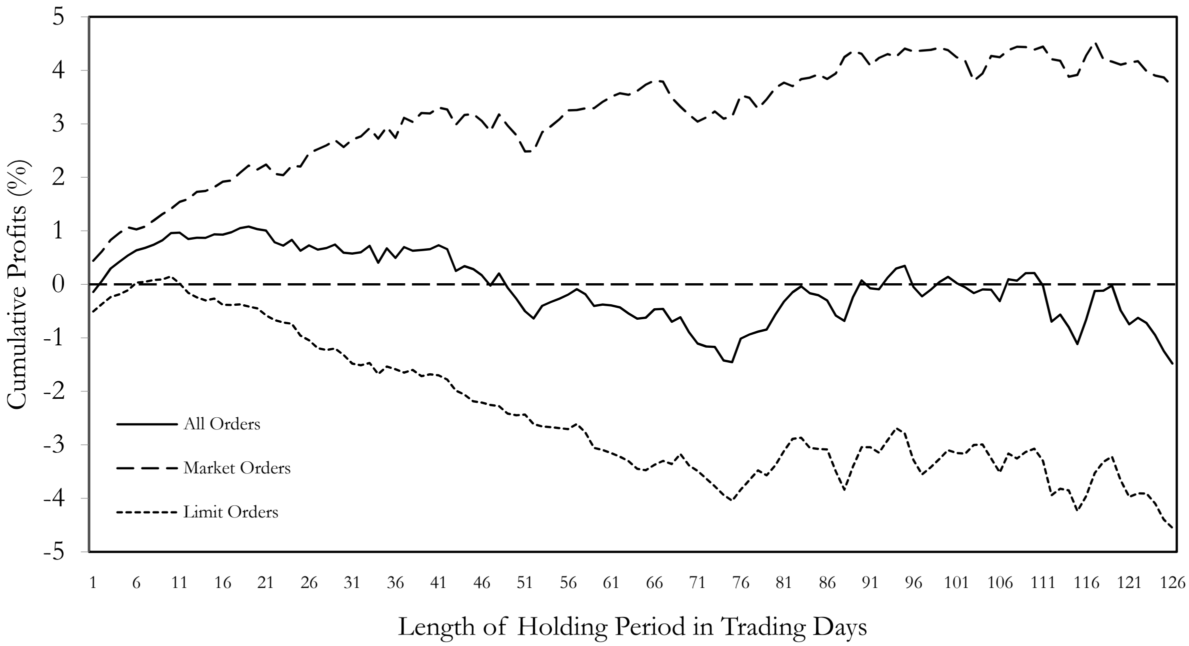

Figure 1. Returns on individual investors' buy-minus-sell portfolios conditional on order choice. This figure plots the average cumulative returns for a strategy that mimics individual investors' purchases and sales. I construct a buy (sell) portfolio each day for all trades, for market order trades, and for limit order trades. The buy (sell) portfolio weights different stocks in proportion to the number of purchases (sales) across these stocks. I net purchases and sales for each stock and day so that each stock enters either the buy or the sell portfolio, but not both. I compute the returns without overlap by forming a calendar-time portfolio that rebalances a fraction $\frac{1}{T}$ of the portfolio each day. On day t, I invest $\frac{1}{T}$ of the portfolio in a strategy that buys and sells stocks on day $t-1$; I invest another $\frac{1}{T}$ in a strategy that buys and sells stocks on day $t-2$; and so on. I multiply these one-day returns by the number of days in the holding period. The sample contains Finnish individuals' market and limit order trades from September 18, 1998 through October 23, 2001.

Table I
Returns on Simulated Traders' Orders Executed around Earnings Announcements

This table reports average log-returns for orders executed on days with earnings announcements. The sample comprises all 586 expected (Panel A) and 117 unexpected (Panel B) earnings announcements released during regular trading hours in Finland from September 18, 1998 through October 23, 2001. I divide the trading day into three periods: the before period contains orders executed before the announcement; the during period contains orders executed within the first five minutes following the announcement; and the after period contains orders executed after these five minutes. Each simulated trader randomizes over all stocks when deciding what to buy, and over all holdings when deciding what to sell. t-values are computed from announcement-clustered residuals.

Panel A: Expected Earnings Announcements

			Returns (%)					
Simulated		Number of	Same Day		One Week		Two Weeks	
Trader Type	Period	Trades	Mean	t	Mean	t	Mean	t
Market Orders	Before	4,189	−0.70	−4.40	−0.86	−4.27	−0.66	−3.15
	During	180	−1.95	−2.70	−1.85	−1.64	−2.22	−1.79
	After	11,806	−0.53	−5.58	−0.40	−3.96	−0.48	−4.57
Most-Aggressive	Before	5,099	0.51	2.68	0.56	2.17	0.56	1.84
Limit Orders	During	928	−3.48	−3.06	−6.43	−3.73	−7.35	−3.49
	After	13,742	−0.28	−2.24	−0.37	−2.57	−0.38	−1.65
Less-Aggressive	Before	8,684	2.76	3.03	1.84	1.05	1.53	0.64
Limit Orders	During	5,936	−4.60	−2.02	−8.22	−2.71	−8.58	−3.16
	After	14,209	−1.90	−2.50	−2.60	−2.52	−2.65	−1.70
Least-Aggressive	Before	15,220	5.30	3.22	4.39	1.53	1.71	0.48
Limit Orders	During	8,690	0.85	0.31	−3.55	−1.19	−5.76	−1.73
	After	27,679	−2.36	−2.29	−4.59	−2.49	−6.47	−2.61

Panel B: Unexpected Earnings Announcements

Market Orders	Before	2,334	−0.43	−1.67	−0.03	−0.08	−0.37	−1.06
	During	47	1.48	0.86	3.18	1.25	3.68	1.13
	After	2,490	−0.48	−3.53	−0.66	−3.03	−0.50	−2.04
Most-Aggressive	Before	2,583	0.34	0.62	0.26	0.33	0.03	0.04
Limit Orders	During	386	−12.63	−3.68	−18.87	−4.34	−18.94	−3.47
	After	2,926	−0.34	−2.02	−0.33	−0.87	0.77	1.30
Less-Aggressive	Before	2,814	−0.67	−0.34	−1.22	−0.42	−1.08	−0.21
Limit Orders	During	2,448	−13.66	−2.78	−14.75	−1.60	−15.96	−1.55
	After	2,490	−1.80	−1.37	−5.92	−1.53	−2.55	−0.49
Least-Aggressive	Before	5,943	−1.55	−0.50	−2.42	−0.79	−0.87	−0.13
Limit Orders	During	9,446	−13.44	−3.52	−17.77	−3.13	−21.17	−3.32
	After	6,041	−2.32	−1.57	−7.27	−1.02	−3.21	−0.46

Table II
Returns on Simulated Traders' Buy-Minus-Sell Portfolios

This table reports average cumulative returns for a strategy that mimics simulated traders' purchases and sales. I construct a buy (sell) portfolio each day for each trader type. The buy (sell) portfolio weights different stocks in proportion to the number of purchases (sales) across these stocks. I net purchases and sales for each stock and each day so that each stock enters either the buy or the sell portfolio, but not both. The strategy in this table buys one unit of the buy portfolio and sells one unit of the sell portfolio. I compute the returns without overlap by forming a calendar-time portfolio that rebalances a fraction $\frac{1}{T}$ of the portfolio each day. On day t, I invest $\frac{1}{T}$ of the portfolio in a strategy that buys and sells stocks on day $t-1$; another $\frac{1}{T}$ is invested in a strategy that buys and sells stocks on day $t-2$; and so on. I multiply these one-day returns by the number of days in the holding period. This table reports average returns. t-values appear in parentheses.

	Cumulative Holding Period Return (%)					
Simulated	Length of the Holding Period in Days					
Trader Type	1	5	10	21	63	126
Market Orders	0.000	0.000	0.000	0.000	0.000	0.000
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Most-Aggressive	−0.013	0.178	0.204	0.073	−0.658	−0.812
Limit Orders	(−0.24)	(1.62)	(1.33)	(0.33)	(−1.43)	(−1.01)
Less-Aggressive	−0.655	−0.435	−0.453	−0.614	−2.422	−3.673
Limit Orders	(−7.80)	(−2.31)	(−1.75)	(−1.67)	(−3.21)	(−2.89)
Least-Aggressive	−0.772	−0.395	−0.746	−1.284	−3.991	−7.218
Limit Orders	(−5.59)	(−1.18)	(−1.50)	(−1.70)	(−2.47)	(−2.49)

Table III
Simulation Results on the Influence of Limit Order Use on the Disposition Effect

This table reports regression coefficients and z-values for four logit regressions. The dependent variable takes the value of one when an investor sells a stock. I match each sell with all stocks in the investor's portfolio that are not sold the same day. In these "hold" events, the dependent variable takes the value of zero. The regressors are dummies associated with extreme ($> 30\%$) and moderate ($< 30\%$) capital losses. The regressions also include stock and month fixed effects and the natural logarithm of the number of stocks with capital gains (losses) in the investor's portfolio plus one. z-values are computed from stock-day-clustered residuals. "Low volume stocks" are the 118 stocks with fewer than an average of 10 trades per day. "High volume stocks" are the 94 stocks with more than an average of 10 trades per day. I estimate the regressions separately for the four simulated trader types. Each simulated trader randomizes over all stocks when deciding what to buy and over all holdings when deciding what to sell.

Sample	Simulated Trader Type	Loss Variable: Moderate	Loss Variable: Extreme	N	Pseudo R^2
All Stocks	Market Orders	0.225	0.237	2,301,748	0.002
		(14.73)	(8.88)		
	Most-Aggressive Limit Orders	0.000	−0.013	2,449,401	0.007
		(0.02)	(−0.64)		
	Less-Aggressive Limit Orders	−0.206	−0.239	2,055,317	0.015
		(−4.35)	(−6.15)		
	Least-Aggressive Limit Orders	−0.583	−0.666	2,203,879	0.043
		(−6.89)	(−8.19)		
Low Volume Stocks	Market Orders	0.490	0.547	243,152	0.005
		(24.96)	(22.11)		
	Most-Aggressive Limit Orders	−0.112	−0.320	211,455	0.026
		(−3.96)	(−8.49)		
	Less-Aggressive Limit Orders	−0.331	−0.486	172,563	0.031
		(−8.18)	(−8.42)		
	Least-Aggressive Limit Orders	−0.771	−1.064	168,093	0.067
		(−10.77)	(−10.18)		
High Volume Stocks	Market Orders	0.189	0.205	2,058,596	0.002
		(11.38)	(7.15)		
	Most-Aggressive Limit Orders	0.003	0.004	2,237,946	0.002
		(0.12)	(0.21)		
	Less-Aggressive Limit Orders	−0.203	−0.233	1,882,754	0.009
		(−3.95)	(−5.71)		
	Least-Aggressive Limit Orders	−0.578	−0.659	2,035,786	0.033
		(−6.30)	(−7.57)		

Table IV
Simulation Results on the Influence of Limit Order Use on Contrarian Behavior

This table reports regression coefficients and z-values for four logit regressions. The dependent variable takes the value of one when an investor sells a stock and the value of zero when an investor purchases a stock. I regress this variable against eight variables representing the stock's own past returns. The regressions also include stock and month fixed effects. z-values are computed from stock-month-clustered residuals. "Low volume stocks" are the 118 stocks with fewer than an average of 10 trades per day. "High volume stocks" are the 94 stocks with more than an average of 10 trades per day. I estimate the regressions separately for the three simulated limit order trader types. Each simulated trader randomizes over all stocks when deciding what to buy and over all holdings when deciding what to sell.

		Simulated Trader Type					
	Explanatory	Most-Aggressive Limit Orders		Less-Aggressive Limit Orders		Least-Aggressive Limit Orders	
Sample	Variable	$\hat{b}$	z	$\hat{b}$	z	$\hat{b}$	z
All Stocks	r_0	5.497	11.12	37.453	23.32	38.280	14.39
	r_{t-1}	−0.435	−4.99	5.037	9.26	38.072	14.91
	r_{t-2}	−0.350	−4.98	−1.625	−4.23	7.399	5.24
	r_{t-3}	−0.192	−2.28	−1.843	−5.08	3.660	2.57
	r_{t-4}	−0.227	−3.46	−1.995	−5.52	0.005	0.00
	$r_{[t-19,t-5]}$	−0.041	−1.80	−0.431	−3.80	−0.830	−2.48
	$r_{[t-39,t-20]}$	0.001	0.10	−0.126	−1.74	−0.464	−1.64
	$r_{[t-60,t-40]}$	−0.005	−0.74	−0.007	−0.21	−0.011	−0.15
	N	2,357,882		2,085,795		2,316,129	
	Pseudo R^2	0.013		0.286		0.602	
Low Volume Stocks	r_0	28.138	37.71	47.174	31.86	55.544	22.79
	r_{t-1}	7.254	13.87	22.658	16.45	52.596	19.94
	r_{t-2}	3.110	8.02	8.900	9.49	30.731	12.21
	r_{t-3}	1.996	5.88	5.045	6.95	14.337	6.58
	r_{t-4}	1.511	4.27	2.983	4.79	11.043	5.28
	$r_{[t-19,t-5]}$	0.331	1.93	0.274	1.06	2.049	3.88
	$r_{[t-39,t-20]}$	0.036	0.39	−0.186	−1.05	−0.454	−0.87
	$r_{[t-60,t-40]}$	−0.009	−0.10	−0.120	−0.68	0.307	0.70
	N	165,512		135,196		105,370	
	Pseudo R^2	0.159		0.374		0.679	
High Volume Stocks	r_0	4.555	11.03	37.089	22.14	38.961	14.96
	r_{t-1}	−0.503	−6.44	4.538	8.42	37.842	15.47
	r_{t-2}	−0.362	−5.93	−1.853	−4.70	6.997	5.09
	r_{t-3}	−0.161	−2.23	−1.978	−5.29	3.414	2.39
	r_{t-4}	−0.228	−3.73	−2.079	−5.58	0.072	0.06
	$r_{[t-19,t-5]}$	−0.036	−1.75	−0.430	−3.65	−0.812	−2.26
	$r_{[t-39,t-20]}$	0.001	0.11	−0.118	−1.59	−0.463	−1.72
	$r_{[t-60,t-40]}$	−0.004	−0.73	−0.006	−0.17	−0.032	−0.52
	N	2,192,370		1,950,599		1,998,193	
	Pseudo R^2	0.009		0.283		0.606	

Table V
Returns on Individual Investors' Orders Executed around Earnings Announcements

This table reports average log-returns for orders executed on days with earnings announcements. The sample comprises all 586 expected (Panel A) and 117 unexpected (Panel B) earnings announcements released during regular trading hours from September 18, 1998 through October 23, 2001. I divide the trading day into three periods: the before period contains orders executed before the announcement; the during period contains orders executed within the first five minutes after the announcement; and the after period contains orders executed after these five minutes. This table reports average returns for all trades, market order trades, old limit order trades, and new limit order trades. Old limit orders are orders submitted before the announcement arrives; new limit orders are orders submitted after the announcement arrives. t-values are computed from announcement-clustered residuals.

Panel A: Expected Earnings Announcements								
			Returns (%)					
		Number of	Same Day		One Week		Two Weeks	
Order Type	Period	Trades	Mean	t	Mean	t	Mean	t
All	Before	17,886	−0.50	−0.58	−0.61	−0.51	−0.98	−0.79
Orders	During	4,006	−1.02	−1.87	−2.03	−2.77	−2.61	−3.13
	After	56,867	−0.69	−1.42	−1.65	−2.05	−2.42	−3.00
Market	Before	7,898	−1.08	−0.93	−1.21	−0.76	−1.43	−0.84
Orders	During	1,363	1.62	2.00	2.51	1.99	3.10	2.33
	After	26,638	−0.79	−1.27	−1.40	−1.30	−1.59	−1.64
Old Limit	Before	9,988	−0.04	−0.07	−0.14	−0.15	−0.63	−0.66
Orders	During	2,338	−2.69	−2.00	−4.93	−2.68	−6.20	−3.40
	After	8,665	−0.34	−1.61	−0.79	−1.87	−0.94	−1.32
New Limit	During	305	−0.02	−0.02	−0.11	−0.08	−0.66	−0.39
Orders	After	21,564	−0.69	−1.53	−2.30	−2.41	−4.06	−2.58
Panel B: Unexpected Earnings Announcements								
All	Before	6,866	−1.87	−1.70	0.90	0.77	1.91	1.36
Orders	During	1,773	−4.53	−2.56	−4.34	−1.20	−4.99	−1.20
	After	22,696	−1.38	−2.75	−4.14	−1.62	−3.62	−1.09
Market	Before	3,001	−2.13	−2.66	1.60	0.93	2.86	1.46
Orders	During	402	4.02	1.54	9.17	2.29	9.76	2.78
	After	11,438	−1.45	−2.39	−4.30	−1.63	−4.12	−1.17
Old Limit	Before	3,865	−1.66	−1.12	0.36	0.35	1.18	0.81
Orders	During	1,218	−7.16	−2.59	−8.23	−1.56	−9.22	−1.57
	After	2,114	−1.63	−2.01	−3.38	−1.05	−2.70	−0.76
New Limit	During	153	−6.09	−1.60	−8.88	−1.28	−10.05	−1.35
Orders	After	9,144	−1.23	−2.48	−4.12	−1.70	−3.20	−1.01

Table VI
Returns on Individual Investors' Buy-Minus-Sell Portfolios Conditional on Order Choice

This table reports average cumulative returns for a strategy that mimics individual investors' purchases and sales. I construct a buy (sell) portfolio each day for all trades, market order trades, and limit order trades. The buy (sell) portfolio weights different stocks in proportion to the number of purchases (sales) across these stocks. I net purchases and sales for each stock and day so that each stock enters either the buy or the sell portfolio, but not both. The strategies examined in this table buy one unit of the buy portfolio and sell one unit of the sell portfolio. I compute the returns without overlap by forming a calendar-time portfolio that rebalances a fraction $\frac{1}{T}$ of the portfolio each day. On day t, I invest $\frac{1}{T}$ of the portfolio in a strategy that buys and sells stocks on day $t-1$; another $\frac{1}{T}$ is invested in a strategy that buys and sells stocks on day $t-2$; and so on. I multiply these one-day returns by the number of days in the holding period. This table reports average returns. The associated t-values appear in parentheses. A market orders-minus-limit orders strategy buys one unit of the market order-based portfolio and sells one unit of the limit order-based portfolio. The unexecuted limit orders strategy constructs both the buy and sell portfolios from individuals' unexecuted limit orders. I use a probit model to identify individual investors' unexecuted limit orders in the microstructure data. The sample contains Finnish individuals' market and limit order trades from September 18, 1998 through October 23, 2001.

	Cumulative Holding Period Return (%)					
	Length of the Holding Period in Days					
Order Type	1	5	10	21	63	126
All Orders	−0.144	0.539	0.958	1.006	−0.546	−1.480
	(−1.86)	(2.09)	(2.19)	(1.28)	(−0.26)	(−0.41)
Market Orders	0.442	1.066	1.412	2.239	3.544	3.695
	(4.55)	(3.90)	(3.26)	(2.93)	(1.92)	(1.19)
Limit Orders	−0.507	−0.110	0.147	−0.577	−3.307	−4.551
	(−5.40)	(−0.48)	(0.43)	(−1.00)	(−2.27)	(−1.77)
Market Orders-minus-Limit Orders	0.948	1.176	1.265	2.816	6.851	8.246
	(5.89)	(3.21)	(2.45)	(3.22)	(3.72)	(2.59)
Unexecuted Limit Orders	0.788	1.021	1.188	1.148	1.046	−1.922
	(8.83)	(3.38)	(2.27)	(1.18)	(0.41)	(−0.42)
Unexecuted-minus-Executed Limit Orders	1.294	1.131	1.042	1.725	4.353	2.629
	(9.27)	(3.19)	(1.95)	(1.86)	(2.09)	(0.71)

Table VII
Influence of Limit Order Use on the Disposition Effect in Investor Trading Records

Panel A reports coefficients and z-values for nine logit regressions that measure the strength of the disposition effect. Each day that an investor sells a stock, I match the sale against all stocks in the investor's portfolio that are not sold on the same day. The dependent variable takes the value of one when an investor sells a stock and the value of zero when investors keeps the stock. The regressors are dummies associated with extreme ($> 30\%$) and moderate ($< 30\%$) capital losses. The regressions also include stock and month fixed effects and the natural logarithm of the number of stocks with capital gains (losses) in the investor's portfolio plus one. z-values are computed from stock-day-clustered residuals. "Low volume stocks" are the 118 stocks with fewer than an average of 10 trades per day. "High volume stocks" are the 94 stocks with more than an average of 10 trades per day. Panel B reports average coefficients from investor-level regressions. The regressors are the capital loss dummy variable(s), a limit order dummy variable, this dummy variable's interactions with the loss variables, and the number of stocks with capital gains (losses) in the investor's portfolio (unreported). The limit order dummy takes the value of one for limit order trades. In the first set of columns I report weighted average coefficients. The weights are inversely proportional to the variances of the first-stage estimators. I winsorize the standard errors in the left tail of the distribution at the 5% level. The second set of columns reports the fraction of positive coefficients along with t-values for the test that each fraction is equal to $\frac{1}{2}$.

Panel A: Pooled Logit Regressions

		Order Type					
	Loss	All Orders		Market Orders		Limit Orders	
Sample	Variable	$\hat{b}$	N, R^2	$\hat{b}$	N, R^2	$\hat{b}$	N, R^2
All Stocks	Moderate	−0.81	4,963,777	−0.43	2,218,199	−1.14	2,745,578
		(−93.4)	0.120	(−44.2)	0.104	(−109.9)	0.141
	Extreme	−1.34		−0.92		−1.71	
		(−106.5)		(−69.1)		(−111.8)	
Low Volume Stocks	Moderate	−0.85	642,886	−0.35	276,686	−1.24	366,200
		(−55.1)	0.138	(−16.6)	0.117	(−60.6)	0.170
	Extreme	−1.07		−0.56		−1.52	
		(−52.5)		(−21.0)		(−54.4)	
High Volume Stocks	Moderate	−0.81	4,320,891	−0.44	1,941,513	−1.13	2,379,378
		(−84.9)	0.115	(−41.7)	0.100	(−99.5)	0.135
	Extreme	−1.38		−0.97		−1.75	
		(−100.5)		(−66.9)		(−104.9)	

Panel B: Investor-level Regressions with Limit Order Interactions					
	Independent	Coefficients		Fraction Positive	
Model	Variable	Mean	t	Mean	t
I ($N = 23{,}002$)	Moderate Loss	−0.061	−54.8	0.332	−54.2
	Extreme Loss	−0.087	−71.0	0.297	−67.6
	Limit Order	0.015	30.8	0.576	23.5
	∗ Moderate Loss	−0.033	−30.8	0.428	−22.0
	∗ Extreme Loss	−0.034	−32.5	0.421	−24.1
II ($N = 36{,}163$)	Loss	−0.071	−70.0	0.354	−57.9
	Limit Order	0.016	33.0	0.556	21.4
	∗ Loss	−0.036	−38.9	0.427	−28.0

Table VIII
Influence of Limit Order Use on Contrarian Behavior in Investor Trading Records

Panel A reports coefficients and z-values for nine logit regressions in which the dependent variable takes the value of one when an investor sells a stock and the value of zero when an investor purchases a stock. I regress this dummy variable against eight variables representing the stock's own past returns. The regressions also include stock and month fixed effects. z-values are computed from stock-month-clustered residuals. "Low volume stocks" are the 118 stocks with fewer than an average of 10 trades per day. "High volume stocks" are the 94 stocks with more than an average of 10 trades per day. Panel B reports the average coefficients from investor-level regressions. The regressors are the first five past return variables, a limit order dummy variable, and this dummy variable's interactions with the past return variables. The limit order dummy takes the value of one for limit order trades. The first set of columns reports weighted average coefficients. The weights are inversely proportional to the variances of the first-stage estimators. I winsorize the standard errors in the left tail of the distribution at the 5% level. The second set of columns reports the fraction of positive coefficients and t-values for the test that each fraction is equal to $\frac{1}{2}$.

Panel A: Pooled Logit Regressions

Sample	Order Type	Return Interval Relative to Trading Day t: [0]	[−1]	[−2]	[−3]	[−4]	[−19, −5]	[−39, −20]	[−60, −40]	N, R^2
All Stocks	All Orders	2.18	0.65	0.60	0.59	0.25	0.12	0.13	0.10	2,301,669
		(15.20)	(8.98)	(8.69)	(8.18)	(1.90)	(2.92)	(4.90)	(4.47)	0.012
	Market Orders	−1.18	0.29	0.63	0.46	0.46	0.14	0.12	0.10	1,119,132
		(−7.32)	(3.68)	(6.96)	(5.50)	(5.42)	(2.55)	(4.13)	(3.57)	0.015
	Limit Orders	6.79	1.11	0.70	0.74	0.22	0.11	0.13	0.10	1,182,536
		(17.57)	(9.24)	(6.42)	(5.57)	(1.77)	(2.09)	(3.96)	(3.63)	0.047
Low Volume Stocks	All Orders	1.38	0.38	0.66	0.54	0.82	0.51	0.28	0.28	171,705
		(3.73)	(3.67)	(3.73)	(4.36)	(4.94)	(7.93)	(6.56)	(6.70)	0.014
	Market Orders	−8.85	−1.64	−0.63	−0.95	−0.52	−0.12	0.00	0.16	82,168
		(−7.83)	(−3.24)	(−2.57)	(−3.87)	(−1.94)	(−1.38)	(−0.02)	(1.95)	0.058
	Limit Orders	14.69	2.88	1.73	2.24	2.11	1.21	0.61	0.39	89,536
		(8.41)	(3.68)	(4.47)	(7.51)	(6.32)	(10.73)	(6.85)	(4.14)	0.095
High Volume Stocks	All Orders	2.22	0.66	0.60	0.60	0.24	0.11	0.13	0.10	2,129,964
		(14.79)	(8.64)	(8.30)	(7.86)	(1.69)	(2.81)	(4.75)	(4.27)	0.012
	Market Orders	−0.96	0.34	0.65	0.50	0.46	0.14	0.12	0.10	1,036,964
		(−6.32)	(4.17)	(7.05)	(5.83)	(5.45)	(2.47)	(4.08)	(3.50)	0.014
	Limit Orders	6.51	1.07	0.67	0.70	0.18	0.09	0.13	0.10	1,093,000
		(16.93)	(8.82)	(5.99)	(5.25)	(1.38)	(1.82)	(3.82)	(3.43)	0.045

Panel B: Investor-level Regressions with Limit Order Interactions (N = 16,094)				
	Coefficients		Fraction Positive	
Explanatory Variable	Mean	t	Mean	t
r_0	−0.264	−14.1	0.473	−6.9
r_{t-1}	0.123	5.7	0.532	8.0
r_{t-2}	0.116	5.7	0.532	8.1
r_{t-3}	0.044	1.8	0.516	4.0
r_{t-4}	−0.014	−0.6	0.510	2.6
Limit Order	−0.019	−10.8	0.476	−6.0
$* r_0$	1.470	56.8	0.691	52.5
$* r_{t-1}$	0.193	6.1	0.527	6.7
$* r_{t-2}$	0.058	1.9	0.510	2.5
$* r_{t-3}$	0.153	4.0	0.512	3.0
$* r_{t-4}$	0.035	1.0	0.502	0.5

Table IX
Intraday Returns in Transactions between Individual and Institutional Investors

This table reports same-day returns for individual investors' and institutional investors' executed limit orders. The sample consists of all trades on the Helsinki Stock Exchange from September 18, 1998 through October 23, 2001, where both sides have been successfully matched to the FCSD data set. Average returns are computed separately depending on who placed the limit order and who hit the limit order by submitting a market order. Each executed limit order's return is computed as the log-return from the transaction price to the closing bid-ask spread midpoint. The signs are reversed for sell limit orders so that positive numbers indicate better performance. t-values are computed from stock-day-clustered residuals.

		Return from Transaction to the Close (%)							
Limit		Market Order Investor							
Order	Order	Individual			Institution			Both	
Investor	Direction	N	Mean	t	N	Mean	t	Mean	t
Individual	Buy	250,006	0.115	2.90	385,216	−0.293	−5.14	−0.133	−2.84
Investor	Sell	239,729	0.508	10.50	352,440	−0.049	−1.22	0.176	4.42
	Both	489,735	0.307	23.42	737,656	−0.177	−7.45	0.016	1.03
Institutional	Buy	259,712	0.244	6.68	1,099,757	−0.020	−0.29	0.030	0.48
Investor	Sell	311,527	0.544	9.27	1,192,809	0.031	0.47	0.137	2.21
	Both	571,239	0.408	17.85	2,292,566	0.006	1.04	0.086	12.19
Both	Buy	509,718	0.181	5.30	1,484,973	−0.091	−1.46	−0.022	−0.41
	Sell	551,256	0.528	10.66	1,545,249	0.013	0.22	0.148	2.85
	Both	1,060,974	0.361	24.29	3,030,222	−0.038	−4.76	0.065	10.81