Contrarian Trades and Disposition Effect: Evidence from Online Trade Data

Hayato Komai[a] **Ryota Koyano**[b] **Daisuke Miyakawa**[c]

Abstract

Using online stock trading records in Japan for 461 individual investors and 2,779 stocks over the periods from October 2014 to September 2015 and high-frequency data for the individual stock prices, we estimate the investors' trading activities accounting for buying and selling stocks conditional on the observed returns of those stocks. The results obtained from our estimation show, first, that the individual investors make contrarian trades, i.e., tend to buy stocks exhibiting lower past return. Second, we also found that the individuals are disposition investors that are willing to realize their capital gain but reluctant to realize losses. Third, we confirm that not only the daily-level return measure but also the intraday return largely explains investment actions.

Keywords: Contrarian, disposition effect, individual investors, online trade, high-frequency data
JEL classification: G11, G02

[a] Video Research Interactive Inc., komai@videoi.co.jp
[b] Video Research Interactive Inc., koyano@videoi.co.jp
[c] Hitotsubashi University, dmiyakawa@ics.hit-u.ac.jp

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 mainly because their trading activities could affect security prices in different ways from that associated with institutional investors in various dimensions. The two major patterns reported in the extant studies on individual investors' behavior are "contrarian trading" and "disposition effect". On the one hand, the former accounts for the trading pattern goes against the consensus observed in the market. On the other hand, the latter corresponds to selling stocks with strong past returns and holding onto losers.

We should note that 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) have been largely yet separately documented in literature. Only a limited number of studies have paid an attention to the simultaneous treatment of these two stylized facts. To be fair, it is still an open question whether or not these two trading patterns can be simultaneously confirmed.

It should be also noted that the abovementioned studies exclusively rely on the data accounting for the investments through 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. 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.

Furthermore, regarding the determinants of individual investor activities, most of the extant studies have not necessarily take care of the intraday return information but relied almost exclusively on daily frequency data. This mainly reflects the data limitation. In order to analyze how intraday return affects investor activities, we need to precisely measure not only the returns measured 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 intraday return as the determinants of investor activities due to the difficulty to access to the latter information, it is suggestive to examine it especially in the context of online trading by individual investors.

Against these three background discussions, the present paper examines the pattern of individual investors' online trading activities by using both the intraday and daily frequency return information as well as individuals' investment activities with precise time-stamp. To illustrate, if investors tend to buy stocks immediately after the stocks showing negative return, we can confirm that 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. Taking advantage of the huge information stored in our data, we also analyze the return measured over which window is more informative for predicting investment activities through, for example, examining the statistical significance and economic significance associated with the estimates.

2. Empirical analysis

2.1. Methodology

Consider 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 $r(i,t,\Delta t)$, 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, 1 week, 2 weeks, 3 week, or 1 month, determines whether the investor i takes a specific trading action j consisting of $j \in \{buy, sell\}$. Note that as we count the number of the days by referring business day, for example, 1week corresponds to $\Delta t = 5\ days$, and 1 month corresponds to $\Delta t = 20\ days$. We call this return $r(i,t,\Delta t)$ as overlapped return.

To control for the aggregate macro shock, 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 return is, then converted to one-minute return so that the magnitude is comparable with each other.

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

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

where

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

Assuming the normal distribution for $\varepsilon(i,j,t)$, we can estimate the coefficients (α^j, β^j) through maximum-likelihood estimation. We are interested in the sign of these coefficients for each $j \in \{buy, sell\}$ and for different configurations of Δt and τ. If we find $\beta^{buy} < 0$ for a specific Δt (e.g., one-day), 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 $[t - 1\ day, t]$. 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, $r(i,t,\Delta t)$ associated with small

Δt largely matters, which will be tested in this paper.

2.2. Data

The dataset we use to estimate the equation (1) consists of the following two databases. First, *WebReport database* constructed by VRI Inc. provides the internet log records of around 12,000 individuals, which are chosen by RDD (Random Digit Dialing) procedure. The original data are obtained through the customized software installed to each individual's own PC, which records all the internet access logs for the PC under explicit agreement of the individuals. 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. Out of this large dataset, we pick up 461 individual investors' trading records for 2,779 stocks in four internet security firms over the periods from October 2014 to September 2015. Second, we employ the high-frequency stock price data obtained from Tokyo Stock Exchange. Merging it to the abovementioned 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 action taken by each individual and consider the five days prior to the timing of the action as the window of our analysis for such an action. 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 five days up to each investment action. Regarding the independent variables, we employ the return data of the stocks experiencing some action over the periods from one month prior to the action. Intuitively, such data configuration implies that we assume when individual investors decide whether or not to take some action on a specific stock, they have been paying attention to the stock for the last five days prior to the decision and taking into account the returns up to one month prior to the action for their decision.

Regarding the returns measured from our 45 million observations for the triplet (i.e., buy, sell, and watch) spanning over each individual, stock, five days prior to action, as well as one month window for returns, Table 1 summarize the action and $r(i, t, \Delta t)$. Obviously, the return measure accounting for longer periods shows larger dispersion even after we transform it in one-minute return. Thus, we need to take into account this feature when we evaluate the contributions of each return measure as the determinants of investment actions.

2.3. Results

Panel (a) and (b) of Table 2 summarize the results of the two sets of fourteen probit estimations, which repeat the same regression for the equation (1) for each action (j) and each interval for which return is measured. We show the estimated coefficients associated with the return measure (i.e., β^j) and omit the constant term from the table for saving the space.

First, we can confirm that the action denoted by $j = buy$ follows negative return in all the cases except for that we employ the returns measured for relatively long periods (i.e., $[t - 1\,month, t]$ and $[t - 3\,weeks, t]$. This strongly implies that the individual investors make contrarian trades, in which they tend to buy stocks exhibiting lower return, and the returns closer to the timing of buying action play more significant role as the determinants of buying action. 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 coefficients associated with each return (see Figure 1 where we show the point estimates over the windows) but also the different dispersion of the return over different windows we use to measure return. Panel (a) of Figure 2 plots the multiplication of the point estimates significantly away from zero and the standard deviation of each return corresponding to each window. We can see that, in terms of the economic impact associated with the change in return by one standard deviation, not only the daily-level return measure (e.g., $[t - 2\,days, t]$ and $[t - 1\,day, t]$) but also the intra-day return largely contribute to buying action although the economic impact declines as the window becomes closer to the timing of action.

Second, we can also confirm that the action denoted by $j = sell$ follows positive returns in all the case except for that we employ $[t - 1\,minute, t]$ for measuring return. 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 this our dataset. 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. Different from the case of buying action, among a number of return measures corresponding to different windows, the returns closer to the timing of action do not necessarily show the estimates for β^{sell} statistically away from zero (see also Figure 1 where we show the point estimates over the windows). Similar to the case of buying action, Panel (b) of Figure 2 plots the multiplication of the point estimates significantly away from zero and the standard deviation of each return corresponding to each window. While we can see that, for selling action, the daily-level returns largely explain the action, we should also note that the intraday return also 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 subtle difference between the cases of buying and selling, these presented results jointly suggest that the two systematic patterns reported in the extant studies are confirmed for online stock trading and the return measured over relatively short periods explain the behavior up to some extent.

3. Conclusion

In this paper, using online stock trading records, we estimate the investors trading activities of buying and selling stocks conditional on the observed return of those stocks. These result jointly 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.

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Table 1 Summary statistics of action and overlapped return

OBS	Var	Min	1st	Median	Mean	3rd	Max	SD
46,769,027	buy	0.00000	0.00000	0.00000	0.00007	0.00000	1.00000	0.00853
46,769,027	sell	0.00000	0.00000	0.00000	0.00005	0.00000	1.00000	0.00682
46,769,027	watch	0.00000	0.00000	0.00000	0.00172	0.00000	1.00000	0.04149
46,769,027	[t - 1 month, t]	-90.09	-5.35	-0.68	1.60	4.58	1,800.00	25.29
46,769,027	[t - 3 weeks, t]	-87.41	-4.38	-0.49	1.42	3.95	1,791.00	21.65
46,769,027	[t - 2 weeks, t]	-87.57	-3.38	-0.37	1.10	3.13	910.30	16.33
46,769,027	[t - 1 week, t]	-85.14	-2.24	-0.23	0.67	2.07	884.50	9.86
46,769,027	[t - 4 days, t]	-84.11	-1.97	-0.19	0.57	1.83	885.60	8.61
46,769,027	[t - 3 days, t]	-83.82	-1.65	-0.15	0.45	1.54	897.70	7.30
46,769,027	[t - 2 days, t]	-83.72	-1.27	-0.10	0.31	1.18	914.10	5.88
46,769,027	[t - 1 day, t]	-80.77	-0.76	-0.05	0.13	0.71	915.30	4.16
46,769,027	[t - 180 minutes, t]	-80.49	-0.56	-0.03	0.13	0.51	911.90	3.70
46,769,027	[t - 120 minutes, t]	-80.50	-0.34	-0.02	0.09	0.31	908.20	3.03
46,769,027	[t - 60 minutes, t]	-80.67	-0.14	-0.01	0.04	0.13	901.80	2.11
46,769,027	[t - 30 minutes, t]	-80.72	-0.06	0.00	0.02	0.06	902.40	1.48
46,769,027	[t - 15 minutes, t]	-80.75	-0.01	0.00	0.00	0.01	903.20	0.65
46,769,027	[t - 1 minute, t]	-80.77	0.00	0.00	0.00	0.00	903.20	0.29
46,769,027	[t, t + 1 minute]	-80.77	0.00	0.00	0.00	0.00	903.20	0.32
46,769,027	[t, t + 15 minutes]	-80.75	-0.01	0.00	0.00	0.01	903.20	0.72
46,769,027	[t, t + 30 minutes]	-93.76	-0.06	0.00	0.02	0.05	902.40	1.80
46,769,027	[t, t + 60 minutes]	-93.83	-0.14	-0.01	0.05	0.13	901.80	2.58
46,769,027	[t, t + 120 minutes]	-94.04	-0.34	-0.02	0.09	0.31	908.20	3.72
46,769,027	[t, t + 180 minutes]	-94.23	-0.55	-0.03	0.14	0.51	911.90	4.62
46,769,027	[t, t + 1 day]	-94.47	-1.01	-0.06	0.33	0.97	914.10	6.51
46,769,027	[t, t + 2 days]	-97.67	-1.45	-0.10	0.57	1.43	904.20	9.47
46,769,027	[t, t + 3 days]	-99.34	-1.82	-0.12	0.79	1.81	899.40	11.93
46,769,027	[t, t + 4 days]	-101.30	-2.13	-0.15	0.98	2.16	903.10	14.18
46,769,027	[t, t + 1 week]	-103.30	-2.41	-0.17	1.13	2.45	906.40	16.27
46,769,027	[t, t + 2 weeks]	-103.00	-3.83	-0.46	0.95	3.37	1,262.00	22.50
46,769,027	[t, t + 3 weeks]	-105.90	-4.63	-0.60	0.82	3.79	954.30	24.93
46,769,027	[t, t + 1 month]	-107.90	-5.54	-0.88	0.68	4.30	1,103.00	27.31

Table 2 Single return model with overlapped periods

Panel (a) Buy

Action (j)	Model	Return interval	Coef β(j)
Buy	Single	[t - 1 month, t]	-0.0003
Buy	Single	[t - 3 weeks, t]	-0.0001
Buy	Single	[t - 2 weeks, t]	-0.0007 **
Buy	Single	[t - 1 week, t]	-0.0037 ***
Buy	Single	[t - 4 days, t]	-0.0040 ***
Buy	Single	[t - 3 days, t]	-0.0059 ***
Buy	Single	[t - 2 days, t]	-0.0084 ***
Buy	Single	[t - 1 day, t]	-0.0103 ***
Buy	Single	[t - 180 minutes, t]	-0.0127 ***
Buy	Single	[t - 120 minutes, t]	-0.0149 ***
Buy	Single	[t - 60 minutes, t]	-0.0156 ***
Buy	Single	[t - 30 minutes, t]	-0.0168 ***
Buy	Single	[t - 15 minutes, t]	-0.0193 ***
Buy	Single	[t - 1 minute, t]	-0.0218 **

Panel (b) Sell

Action (j)	Model	Return interval	Coef β(j)
Sell	Single	[t - 1 month, t]	0.0008 ***
Sell	Single	[t - 3 weeks, t]	0.0009 ***
Sell	Single	[t - 2 weeks, t]	0.0013 ***
Sell	Single	[t - 1 week, t]	0.0022 ***
Sell	Single	[t - 4 days, t]	0.0022 ***
Sell	Single	[t - 3 days, t]	0.0021 ***
Sell	Single	[t - 2 days, t]	0.0019 ***
Sell	Single	[t - 1 day, t]	0.0018 ***
Sell	Single	[t - 180 minutes, t]	0.0016 ***
Sell	Single	[t - 120 minutes, t]	0.0016 ***
Sell	Single	[t - 60 minutes, t]	0.0016 ***
Sell	Single	[t - 30 minutes, t]	0.0016 ***
Sell	Single	[t - 15 minutes, t]	0.0018 *
Sell	Single	[t - 1 minute, t]	0.0015

Note: The table summarizes the results of fourteen probit estimations, which repeat the same regression for the equation (1) for each action (j) and the return interval. We show the estimated coefficients associated with the return measure (i.e., β^j) and omit the constant term for saving the space. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Figure 1 Estimated coefficients

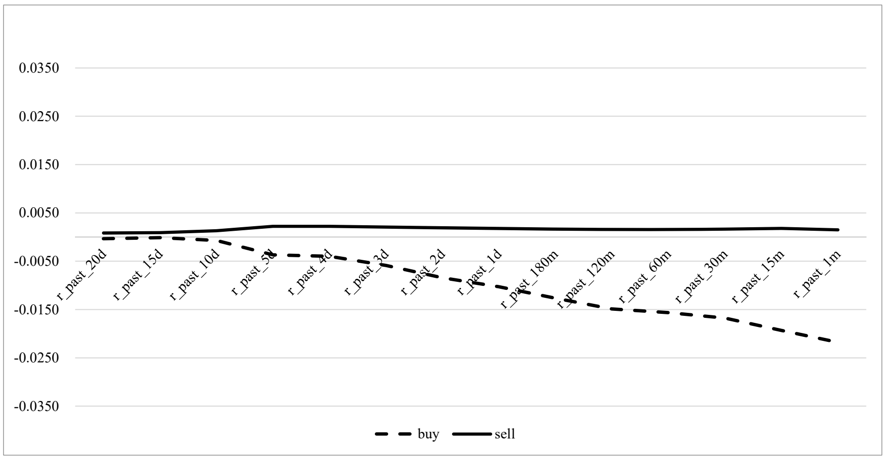
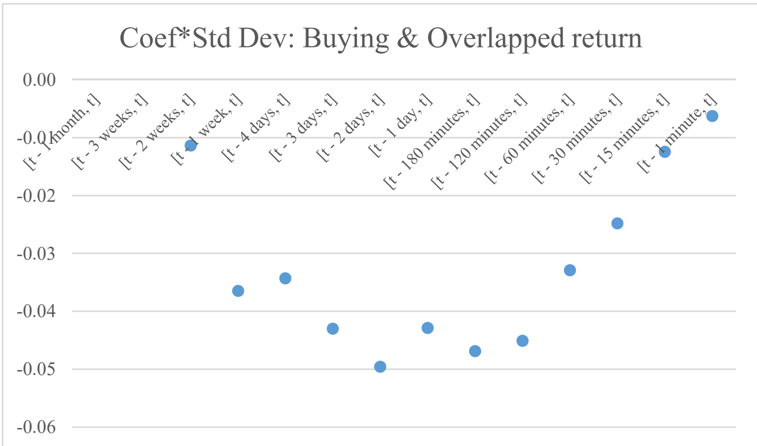


Figure 2 Economic impact

Panel (a) Buy



Panel (b) Sell