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Contrarian Trades and Disposition Effect: Evidence from Online Trade Data

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Abstract

Using the data accounting for 793 retail investors' online trading actions (i.e., buy and sell) targeting 3,420 Japanese stocks measured in virtually every seconds from April 2013 to March 2016, we identify the association of those precisely measured trading actions with the daily and intraday returns of those stocks. The results obtained from our estimation show that, on average, the individual investors make contrarian trades and are disposition investors with respect to intraday return. We also confirm that the intraday returns explain investment actions to much larger extent than the daily-level return does for frequent traders, large-cap stocks, and female investors. These results suggest that the determinants of investment actions crucially depend on the heterogeneity of individuals and stocks.

JEL Classification Number: G11, G02

Key Words: *Contrarian*; *disposition effect, retail investors*; *online trade; high-frequency data*

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1. Introduction

The trading pattern of individual (retail) investors has long been large interests of both academic researchers and practitioners (Barber and Odean 2013). This is partly because their trading actions tend to be behavioral and thus could affect security prices in different ways from that associated with institutional investors in various dimensions. Among those, the two major patterns of individual investors reported in the extant studies are "contrarian trading" and "disposition effect". The former accounts for the trading pattern goes against the consensus observed in the market while the latter corresponds to selling stocks with strong past returns and holding onto losers. As these two patterns could generate moderate price dynamics, it has been considered, for example, as a supporting evidence for individual investors' liquidity provision to markets.

Regarding these two behavioral patterns, we should first note that most of the extant studies on the contrarian trade (Choe et al. 1999; Grinblatt and Kelharju 2000, 2001; Griffin et al. 2003; Kaniel et a. 2008) and the disposition effect (Shefrin and Statman 1985; Odean 1998; Grinblatt and Keloharju 2001) rely on the data accounting for the investments through large brokerage firms. Although some of the studies intensively employ the information obtained from not only large discount brokerage firms but full-service brokerage firms, we still do not know if such trading patterns are pervasive in other investment environments such as online stock trading. It has been reported that the introduction of online trading has made it much easier for individual investors to participate financial market, and thus contributed to the growth in the number of individual investors in financial markets (Barber and Odean 2002). Given the presumption that those who recently enter the financial markets might exhibit different behavioral patterns from those have been transacted with brokerage firms, it is appropriate to empirically document the patterns of online individual investors' trading activity.

Second, regarding the analyses on the determinants of individual investor actions, it should be noted that most of the extant studies have not necessarily taken care of the intraday investment actions but relied almost exclusively on the action data measured by daily frequency. This simply reflects the data limitation. In order to analyze how return affects detailed investor activities within a day, we need to precisely measure not only the returns over short periods (e.g., minute-by-minute) but also investor activities with precise time-stamp. Given the extant studies have not been fully analyzed the role of return as the determinants of intraday investment activities due to the difficulty to access to the latter information, it is suggestive to examine it especially in the context of online trading where presumably a large number of so-called "day traders" invest.

Third, we should also note that the contrarian trade and the disposition effect have been largely yet separately documented in the abovementioned literature. Only a limited number of studies have paid an attention to the simultaneous treatment of these two stylized facts. For example, Grinblatt and Kelharju (2001) report both the contrarian trade and the disposition effect are observed in their data. However, Barber et al. (2009) document both the buying and selling of individual investors conditional on stock returns to report that individual investors not only sell but also buy stocks with strong past returns, which apparently contradicts to the contrarian trade. To be fair, it is still an open question whether or not these two trading patterns can be simultaneously confirmed.

Against these three backgrounds, first, the present paper examines the pattern of individual investors' online trading actions by using both the records of individuals' investment activities with precise time-stamp as well as intraday and daily frequency return information. Using these unique online stock trading data recorded for four online security firms located in Japan, which account for 793 individual investors and 3,420 stocks over the periods from April 2013 to March 2016, as well as high-frequency data accounting for the individual stock prices, we estimate the investors' responses to the observed returns of those stocks. The responses are measured either buying or selling a specific stock. Estimating the discrete responses (i.e., buy or not, sell or not) to the past return measured over various windows of periods prior to the response, we document the patterns of online individual investors' trading action. If investors tend to buy stocks immediately after the stocks showing negative return, we can interpret it as the individuals are contrarian. Similarly, if investors tend to sell stocks immediately after the stocks showing positive profit but not after showing loss, we can confirm that the disposition effect is pervasive even in online trading environment. Second, we also analyze the returns measured over which window are more informative for explaining investment actions. For this purpose, we examine both the statistical significance and economic significance associated with the estimates. Starting from the model employing only one single window for measuring a return over a specific time period prior to the exact timing of investment action (e.g., past 1 hour prior to a buy action), we also run the model incorporating multiple windows for measuring returns (e.g., past 2 hours to 1 hour, past 1 hour to past 30 minutes, and so on) so that we see which return information contributes to better explanation of investment actions. Third, we also examine how the association between investment actions and past returns depends on the characteristics of investors and stocks. It is natural to presume that, for example, investors (e.g., day traders) paying more attention to stock markets tend to employ the information they have just obtained, and thus react more timely to intraday return. Taking advantage of the rich information accounting for both individual investors and traded stock, we examine if there is any systematic dependence of the above-mentioned behavioral patterns on those characteristics.

The results obtained from our empirical analysis are summarized as follows: First, the individual investors, on average, make contrarian trades. They tend to buy stocks exhibiting lower return, and not only the daily-level return but also the intra-day return explains their buying action. Second, we also found that the individuals are disposition investors. They are willing to realize their capital gain after observing positive benchmark-adjusted return measured over various windows.

Again, both the daily-level return and intra-day return explain the selling action. Interestingly, our back-of-the-envelope calculation further shows that, on average, over the three hours (30 minutes) after individual investors' buying (selling) stocks, the return shows -2.4% (+0.3%) returns statistically significantly away from zero. This result implies the large rooms for retail investors to improve their investment performance by waiting for a while to trade. The two behavioral patterns we found are highly robust against, for example, excluding the investment actions made after market was closed, focusing on the shorter data periods, employ various alterative configurations accounting for "inaction" (i.e., the case of no action in the estimation), extending the periods over which we measure returns, employing alternative configurations accounting for the width of return windows, using linear probability model instead of probit estimation, and controlling for various fixed effects accounting for date-specific, hour-specific, minute-specific, hour-date-specific, investor-specific, and/or stock-specific unobservable factors. The results suggest that the two behavioral patterns reported in the extant studies are confirmed for online stock trading. Third, from the subsample estimations based on the investment frequency of each investors, we found that the intraday returns explain investment actions to much larger extent than the daily-level return does for frequent traders. Also, the dependency of traders' action on the intraday return becomes stronger for the case of large-cap stocks and female investors (in the case of buy action for female). These results imply that the determinants of investment actions crucially depend on the heterogeneity of individuals and stocks. To summarize, the results from our analysis provide great support to the evidence established in the extant studies, which have been using the data accounting for the transaction through brokerage firms and daily-frequency return information, by further identifying the importance of intraday return information governing online investors' actions within a day and the specific conditions under which such behavioral patterns become more apparent.

The contributions of the present paper are at least threefold. First, as far as we concern, this is the first paper to empirically confirm the behavioral patterns of contrarian trading and the disposition effect in the context of online stock trading, which has not been intensively examined due to the difficulty to access comprehensive online trading data. Second, the present paper contributes to the discussion on the examination of those two pattern of individual investors through the employment of individual investment activity records and stock prices both measured in very short time-grid, and document the fact that the return information measured over such short time-grid is informative, especially for frequent trades, large-cap stocks, female investors. Third, against the mixed results in the extant studies (e.g., Barber et al. 2009; Grinblatt and Keloharju 2001), our estimate results based on these precise data provide consistent pictures with separately documented trading patterns.

The rest of the paper proceeds as follows. Section 2 briefly reviews the relevant literature and discusses the contribution of this study, while Section 3 and 4 describes the empirical methodology and the data we use for our analysis. Section 5 then presents and discusses the results, and Section

6 concludes.

2. Related studies

As a prominent paper documenting the contrarian trade pattern, Choe et al. (1999) employs Korean stock exchange data to document that Korean individual investors showed contrarian trade pattern during the Asian financial crisis in the end of 1990s. In the similar spirit, Grinblatt and Kelharju (2000, 2001) establish such a pattern by using the individual trading information in Finland. Griffin et al. (2003) also focus on the individual investors in Nasdaq 100 securities and find net individual trading negatively followed past intra-daily excess stock returns. Finally, Kaniel et al. (2008) focuses on returns for a large cross-section of NYSE stocks, and find that individuals tend to buy stocks following declines in the previous month and sell following price increases.

The disposition effect is documented, for example, in Odean (1998), which uses the individual trade records provided by stock brokerage firms, reports that winner stock is more likely to be sold earlier while the losers tend to be held onto. Grinblatt and Keloharju (2001) used the individual trade information to regress the dummy variable accounting for selling activity on the past return of the stock, and confirm the positive association between the selling and the past return. As another example, Shapira and Venezia (2001) employ the individual stock trade records provided by brokerage firms in Israel. They document the duration of round trip, which is measured as a length of period between stock purchase and selling, tends to be shorter for winner than for loser. Note that some extant studies (Lakonishok and Smidt 1986; Ferris et al. 1988) discuss the aggregate implication of these two trading patterns and presume that it contribute to the stabilization effect of stock prices.

Regarding the individual heterogeneity, for example, Grinblatt and Keloharju (2001) report that less sophisticated investors including individuals, government, and NPOs are more likely to show the disposition effect. They report that foreign investors tend to be momentum investors while domestic investors tend to show the disposition effect. Odean (1998) also reports higher tendency for individual investors to exhibit the disposition effect. Shapira and Venezia (2001) confirms that the disposition effect is observed both for individual and institutional investors, but the former shows higher tendency of the disposition effect. Choe et al. (2005) and Kang and Stulz (1997) also provide the discussion related to the heterogeneity among investors.

As already mentioned, the employment of the data accounting for individuals' online trading activities with precise time-stamp combined with high-frequency stock price data differentiates the present study from the abovementioned studies. For example, although Griffin et al. (2003) employ the intraday return as the independent variables, the investment actions are measured only in daily-frequency, which makes it difficult to examine the precise association between investment actions and returns over finely measured windows. As far as we concern, the present paper is the first to employ the data allowing such study, and thus complement the discussions in the extant studies.

Note that the two patterns associated with individual investors have been interpreted in the context of behavioral finance such as loss-aversion (Kahneman and Tversky 1979) and anchoring. We do not provide a comprehensive list of studies accounting for the interpretation of the trading pattern but focus on the documentation of the empirical facts in the present paper.

3. Empirical methodology

Consider an individual investor i faces the trading opportunity (i.e., buy and sell) of the stock s at time t. We assume that the return of the stock s denoted as $r(i,s,t,\Delta t)$, which is measured over the past time horizon $[t-\Delta t, t]$ where Δt takes either 1 minute, 15 minutes, 30 minutes, 60 minutes, 120 minutes, 180 minutes, 1 day, 2 days, 3 days, 4 days, or 1 week, determines whether the investor i takes a specific trading action j consisting of $j \in \{buy, sell\}$ for stock s. Note that as we count the number of the days by referring business day, for example, 1week corresponds to $\Delta t = 5\ days$. We call this return $r(i,s,t,\Delta t)$ as "overlapped" return.

Alternatively, we define the return of the stock s denoted as $r(i,s,t2'(\tau),t2)$, which we call as "non-overlapped" return and is measured over the time horizon $[t2'(\tau), t2(\tau)]$ where $[t2'^{(\tau)}, t2(\tau)]$ takes one of the non-overlapped intervals [*t*-1 minute, *t*], [*t*-15 minutes, *t*-1 minute], [*t*-30 minutes, *t*-15 minutes], [*t*-60 minutes, *t*-30 minutes], [*t*-120 minutes, *t*-60 minutes], [*t*-180 minutes, *t*-120 minutes], or [*t*-1 day, *t*-180 minutes] measured for each data point *t*. Then, we assume the vector of $r(i,s,t2'(\tau),t2(\tau))$ determines whether the investor i takes a specific trading action j for the stock s at time *t*.

In order to focus on the return associated with each individual stock, we subtract the return of market index (TOPIX) from the return measured for each individual stock and compute the benchmark-adjusted return. All these benchmark-adjusted returns are converted to one-minute return measured as percentage points so that the magnitude is comparable with each other.

Let $L(i,j,s,t)$ as a dummy variable taking the value of one if the investor i takes the action j for stock s at time t while zero otherwise. This can be modeled as the following probit specification where L^* denotes the latent variable:

$$L(i,j,s,t) = \begin{cases} 1\ if\ L^*(i,j,s,t) \geq 0 \\ 0\ if\ L^*(i,j,s,t) < 0 \end{cases} \tag{1}$$

where

$$L^*(i,j,s,t) = \alpha^j + \beta^j r(i,s,t,\Delta t) + \varepsilon(i,s,j,t) \quad \text{for} \quad j \in \{buy, sell\}$$

Alternatively, we consider the following model where the vector of the not-overlapped returns jointly determine investors' action.

$$L(i,j,s,t) = \begin{cases} 1 \; if \; L^*(i,j,s,t) \geq 0 \\ 0 \; if \; L^*(i,j,s,t) < 0 \end{cases} \tag{2}$$

where

$$L^*(i,j,s,t) = \alpha^{j(\tau,multi)} + \sum_\tau \beta^{j(\tau,multi)} r(i,s,t2'(\tau),t2(\tau)) + \varepsilon(i,j,s,t) \;\; \text{for} \;\; j \in \{buy, sell\}$$

Assuming the normal distribution for $\varepsilon(i,j,s,t)$, we can estimate the coefficients (α^j, β^j) and $(\alpha^{j(\tau,multi)}, \beta^{jj(\tau,multi)})$ through maximum-likelihood estimation, and compute the marginal effects of each return evaluated at mean. We are interested in the sign of these coefficients and the marginal effects for each $j \in \{buy, sell\}$ and for different configurations of Δt and τ. Taking the model represented by the equation (1), suppose we find $\beta^{buy} < 0$ for a specific Δt. Then, we can infer that individual investors in our dataset are more likely to buy a stock when the stock exhibits negative return over the period $[t - \Delta t, t]$. In other words, those individuals tend to buy losers in terms of the past return. Note that the choice of Δt reflects to what extent each individual investor takes into account the stock return. If the investors pay great attention to minute-by-minute stock price dynamics, $r(i,s,t,\Delta t)$ associated with small Δt largely matters, which will be tested in the present paper.

4. Data

The dataset we use to estimate the equation (1) and (2) consists of the following two databases. First, *WebReport database* constructed by VRI Inc. provides the internet log records of around 12,000 individuals with the basic characteristics of those individuals, who are chosen by RDD (Random Digit Dialing) procedure. The original data are obtained through the customized software installed to each individuals' own PC, which records all the internet access logs through the PCs in each second under an explicit agreement between VRI Inc. and each individual. For the analysis on the present paper, we employ the internet log records over the periods from April 2013 to March 2016. Based on the internet access log information, we extract the log data related to individual investors' stock trading activities such as buying and selling through online trading through four Japanese security firms. The data include 793 retail investors for 3,420 Japanese stocks.[1] Second, we employ the high-

[1] We also have an access to the so-called *WebPAC2* database, which is an auxiliary data set to the *WebReport* database and stores the detailed characteristics of 6,000 investors out of the 12,000 individuals targeted by *WebReport* database. The information spans from education, income, occupancy, etc. In the current version of the paper, we have not used these individual characteristics available only in the *WebPAC2* database and leave the exercises employing it to our future research tasks.

frequency stock price data obtained from Tokyo Stock Exchange (TSE). Merging it to the above-mentioned individual investors' trading records with precise time-stamp, we construct the dataset we use for our estimation.

For setting up the dataset, we identify the actions $j \in \{buy, sell\}$ specifically targeting a stock s and taken by each individual i. Then, we define a dummy variable taking value of one for this action and zero for the records that the individual i is "watching" the order screen of the stock s in their PC monitor. In other words, we compare the investment action actually taken by individuals and inaction by the individuals in terms of its determinants (i.e., returns) with considering the moment of watching the stock s.[2] Note that to measure the timing of each action, we set up 10-minute window and treat the first second of the window as the timing of action when a specific action falls in this interval. We employ this approach to measure the timing of action given the potential delay of electronic transaction in online trading and the possible incompatibility of return data provided by TSE and the ones shown in investors' PC monitor. Further note that, in the case that investment actions are taken during the time when market is closed, we have treated the timing of the most recent market closing (i.e., 11:30 for the break from 11:30 to 12:30 and 15:00 after market is close) as the timing of action.[3]

Regarding the independent variables, we employ the return data of the stocks experiencing some action over the periods from one week (i.e., five business days) prior to the action.[4] Intuitively, this means that individual investors are assumed to decide whether or not to take some action for a specific stock when they are watching the order screen of the specific stock, and take into account the returns up to one week prior to the action for their decision.

First, we summarize the dataset based on the trading activities (i.e., action). The first three columns of Table 1 shows the summary statistics of the actions recorded in our dataset. While watching ($watch$) consists of a large part of the data, there are a certain number of $j \in \{buy, sell\}$.[5] The fourth column shows the dummy variable (mk) taking value of one if the action is taken during the stock market is open. We can see that more than 60% of the records are observed when the market is open. Regarding the gender and age, more than 60% of the records are male individuals and the samples are concentrated in the age older than 50. The variables $indiv\_sell\_many$ and $indiv\_buy\_many$ are the dummy variables taking value of one if the recorded individuals are the ones selling or buying stock more times than the median level measured from our data, respectively.

[2] Although it is only a small number of observations, there are the cases that individual investors suddenly buy or sell a specific stock without opening the screen to watch the stock. Alternatively, we will also consider the five days or one day prior to the timing of the action (i.e., buy or sell) as the window of our analysis. In this case, we are comparing the investment action actually taken by individuals and inaction by the individuals in terms of its determinants (i.e., returns) with considering the five days or one day up to each investment action.

[3] We will do a robustness check taking care of this issue in the later section.

[4] As will show later, alternatively, we employ the return information over the past 20 business days.

[5] In the present paper, we only focus on buy or sell given watching. In this sense, we are examining the intensive margin of the trading actions. We leave the analysis on the extensive margin of trading (i.e., watch or not) for future study.

The variables $core\_code30$ is the dummy variable taking value of one if the stock targeted by actions are in the list of stocks employed to construct TOPIX core 30.

Second, regarding the returns measured from our 0.28 million observations for the triplet (i.e., buy, sell, and watch) spanning over each individual and stock as well as one week window for returns, Panel (a) of Table 2 summarizes $r(i, t, \Delta t)$ and Panel (b) of Table 2 summarizes $r(i, t2'(\tau), t2(\tau))$, respectively.[6] Obviously, the return measure accounting for longer window shows larger dispersion even after we transform it in benchmark-adjusted one-minute return. We need to take into account this feature when we evaluate the contributions of each return measure as the determinants of investment actions.

5. Estimation results

5.1 Action and past return

Panel (a) and (b) of Table 3 summarize the results of the two sets of eleven probit estimations, which repeat the same regression for the equation (1) for each action (*j*) and each interval over which return is measured. We show the marginal effects evaluated at mean associated with the return measure.

First, we confirm that the action denoted by $j = buy$ follows negative return in all the intervals over which return is measured except for the case of r_past_30m (i.e., benchmark-adjusted minute-return over the past 30 minutes to the timing of action $j = buy$), which is not statistically away from zero. These results strongly imply that the individual investors make contrarian trades, in which they tend to buy stocks exhibiting lower return. From the fact that the returns closer to the timing of buying action still play significant role as the determinants of buying action, we also confirm that the intraday return immediately matters for investment actions, which has not been documented in the extant studies (e.g., Griffin et al. 2003).

Regarding the economic impact associated with the past return onto the likelihood of buying action, we need to take into account not only the size of the point estimates of the marginal effects associated with each return (see Panel (a) of Figure 1 where we show the point estimates over the windows) but also the dispersions of the returns over different windows we use to measure return. Panel (a) of Figure 2 plots the multiplication of the point estimates of the marginal effects and the two standard deviations (times -1) of each return corresponding to each window (see the items marked by black circle).[7] We can see that, in terms of the economic impact associated with the decline in return by two standard deviation, not only the daily-level return measure (e.g., r_past_2d and r_past_1d accounting for the returns over $[t - 2\ days, t]$ and $[t - 1\ day, t]$, respectively)

[6] See the appendix for the correlation matrices of these return measures.
[7] For presentation purpose in this figure, we replace the point estimates which are not statistically significantly away from zero with 0.

but also the intra-day return largely contribute to buying action.

Second, we confirm that the action denoted by $j = sell$ follows positive returns in all the cases. This suggests that the individuals are disposition investors who are willing to realize their capital gain after observing positive benchmark-adjusted return. One remark is that we do not use any information associated with the timing for each investor to buy the stock, which is then sold in the data. Given the disposition effect is characterized as selling stocks with strong past returns and holding onto losers, the current analysis using only the return information over the recent periods might not be ideal to identify the disposition effect. Nonetheless, the strong relationship between the returns measured over various windows and the selling action of investors up to some extent implies the existence of disposition effect. Similar to the case of buying action, even the returns closer to the timing of action show the estimates for marginal effects statistically away from zero (see also Panel (b) of Figure 1 where we show the point estimates over the windows). Similar to the case of buying action, Panel (b) of Figure 2 (see the items marked by black circle) plots the multiplication of the point estimates of marginal effects and the two standard deviations of each return corresponding to each window. We can see that the daily-level returns largely explain the action. Nonetheless, we should also note that the intraday returns explain the selling action although the economic impact is relatively small. These results suggest that individual investors use the information over relatively longer periods to take selling actions than they do for buying actions. While there is such a difference between the cases of buying and selling, the presented results jointly suggest that the two behavioral patterns reported in the extant studies are confirmed for online stock trading, and the return measured over relatively short periods explain the behavioral investment actions within a day.

Panel (a) and (b) of Table 4 summarize the results of the two probit estimations for the equation (2) for each action (j). We show the estimated marginal effects associated with the return measure evaluated at mean. As Panel (c) and (d) of Figure 1 which plots the point estimates of the marginal effects with the 95% confidence band for it show, the basic implication we can obtain from the estimation of the equation (2) is consistent with the abovementioned results. First, in the case of $j = buy$, once we include all the return measures corresponding to each non-overlapped window, almost all the returns explaining the investment action are found to be the intraday returns. In particular, the non-overlapped returns such as r_past_60m (i.e., benchmark-adjusted minute-return over the past 60 minutes to the past 30 minutes prior to the action $j = buy$), r_past_120m (i.e., over the past 120 minutes to the past 60 minutes), and r_past_180m (i.e., over the past 180 minutes to the past 120 minutes) largely explain the investment action. Second, in the estimation of $j = sell$ using all the return measures as the independent variables, daily returns (e.g., r_past_2d and r_past_3d, i.e., benchmark-adjusted minute-return over the past two days to the past one day and two days prior to the action $j = sell$, respectively) matter more than the case of $j = buy$. While the intraday returns explain the investment action to some extent, this result again implies that individual investors take some time to process the return information for selling than for buying stocks.

Using these results from the model with multiple returns corresponding to non-overlapped returns, we plot the result of the same exercise as we did for the case of overlapped return (see the items marked by cross and connected by a solid line shown in Panel (a) and Panel (b) of Figure 2). In this case, we plot the multiplication of the point estimates of the marginal effects and the two standard deviation (times -1 in the case of buying) of each return corresponding to each window. First, we confirm again that the intraday returns are the major sources of buying action. Second, regarding selling action, we can reconfirm that the daily-revel returns are the main explanatory variables for the selling action although the intraday return marginally contributes to selling action. These are consistent with the results we have already obtained.

5.2 Action and future return

Does the investment action predict future return? If selling action proxies for supply pressure in the market, the returns following selling action would show negative value. Also, if buying action proxies for demand pressure in the market, it could be the case that the returns following buying action show positive value. In order to test this intuition, we measure the benchmark-adjusted return of stock s bought or sold by individual i denoted by $r(i,s,t3(\tau),t3')$, which is measured over the time horizon $[t3(\tau),t3'(\tau)]$ where $[t3(\tau),t3'(\tau)]$ takes either [0, 1 minute], [1 minute, 15 minutes], [15 minutes, 30 minutes], [30 minutes, 60 minutes], [60 minutes, 120 minutes], [120 minutes, 180 minutes], and [180 minutes, 1 day]. Then, we estimate the association between the vector of $r(i,s,t3(\tau),t3'(\tau))$ and the investor i's specific trading action j for the stock s.

$$L(i,j,t) = \begin{cases} 1\ if\ L^*(i,j,s,t) \geq 0 \\ 0\ if\ L^*(i,j,s,t) < 0 \end{cases} \quad (3)$$

where

$$L^*(i,j,s,t) = \alpha^{j(\tau,multi,future)} + \sum_\tau \beta^{j(\tau,multi,future)} r(i,s,t3(\tau),t3'(\tau)) + \varepsilon(i,j,t)$$

for $j \in \{buy, sell\}$

Table 5 and Figure 3 summarize the results. First, we confirm that the buying action is associated with negative future returns significantly away from zero over each non-overlapped windows up to the three hours after buying action. In order to see the economic implication of the results, our back-of-the-envelope calculation shows that, on average, over such three hours after individual investors' buying stocks, the return shows -2.4% returns.[8] Second, we can also see that the selling

[8] For this calculation, we compute the minute return over such three hours as {(1-0.0170)*(1-0.0058)*(1-0.0071)*(1-0.0185)*(1-0.0259)*(1-0.0083)} to the power of one-sixth. Then, compute the compound return over 180 minutes.

action is associated with positive returns significantly away from zero over each windows up to 30 minutes after the selling action. Again, our back-of-the-envelope calculation shows that, on average, the return shows +0.3% returns statistically significantly away from zero over the 30 minutes. This result implies the rooms for retail investors to improve their investment performance by waiting for a while to trade.

5.2 Robustness check

In this section, we check the robustness of our empirical results with taking into account various concerns about it.

5.2.1 Timing of action

As we have already mentioned, in the case that investment actions are taken during the time when market is closed, we have treated the timing of the most recent market closing (i.e., 11:30 for the break from 11:30 to 12:30 and 15:00 after market is close) as the timing of action. This means that we are assuming investors virtually ignore the elapse of time after those market breaks begin. Given some information inducing investment actions can be observed by investors during such elapse of time, however, this treatment could lead to substantial measurement error associated with returns. Thus, we exclude the data corresponding to the actions taken during the break of markets and repeat the estimation of the equation (2).

The estimated marginal effects are shown in Figure 4. Same as in the previous figures, we replace the marginal effects statistically not away from zero with 0. From these results, we confirm the robustness of the results associated with buying and selling actions. The three intraday returns r_past_60m, r_past_120m, and r_past_180m are the drivers of the action. Also, both the daily and intraday returns explain selling action.

5.2.2 Alternative data periods

We have so far used the investment records from April 2013 to March 2016. In order to see the robustness of the results in the case of sub-periods, we pick up the periods from October 2014 to December 2015, over which we had substantial hike and drop of TOPIX, and repeat all the estimation. From the estimated results, we confirm the robustness of the results associated with buying and selling actions

5.2.3 Configuration for inaction status

As we have already explained in detail, we are treating the records of $j = watch$ as the case of $L(i, j, s, t) = 0$. Although it is only a small number but it could be the case that individual investors buy or sell stocks without going through watching status. Thus, we employ the following two alternative configurations accounting for such "inaction" state accounting for $L(i, j, s, t) = 0$. First, we use five days prior to each action as $L(i, j, s, t) = 0$. In other words, after identifying the actions taken by each individual, we set up the five days of "look-back" periods prior to the timing of the action and use it as the window of our analysis for the action. Second, we change the configuration associated with the number of days prior to the timing of the action to one day. Again, we can confirm the robustness of our results.

5.2.4 Periods for return measure

We have so far employed the vector of returns of the stocks experiencing some action over the periods from one week prior to the action. In order to see the robustness of our results, we extending the return measures up to the past 20 business days (i.e., one month) and employ [*t*-3 week, *t*-2 weeks], and [*t*-1 month, *t*-3 week] on top of the current sets of return windows. Intuitively, this means that we are assuming individual investors decide whether or not to take some action on a specific stock with taking into account the returns up to one month (i.e., 20 business days) prior to the action for their decision. Again, we can confirm the robustness of our results.

5.2.5 Windows for return measure

As an alternative way to set up the return windows, we estimate the following model with $r(i, \mathrm{s}, t3'(\tau),\ t3(\tau))$, which we call as non-overlapped constant-interval return and is measured over the time horizon $[t3'(\tau), t3(\tau)]$ where $\{t3'(\tau), t3(\tau)\}$ takes one of the fifty non-overlapped constant intervals with 30-minute constant window {*t*-30 minute, *t*}, {*t*-60 minutes, *t*-30 minute}, $\cdots$, {*t*-1470 minutes, *t*-1440 minutes}, or {*t*-1500 minutes, *t*-1470 minutes} measured for each data point *t*. As one day corresponds to 300 minutes, we examine the responses of investor actions to each return measured over 30 minutes window over the past five days prior to each action. Then, we assume the vector of $r(i, \mathrm{s}, t3'(\tau), t3(\tau))$ determines whether the investor i takes a specific trading action j for stock s at time *t*. Table 6 shows the summary statistics of these return measures.

$$L(i,j,s,t) = \begin{cases} 1\ if\ L^*(i,j,s,t) \geq 0 \\ 0\ if\ L^*(i,j,s,t) < 0 \end{cases} \tag{4}$$

Where

$$L^*(i,j,s,t) = \alpha^{j(multi')} + \textstyle\sum_\tau \beta^{j(\tau,multi')} r\big(i,s,t3'(\tau),\ t3(\tau)\big) + \varepsilon(i,j,s,t) \ \text{ for } \ j \in \{buy, sell\}$$

The two panels of Figure 5 summarize the point estimates of the marginal effects. For the presentation purpose, we replace the estimates not statistically away from zero with 0. Consistent with the results we have presented so far, the returns relatively close to the timing of action show negative (positive) coefficients statistically away from zero for the case of $j = buy$ $(sell)$. This suggests that our empirical findings are robust to the choice of intervals over which we measure return.

5.2.6 LPM and fixed effects

Given the presumption that there are substantial heterogeneities of investment actions associated with date (e.g., some economic events and/or shocks), hours (e.g., morning vs. afternoon), minute, individual investors (e.g., gender), and stocks (e.g., liquidity), it is important to control for those unobservable individual effects. For this purpose, first, we estimate the linear probability model (LPM) having exactly same dependent and independent variables as we have in the equation (2) and confirm that the estimated coefficients show the same patterns of its signs and statistical significance we found for the marginal effects from the estimation of the equation (2). Then, we estimate the following five linear probability models with controlling for the fixed effects associated with (i) date-specific, hour-specific, and minute-specific unobservable factors, (ii) date- and hour-date-specific unobservable factors, (iii) individual investor-specific unobservable factor, (iv) stock-specific unobservable factor, and (v) individual investor- and stock-specific unobservable factors, respectively. In all these cases, we confirm that the estimated coefficients show the same patterns of its signs and statistical significance.[9]

5.5 Heterogeneous behavioral pattern

The behavioral patterns on individual investors we have confirmed so far is unconditional on investor and stock profiles. In this section, we investigate how the observed behavioral pattern is interacted with individual- and stock-level heterogeneity.

First, we focus on the frequency of each individual's trading. It is natural to presume that those who are trading very often (i.e., "traders") are more likely to pay great attention to minute-by-minute price dynamics of stocks than those who trade less frequently (i.e., "investors"). The data we are using in the present study provide ideal environment to test this intuition. The two panels of Figure 5 summarize the point estimates of the marginal effects based on the two probit estimations of the equation (2) using two subsamples labeled as (i) "Traders" which corresponds to those who takes a larger number of investment actions (buy or sell) than the median level of the data and (ii) "Investors" taking a smaller number of actions than the median. It is clear that only the "traders" react to the intraday returns. Somewhat interestingly, regarding the buy action, we can also see that

[9] Other robustness checks we are planning to do are the follows: (i) Conditioning the sample on the ones not having individual i's selling on stock s action prior to individual i's buying action on stock s so that we can exclude the case of buying from short-cover motives, (ii) explicitly controlling for market upturn and downturn by, for example, including the market return to the list of independent variables, and (iii) using return measures which are not benchmark-adjusted to take into account the possibility that individual investor only care about the absolute level of return.

over some specific return windows (e.g., "r_past_30m" over the past 30 minutes to the past one minute and "r_past_2d" over the past two days to the past one day), the "investors" behave even as market followers. Regarding the sell action, we can also see that the "investors" do not react to the very recent information. These comparison makes it clear how the determinants of investment actions depend on investor heterogeneity.

Second, we focus on the status of large-cap stocks. Large-cap stocks are considered as the ones with larger liquidity and thus, it is less likely to be mispriced. If individual investors take into account this feature, on the one hand, we can presume that it is less likely for the large-cap stock to become the target of the behavioral patterns documented in the present paper. On the other hand, if individual investors are facing some sort of recognition constraint and can pay an attention only to major (i.e., large-cap) stocks, it is more likely for the large-cap stock to become the target of the behavioral patterns. Figure 6 summarize the point estimates of the marginal effects based on the two probit estimations of the equation (2) using two subsamples labeled as (i) "Large-cap" which corresponds to the case that stock s are the components of the TOPIXS-Core 30 and "Not" corresponding to the other stocks. It turns our that behavioral patterns are much stronger for the large-cap stock than for the other stocks. This clear difference implies that individual investors are facing some constraints associated with the recognition of stocks.

Finally, we take into account the difference in investor gender. Specifically, we split our sample based on the gender of investors and redo all the estimation. Figure 7 summarizes the results of the exercise using non-overlapped return window and including all the return. First, we find that regardless of investor gender, the pattern of contrarian trade and disposition effect are observed. Second, nonetheless, we can see that the absolute values of estimated marginal effects for female investors in the case of buying action are much larger than that for male investors. Third, in terms of the disposition effect, the difference between female and male are less clear. These results suggest that gender difference in terms of the two major behavioral investment patterns are not consistently observed for buying and selling action. Note that, as gender could correlate with other individual attributes in our date, we need to simultaneously take into account other characteristics, which we will do in our future research.[10]

6. Concluding remarks

Using online stock trading records, we empirically document the investors trading activities of buying and selling stocks measured with precise time-stamp conditional on the daily and intraday returns of those stocks. The results obtained from our estimation show that the individual investors make

[10] As mentioned in the previous section, we are planning to use the detailed characteristics (e.g., education, income, occupancy, risk aversion, hobby etc) of 6,000 investors out of the 12,000 individuals, which is stored in the *WebPAC2* database.

contrarian trades and the individuals are disposition investors. These results suggest that the two systematic patterns reported in the extant studies are confirmed for online stock trading, and such pattern is driven not only by daily-level return information but also intra-day return. We further confirm that those behavioral patterns crucially depend on the heterogeneity of individual investors and stocks. Unlike the extant studies, these results are based on the data accounting for the investment actions and returns measured over very short time-grid, and thus provide much more clear picture of those behavioral patterns than the extant studies did.

The research presented in this study could be expanded in a number of directions. One such direction would be the complete employment of all the available data in the original dataset as we partly did in the current version of the paper. This allows us to control a number of additional unobservable characteristics associated with, for example, the online security firms and other group-fixed factors (e.g., age, region, climates etc.). Second, such extensive data also allows us to employ more sophisticated methods (e.g., machine learning) for identifying the valid predictors for investor actions. In this direction, we should also pay an attention to the sentiments in stock markets (e.g., sudden shocks from natural disasters and/or political turmoil). Third, based on the results, we can construct investment strategy utilizing individual investment information and test the performance of it. Fourth, a further potentially interesting extension would be to differentiate the results obtained in the present paper by using individual profile (e.g., education, income, occupation etc.) more intensively. Fifth, it is also a promising direction to employ other internet access information. For example, it is sensible to ask whether or not the pattern of individual investors' action depend on other (e.g., distracted) information, which could be proxied for by other internet access (e.g., shopping site) simultaneously done by the individuals. We believe all of these extensions would provide further insights to gain a better understanding of the individual investors' behavior and its impact on financial markets.

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Figure and Table

Table 1: Summary statistics of actions

Variable		Obs	Mean	Std. Dev.	Min	Max
buy	1 if buy	281658	0.04	0.20	0	1
sell	1 if sell	281658	0.03	0.16	0	1
watch	1 if watching	281658	0.97	0.16	0	1
mk	1 if MKT open	281658	0.66	0.48	0	1
gender_m	1 if male	281658	0.62	0.49	0	1
gender_f	1 if female	281658	0.38	0.49	0	1
age	age	281658	59.74	12.25	12	87
age_12to29	1 if young	281658	0.01	0.07	0	1
age_30to49	1 if middle	281658	0.17	0.38	0	1
age_50over	1 if old	281658	0.82	0.38	0	1
indiv_sell_many	Many sell indiv	281658	0.88	0.32	0	1
indiv_buy_many	Many buy indiv	281658	0.88	0.33	0	1
code_core30	TOPIX core 30	281658	0.16	0.37	0	1

Table 2: Summary statistics of return

Panel (a) Overlapped return

(Unit: %)			OR-yes			
Variable	Definition	Obs	Mean	Std. Dev.	Min	Max
r_past_5d	Over t-5days to t	281658	1.26	14.74	-106.60	894.93
r_past_4d	Over t-4days to t	281658	1.08	12.84	-104.42	893.44
r_past_3d	Over t-3days to t	281658	0.88	11.40	-103.47	885.38
r_past_2d	Over t-2days to t	281658	0.65	10.10	-102.24	889.08
r_past_1d	Over t-1day to t	281658	0.34	8.04	-102.80	903.20
r_past_180m	Over t-180minute to t	281658	0.19	6.29	-103.49	896.81
r_past_120m	Over t-120minute to t	281658	0.11	5.25	-103.28	900.99
r_past_60m	Over t-60minute to t	281658	0.07	4.75	-102.96	901.76
r_past_30m	Over t-30minute to t	281658	0.05	4.29	-102.89	902.30
r_past_15m	Over t-15minute to t	281658	0.03	3.43	-102.86	902.46
r_past_1m	Over t-1minute to t	281658	0.00	0.31	-98.98	31.14
r_future_1m	Over t to t+1minute	281658	0.00	0.37	-79.33	39.78
r_future_15m	Over t to t+15minutes	281658	0.05	2.67	-99.71	847.00
r_future_30m	Over t to t+30minutes	281658	0.08	2.91	-99.74	836.97
r_future_60m	Over t to t+60minutes	281658	0.09	3.04	-99.68	828.74
r_futur~120m	Over t to t+120minutes	281658	0.09	3.24	-99.62	808.51
r_futur~180m	Over t to t+180minutes	281658	0.11	4.24	-100.15	847.10
r_future_1d	Over t to t+1day	281658	0.12	5.37	-102.89	858.95
r_future_2d	Over t to t+2days	281658	0.09	7.36	-103.01	957.33
r_future_3d	Over t to t+3days	281658	0.05	8.61	-102.62	982.11
r_future_4d	Over t to t+4days	281658	0.01	9.88	-103.41	943.93
r_future_5d	Over t to t+5days	281658	0.01	11.11	-105.27	903.01

Panel (b) Non-overlapped return

(Unit: %)			OR-no			
Variable	Definition	Obs	Mean	Std. Dev.	Min	Max
r_past_5d	Over t-5days to t-4days	281658	0.13	5.73	-100.73	914.13
r_past_4d	Over t-4days to t-3days	281658	0.15	4.24	-101.17	801.53
r_past_3d	Over t-3days to t-2days	281658	0.18	3.98	-100.73	397.83
r_past_2d	Over t-2days to t-1day	281658	0.28	5.45	-100.73	914.13
r_past_1d	Over t-1day to t-180minute	281658	0.15	5.21	-101.93	889.41
r_past_180m	Over t-180minute to t-120minute	281658	0.08	3.37	-102.40	874.21
r_past_120m	Over t-120minute to t-60minute	281658	0.04	2.18	-100.08	850.17
r_past_60m	Over t-60minute to t-30minute	281658	0.02	1.99	-102.51	847.42
r_past_30m	Over t-30minute to t-15minute	281658	0.02	2.58	-99.82	845.93
r_past_15m	Over t-15minute to t-1minute	281658	0.03	3.41	-102.88	902.44
r_past_1m	Over t-1minute to t	281658	0.00	0.31	-98.98	31.14
r_future_1m	Over t to t+1minute	281658	0.00	0.37	-79.33	39.78
r_future_15m	Over t+1minute to t+15minutes	281658	0.05	2.64	-99.71	846.99
r_future_30m	Over t+15minutes to t+30minutes	281658	0.03	1.11	-98.96	51.60
r_future_60m	Over t+30minutes to t+60minutes	281658	0.00	0.84	-98.96	51.22
r_futur~120m	Over t+60minutes to t+120minutes	281658	0.01	1.06	-89.69	63.62
r_futur~180m	Over t+120minutes to t+180minutes	281658	0.01	2.65	-88.10	850.40
r_future_1d	Over t+180minutes to t+1day	281658	0.01	3.23	-101.85	864.17
r_future_2d	Over t+1day to t+2days	281658	-0.05	4.44	-101.35	874.95
r_future_3d	Over t+2days to t+3days	281658	-0.05	4.14	-101.35	914.13
r_future_4d	Over t+3days to t+4days	281658	-0.04	4.80	-102.11	914.13
r_future_5d	Over t+4days to t+5days	281658	-0.01	4.80	-101.35	914.13

Table 3 Single return model with overlapped periods

Panel (a) Buy

model	action	exp	estimate	std.error	
probit	buy	r_past_5d	-0.0019	0.0004	***
probit	buy	r_past_4d	-0.0023	0.0004	***
probit	buy	r_past_3d	-0.0025	0.0005	***
probit	buy	r_past_2d	-0.0032	0.0006	***
probit	buy	r_past_1d	-0.0031	0.0009	***
probit	buy	r_past_180m	-0.0024	0.0012	**
probit	buy	r_past_120m	-0.0134	0.0014	***
probit	buy	r_past_60m	-0.0138	0.0018	***
probit	buy	r_past_30m	-0.0015	0.0023	
probit	buy	r_past_15m	-0.0248	0.0036	***
probit	buy	r_past_1m	-0.0192	0.0106	*

Panel (b) Sell

model	action	exp	estimate	std.error	
probit	sell	r_past_5d	0.0024	0.0002	***
probit	sell	r_past_4d	0.0027	0.0003	***
probit	sell	r_past_3d	0.0026	0.0003	***
probit	sell	r_past_2d	0.0023	0.0003	***
probit	sell	r_past_1d	0.0019	0.0003	***
probit	sell	r_past_180m	0.0021	0.0004	***
probit	sell	r_past_120m	0.0023	0.0005	***
probit	sell	r_past_60m	0.0019	0.0005	***
probit	sell	r_past_30m	0.0018	0.0006	***
probit	sell	r_past_15m	0.0019	0.0007	***
probit	sell	r_past_1m	0.0746	0.0136	***

Note: The tables summarize the results of eleven probit estimations, which repeat the same regression for the equation (1) for each action (j) and the return interval. We show the marginal effects evaluated at mean associated with the return measure (i.e., β^j). ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Table 4 Multiple return model with non-overlapped periods

Panel (a) Buy

model	action	exp	estimate	std.error	
probit	buy	r_past_5d	-0.0012	0.0011	
probit	buy	r_past_4d	-0.0020	0.0012	*
probit	buy	r_past_3d	-0.0004	0.0011	
probit	buy	r_past_2d	-0.0017	0.0011	
probit	buy	r_past_1d	-0.0017	0.0013	
probit	buy	r_past_180m	-0.0069	0.0022	***
probit	buy	r_past_120m	-0.0131	0.0024	***
probit	buy	r_past_60m	-0.0127	0.0030	***
probit	buy	r_past_30m	0.0008	0.0012	
probit	buy	r_past_15m	-0.0246	0.0038	***
probit	buy	r_past_1m	-0.0180	0.0106	*

Panel (b) Sell

model	action	exp	estimate	std.error	
probit	sell	r_past_5d	0.0012	0.0006	**
probit	sell	r_past_4d	0.0032	0.0009	***
probit	sell	r_past_3d	0.0070	0.0012	***
probit	sell	r_past_2d	0.0027	0.0006	***
probit	sell	r_past_1d	0.0013	0.0006	**
probit	sell	r_past_180m	0.0013	0.0009	
probit	sell	r_past_120m	0.0031	0.0021	
probit	sell	r_past_60m	0.0022	0.0014	
probit	sell	r_past_30m	0.0016	0.0011	
probit	sell	r_past_15m	0.0017	0.0007	**
probit	sell	r_past_1m	0.0722	0.0136	***

Note: The tables summarize the results of two probit estimations for the equation (2) for each action (j) and the return interval. We show the marginal effects evaluated at mean associated with the return measure (i.e., β^j). ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Table 5 Multiple return model with non-overlapped periods

Panel (a) Buy

model	action	exp	estimate	std.error	
probit	buy	r_future_1m	-0.0170	0.0101	*
probit	buy	r_future_15m	-0.0058	0.0024	**
probit	buy	r_future_30m	-0.0071	0.0040	*
probit	buy	r_future_60m	-0.0185	0.0051	***
probit	buy	r_future_120m	-0.0259	0.0039	***
probit	buy	r_future_180m	-0.0083	0.0031	***
probit	buy	r_future_1d	-0.0028	0.0018	
probit	buy	r_future_2d	0.0000	0.0010	
probit	buy	r_future_3d	0.0009	0.0009	
probit	buy	r_future_4d	0.0002	0.0008	
probit	buy	r_future_5d	-0.0004	0.0010	

Panel (b) Sell

model	action	exp	estimate	std.error	
probit	sell	r_future_1m	0.0232	0.0120	*
probit	sell	r_future_15m	0.0028	0.0012	**
probit	sell	r_future_30m	0.0070	0.0040	*
probit	sell	r_future_60m	-0.0061	0.0057	
probit	sell	r_future_120m	0.0056	0.0046	
probit	sell	r_future_180m	0.0022	0.0010	**
probit	sell	r_future_1d	0.0005	0.0013	
probit	sell	r_future_2d	-0.0003	0.0012	
probit	sell	r_future_3d	-0.0004	0.0012	
probit	sell	r_future_4d	-0.0026	0.0014	*
probit	sell	r_future_5d	-0.0003	0.0011	

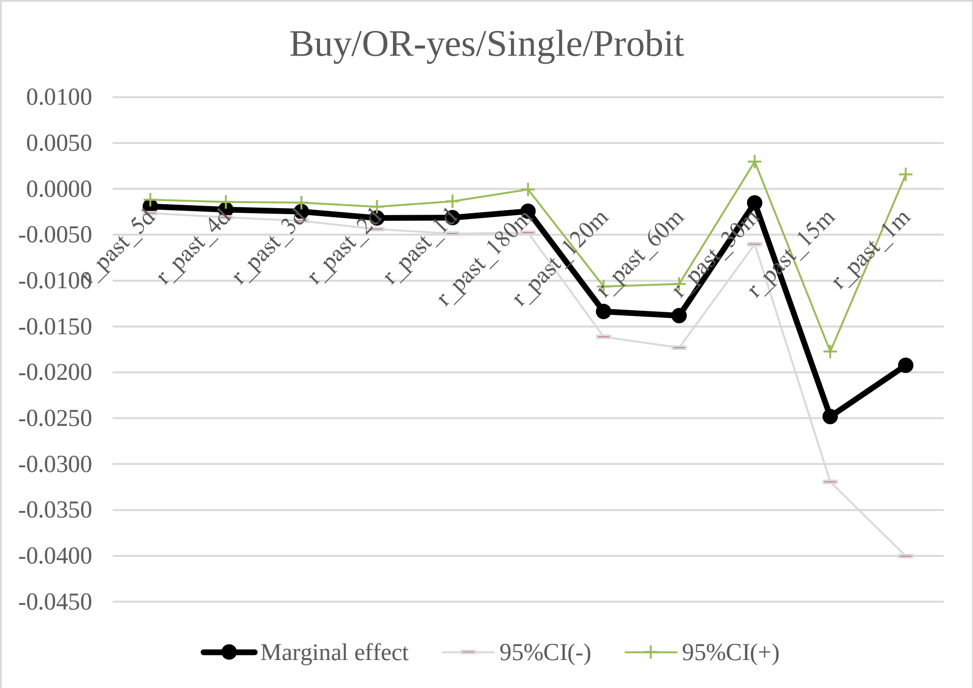
Note: The tables summarize the results of the two probit estimations for the equation (3) for each action (j) and the return interval. We show the marginal effects evaluated at mean associated with the return measure (i.e., β^j). ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Table 6 Summary statistics of the returns over non-overlapped constant windows

(Unit: %)			OR-no			
Variable	Definition	Obs	Mean	Std. Dev.	Min	Max
r_past_1500m	Over t-1500minutes to t-1470minute:	281658	0.04	1.40	-99.61	74.46
r_past_1470m	Over t-1470minutes to t-1440minute:	281658	0.01	0.87	-99.83	56.91
r_past_1440m	·	281658	0.01	1.81	-99.08	871.77
r_past_1410m	·	281658	0.01	0.82	-99.39	38.06
r_past_1380m	·	281658	0.01	1.94	-100.27	848.84
r_past_1350m	·	281658	0.01	0.77	-88.00	43.87
r_past_1320m	·	281658	0.00	0.62	-89.71	38.90
r_past_1290m	·	281658	0.00	0.80	-89.68	41.34
r_past_1260m	·	281658	0.00	1.15	-99.92	395.45
r_past_1230m	·	281658	0.03	4.18	-100.21	893.62
r_past_1200m	·	281658	0.04	1.58	-100.01	74.43
r_past_1170m	·	281658	0.01	0.92	-99.74	73.42
r_past_1140m	·	281658	0.01	0.71	-98.97	35.69
r_past_1110m	·	281658	0.01	0.65	-99.92	38.05
r_past_1080m	·	281658	0.02	1.27	-99.84	301.94
r_past_1050m	·	281658	0.01	1.09	-99.73	301.94
r_past_1020m	·	281658	0.00	0.79	-100.01	48.69
r_past_990m	·	281658	0.01	0.83	-100.47	102.72
r_past_960m	·	281658	0.01	1.42	-100.03	382.87
r_past_930m	·	281658	0.01	1.91	-100.32	61.18
r_past_900m	·	281658	0.06	1.83	-99.70	380.24
r_past_870m	·	281658	0.01	0.88	-99.74	47.58
r_past_840m	·	281658	0.01	0.71	-89.71	32.23
r_past_810m	·	281658	0.01	0.76	-99.43	51.76
r_past_780m	·	281658	0.01	0.96	-99.81	64.89
r_past_750m	·	281658	0.02	0.93	-99.77	49.68
r_past_720m	·	281658	0.01	0.81	-99.74	97.92
r_past_690m	·	281658	0.01	0.92	-99.72	33.15
r_past_660m	·	281658	0.00	0.99	-99.84	36.31
r_past_630m	·	281658	0.01	1.88	-99.87	80.31
r_past_600m	·	281658	0.08	2.03	-99.90	74.62
r_past_570m	·	281658	0.02	0.95	-89.75	61.65
r_past_540m	·	281658	0.02	0.74	-88.64	44.77
r_past_510m	·	281658	0.01	0.77	-100.01	38.05
r_past_480m	·	281658	0.02	1.15	-99.82	105.34
r_past_450m	·	281658	0.03	1.28	-98.99	382.30
r_past_420m	·	281658	0.02	1.26	-98.97	378.72
r_past_390m	·	281658	0.02	1.76	-99.85	836.09
r_past_360m	·	281658	0.02	2.58	-99.09	902.28
r_past_330m	·	281658	0.03	3.14	-102.44	894.18
r_past_300m	·	281658	0.13	3.31	-102.62	836.97
r_past_270m	·	281658	0.03	1.12	-98.95	51.59
r_past_240m	·	281658	0.03	2.48	-99.96	850.21
r_past_210m	·	281658	0.02	1.91	-99.98	836.09
r_past_180m	·	281658	0.03	1.07	-102.87	105.20
r_past_150m	·	281658	0.05	3.14	-99.94	871.26
r_past_120m	·	281658	0.02	0.95	-99.82	44.52
r_past_90m	·	281658	0.02	1.92	-99.79	850.25
r_past_60m	Over t-60minutes to t-30minutes	281658	0.02	1.99	-102.51	847.42
r_past_30m	Over t-30minutes to t	281658	0.05	4.29	-102.89	902.30

Figure 1 Estimated coefficients

Panel (a) Single return model with overlapped periods



Panel (b) Single return model with overlapped periods

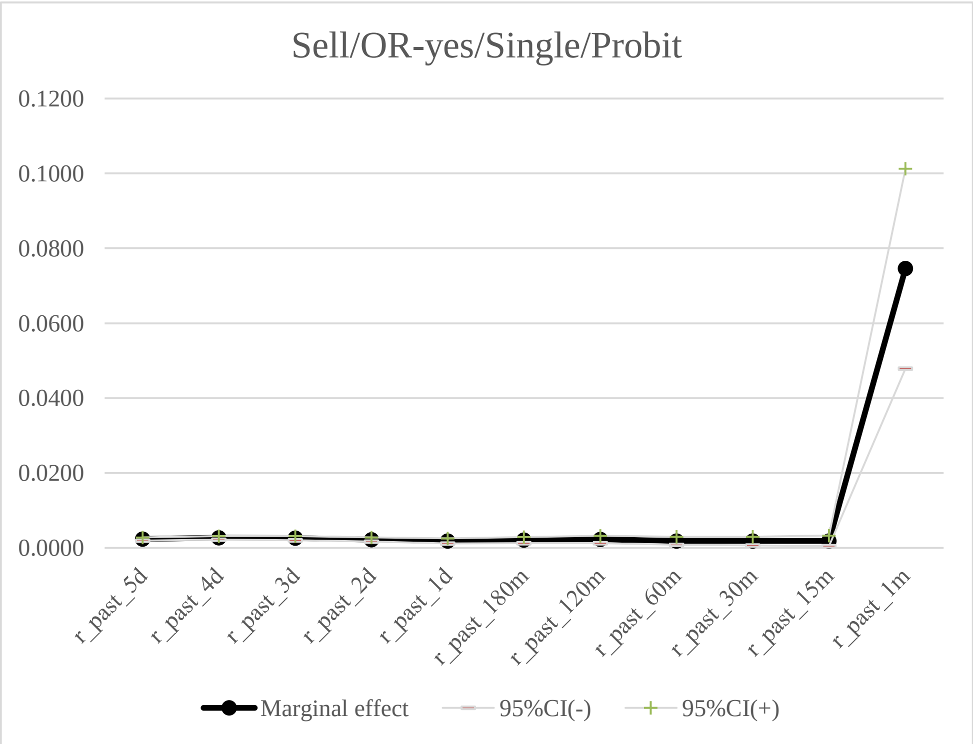
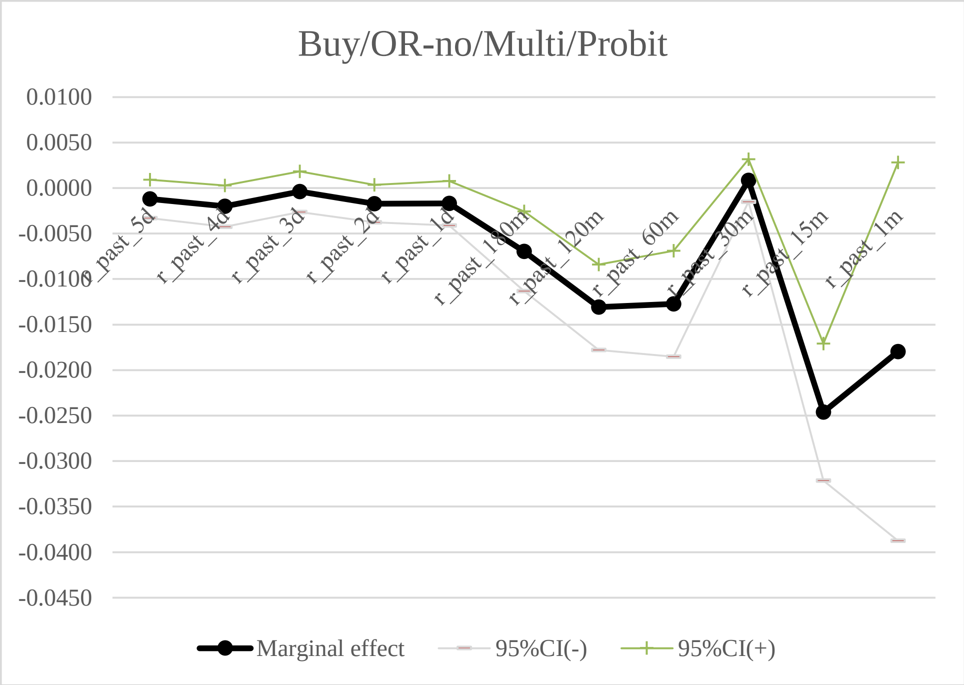


Figure 1 Estimated coefficients (continued)

Panel (c) Multi return model with non-overlapped periods



Panel (d) Multi return model with non-overlapped periods

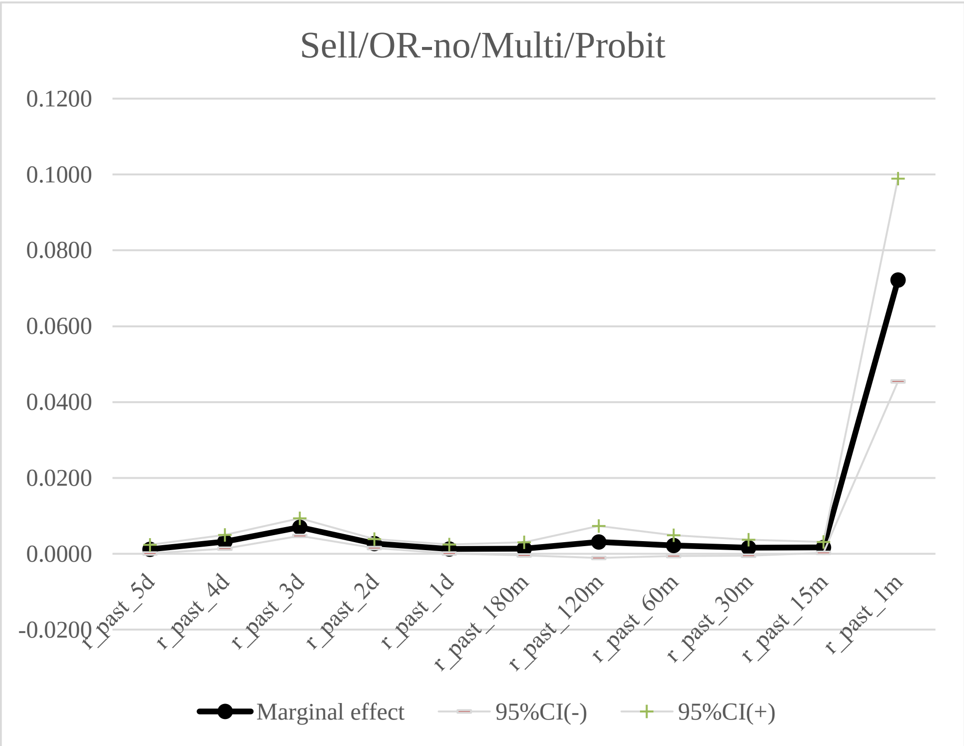
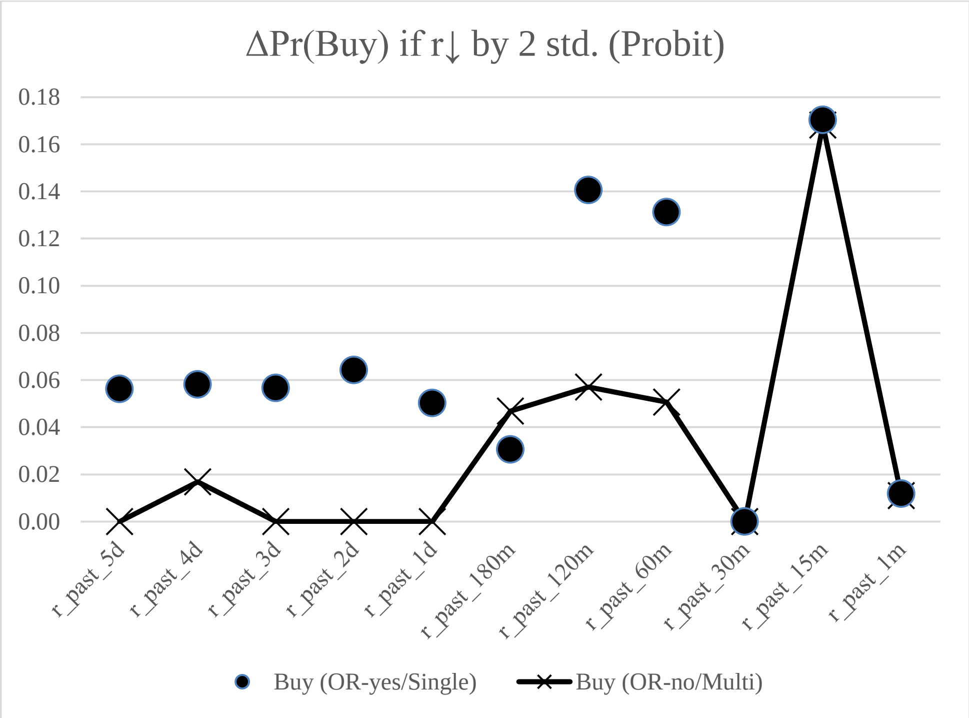


Figure 2 Economic impact

Panel (a) Buy: Single overlapped return



Panel (b) Sell: Single overlapped return

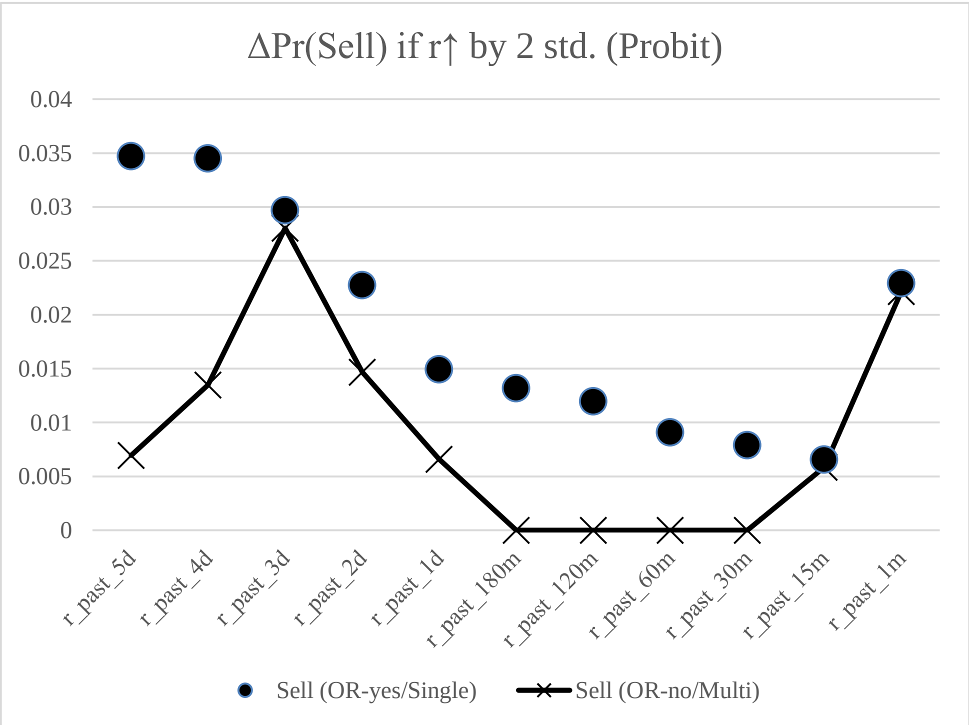
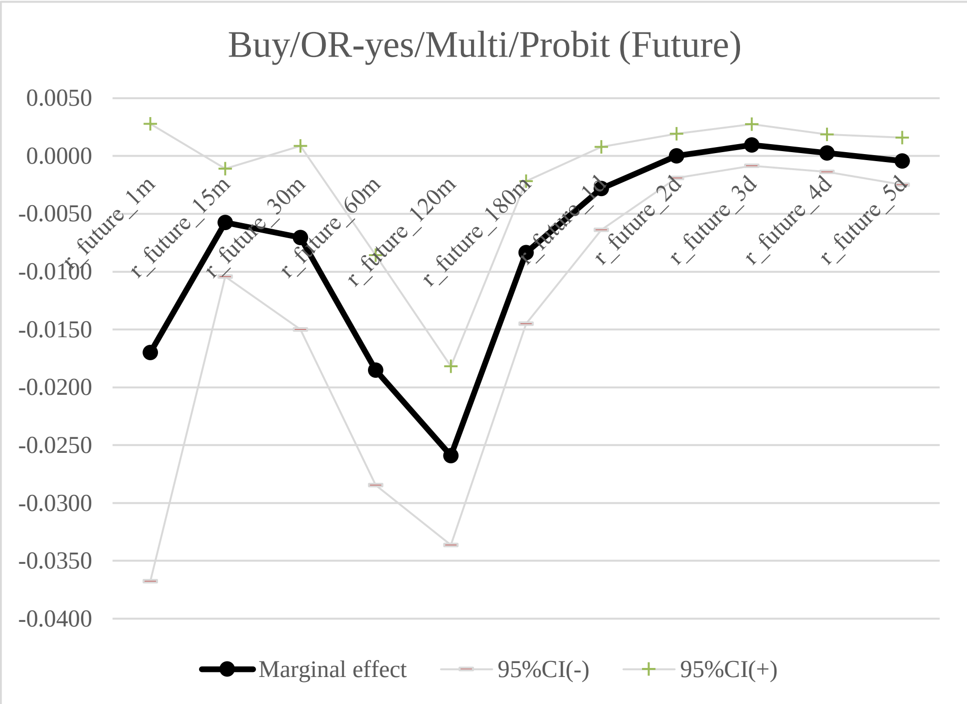


Figure 3 Estimated coefficients

Panel (a) Multi return model with non-overlapped periods



Panel (b) Multi return model with non-overlapped periods

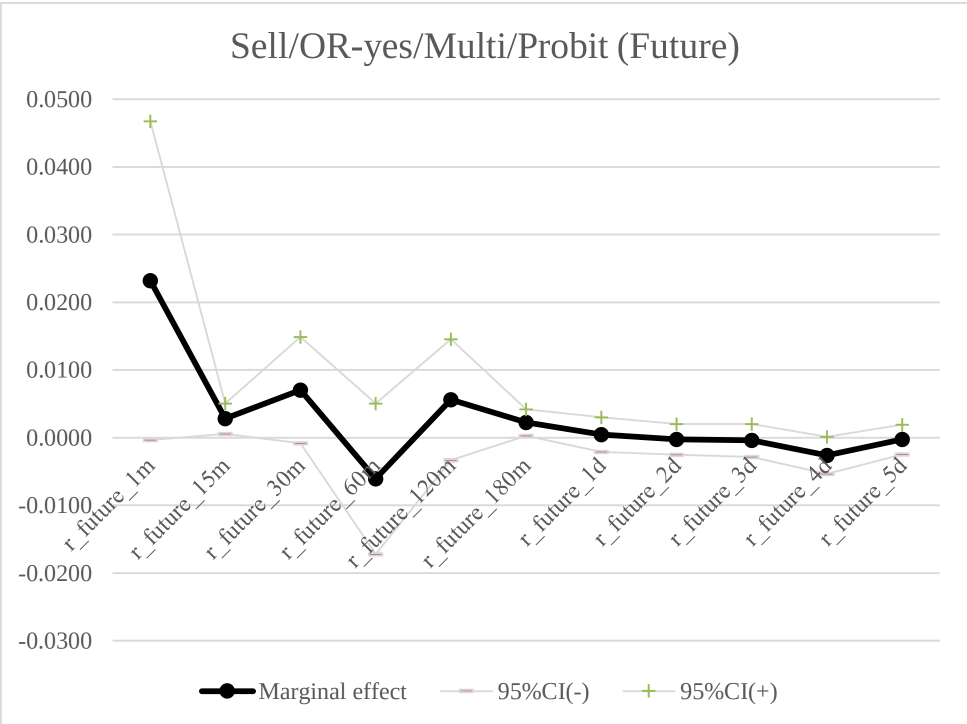
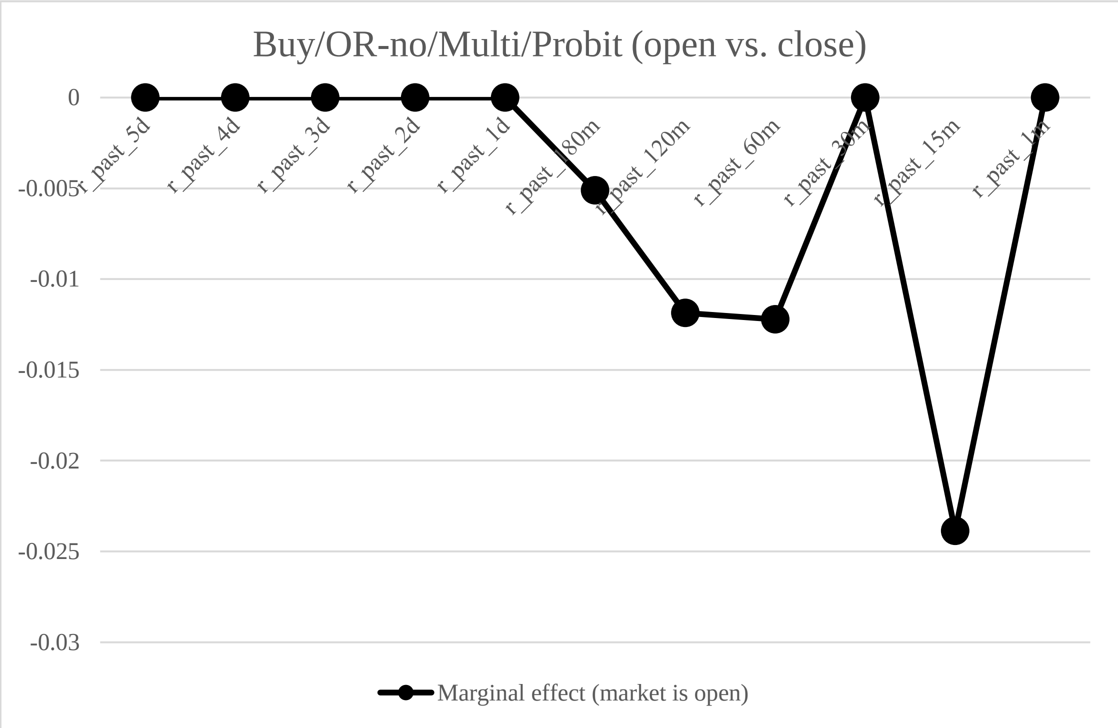


Figure 4 Market open

Panel (a) Buy



Panel (b) Sell

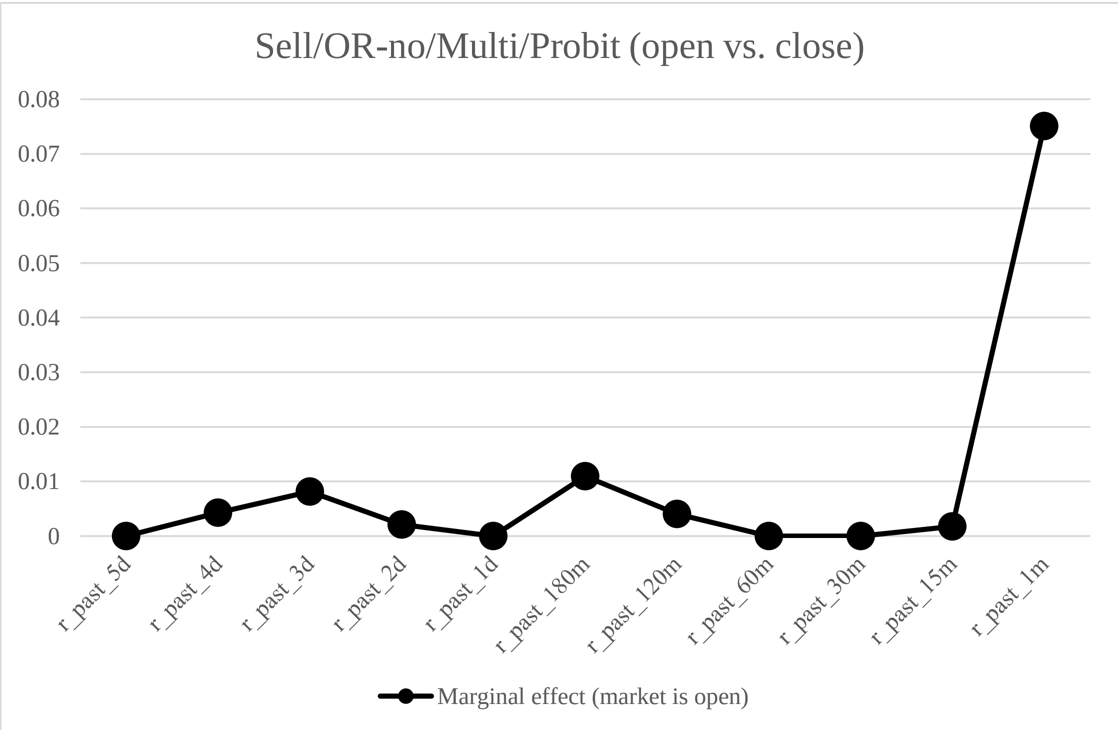
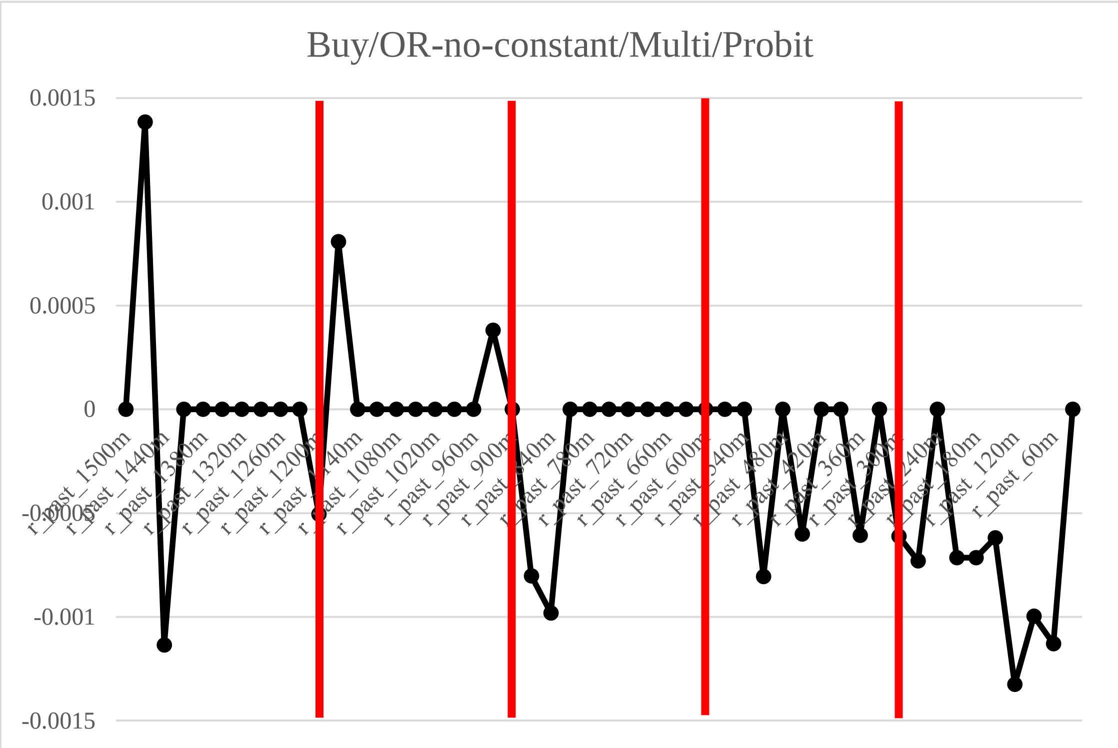


Figure 4 Constant intervals for return measurement

Panel (a) Buy



Panel (b) Sell

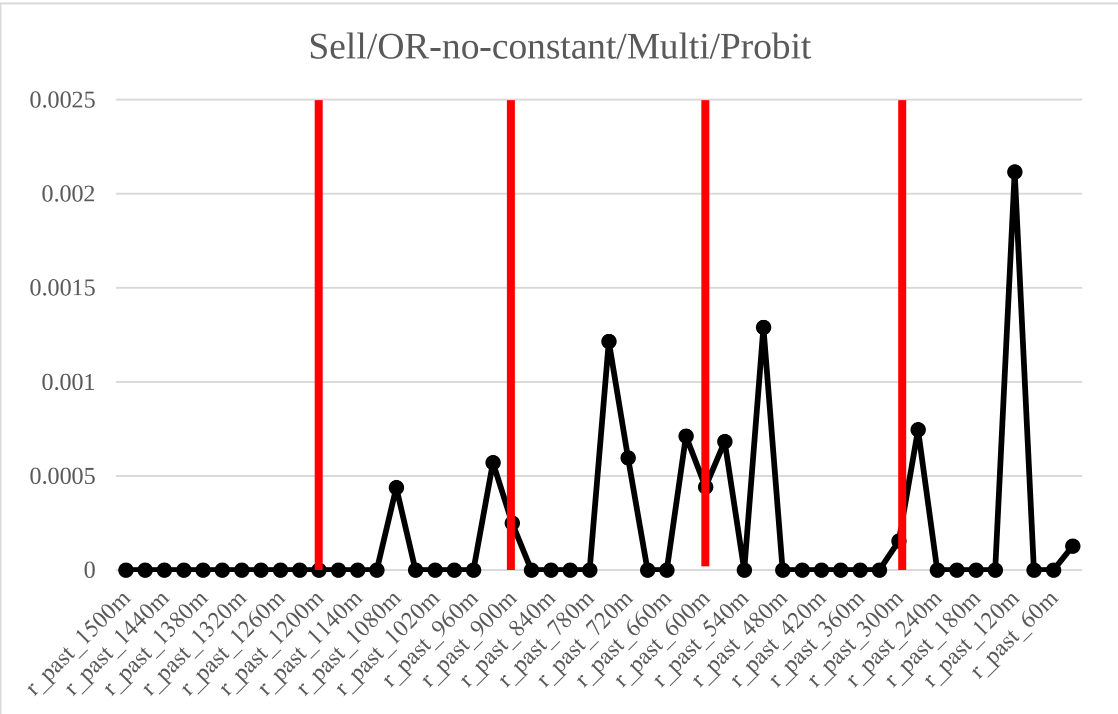
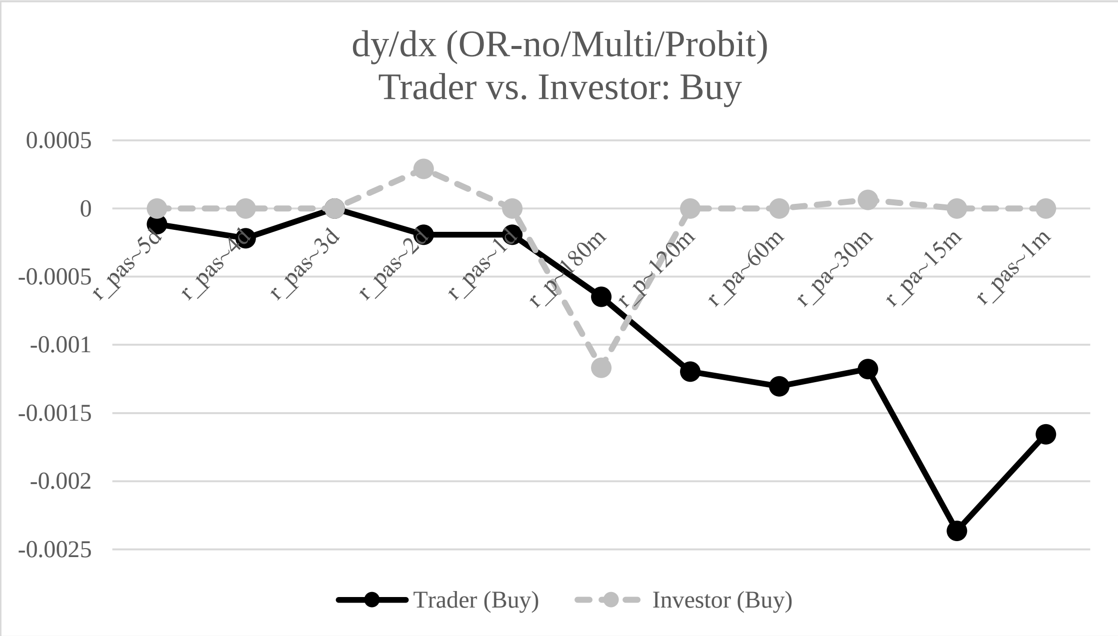


Figure 5 Traders vs. investors

Panel (a) Buy



Panel (b) Sell

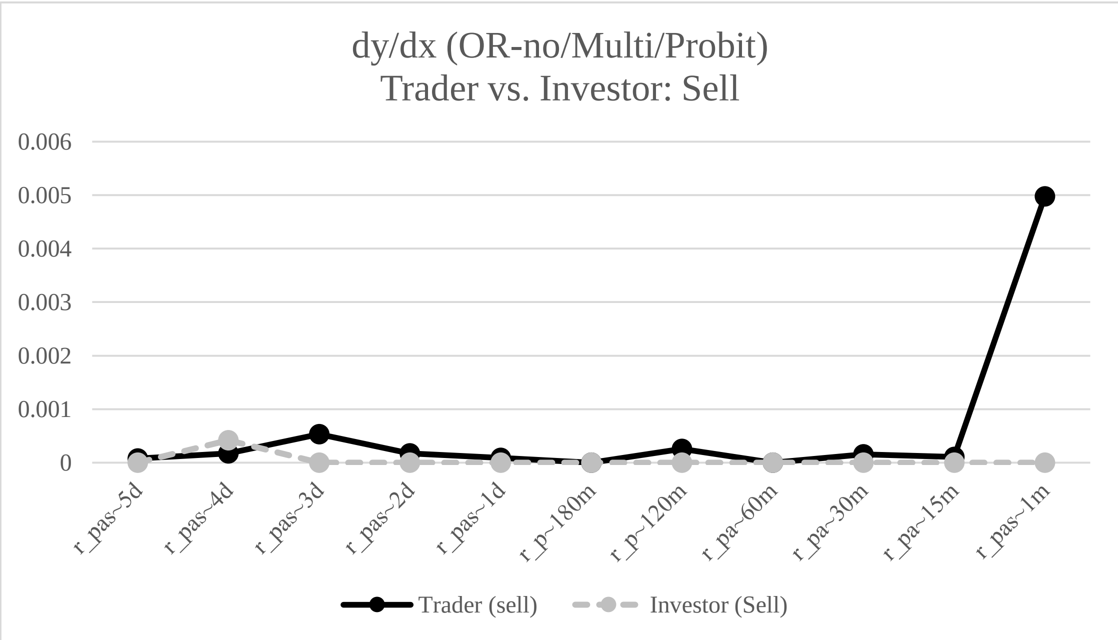
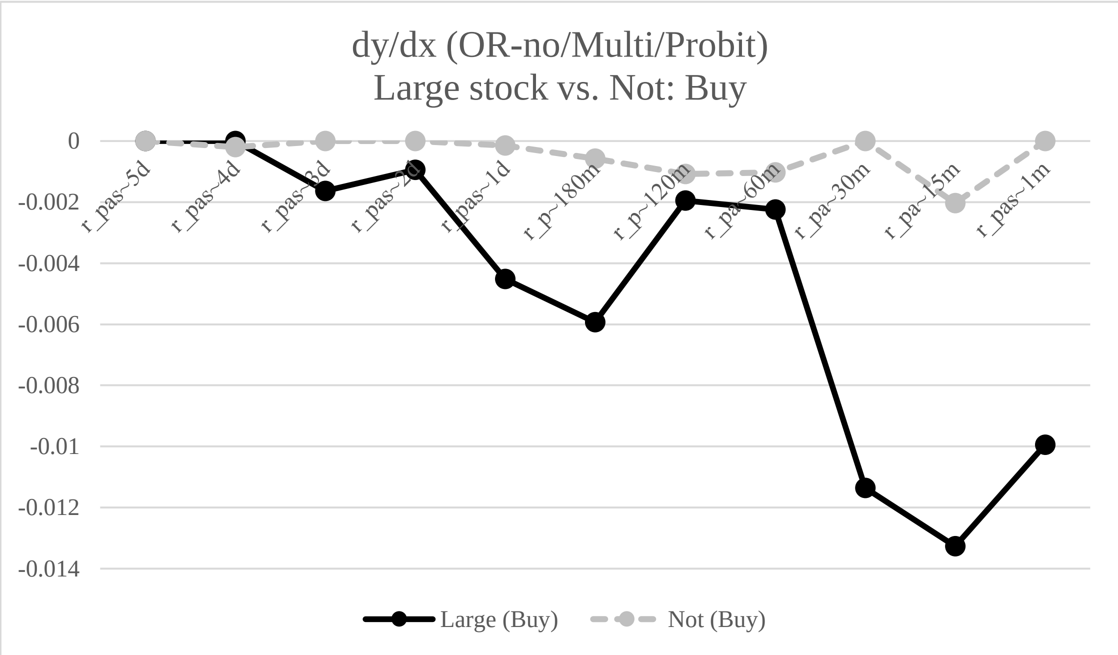


Figure 6 Large-cap vs. small-cap

Panel (a) Buy



Panel (b) Sell

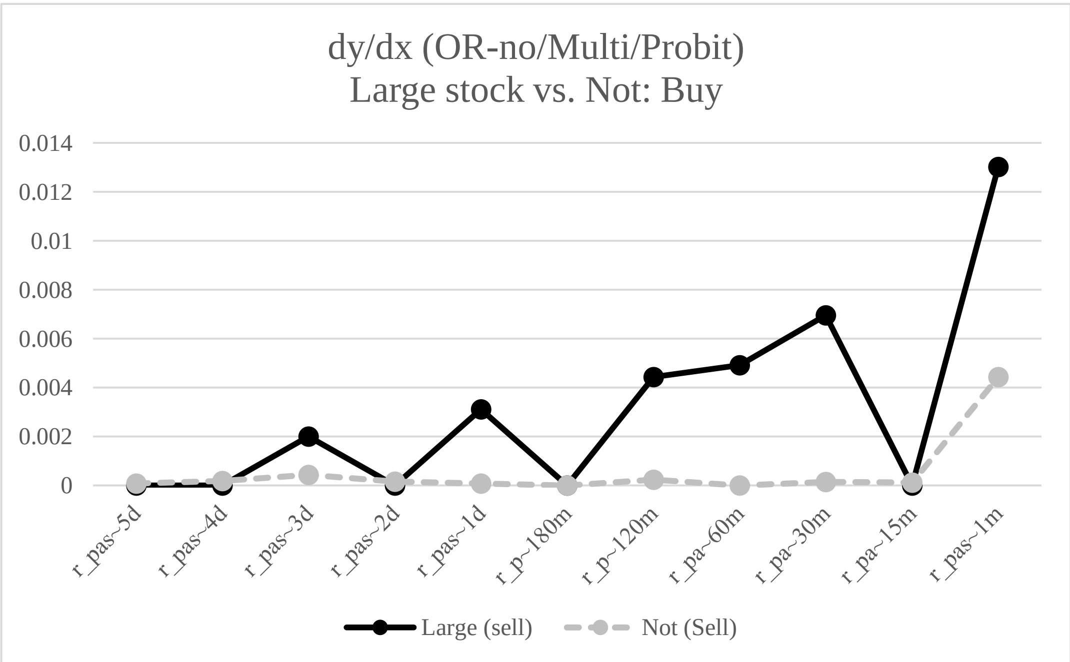
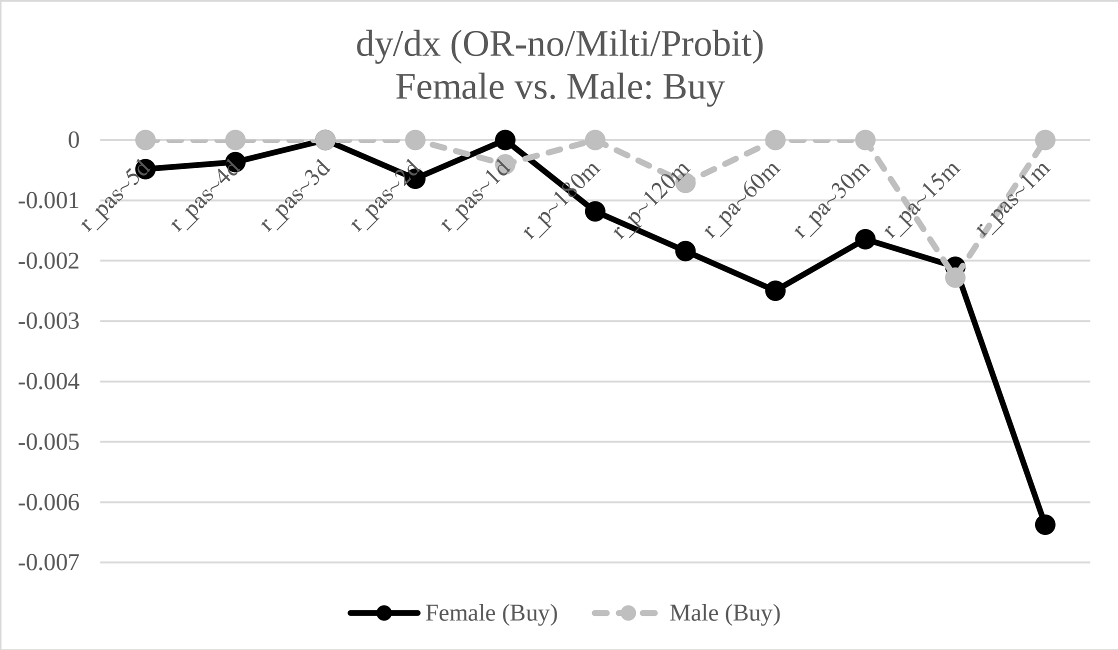
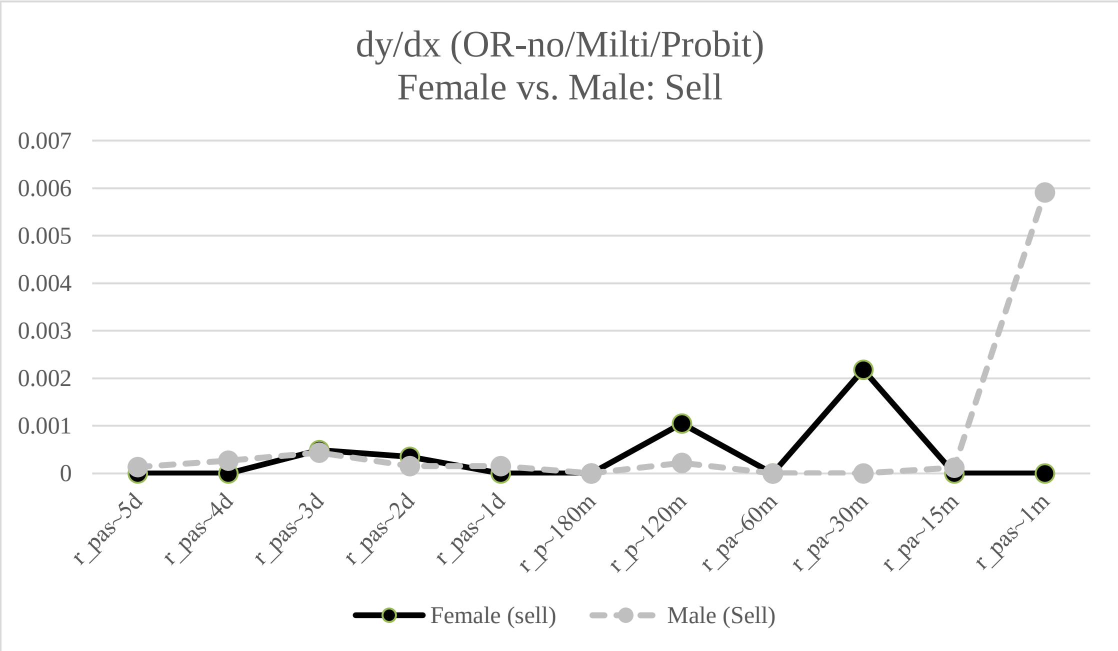


Figure 7 Female vs. male

Panel (a) Buy



Panel (b) Sell



Appendix

Panel (a) Correlation matrix of overlapped return measures

(obs=281,658)	r_past_ 5d	r_past_ 4d	r_past_ 3d	r_past_ 2d	r_past_ 1d	r_past_ 180m	r_past_ 120m	r_past_ 60m	r_past_ 30m	r_past_ 15m	r_past_ 1m
r_past_5d	1										
r_past_4d	0.913	1									
r_past_3d	0.832	0.930	1								
r_past_2d	0.739	0.832	0.925	1							
r_past_1d	0.577	0.656	0.741	0.834	1						
r_past_180m	0.440	0.501	0.567	0.640	0.765	1					
r_past_120m	0.361	0.413	0.468	0.532	0.647	0.845	1				
r_past_60m	0.320	0.368	0.419	0.478	0.588	0.765	0.912	1			
r_past_30m	0.285	0.329	0.376	0.429	0.533	0.691	0.825	0.909	1		
r_past_15m	0.229	0.263	0.302	0.343	0.427	0.552	0.660	0.727	0.802	1	
r_past_1m	0.029	0.034	0.037	0.038	0.040	0.056	0.065	0.070	0.075	0.091	1

Panel (b) Correlation matrix of non-overlapped return measures

(obs=281,658)	r_past_ 5d	r_past_ 4d	r_past_ 3d	r_past_ 2d	r_past_ 1d	r_past_ 180m	r_past_ 120m	r_past_ 60m	r_past_ 30m	r_past_ 15m	r_past_ 1m
r_past_5d	1										
r_past_4d	0.111	1									
r_past_3d	0.021	0.180	1								
r_past_2d	0.022	0.027	0.153	1							
r_past_1d	0.005	0.007	0.007	0.039	1						
r_past_180m	0.002	0.005	0.014	0.056	-0.014	1					
r_past_120m	0.008	0.009	0.003	0.038	-0.014	0.027	1				
r_past_60m	0.003	0.007	0.001	0.028	-0.014	0.009	0.027	1			
r_past_30m	0.000	0.002	0.002	0.013	-0.007	0.004	0.007	0.012	1		
r_past_15m	-0.001	0.001	0.006	0.014	-0.008	0.003	0.006	0.006	0.003	1	
r_past_1m	-0.001	0.004	0.006	0.012	-0.006	0.003	0.006	0.004	0.004	0.001	1