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Sign Matters: Stock Movement Based Trading Decisions of Private Investors

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Abstract: This paper studies the relation between the *sign* of recent returns (an up-down-pattern) and sell and buy decisions of private investors. For our comprehensive data set of Taiwanese private stock market investors we find two striking trading patterns: First, a stock pattern with predominantly positive days triggers significantly more trades by private investors than a pattern with many negative days. Second, following positive days, private investors sell proportionally more stocks than they buy. These results still hold when controlling for returns, absolute returns and stock index returns. To explain this behavior of simultaneously rising or falling buy and sell trades, we construct a simple behavioral model of potential sellers and buyers. We assume that both groups initially have different expectations towards their respective shares and update these before their final decision while observing the price pattern. Together with the well-documented disposition effect, this model can explain the key results and also the observed gender differences.

Keywords
Investment behavior; trading decisions; trend following; contrarian; price patterns

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1 Introduction

Imagine the following investment situation: You want to buy a certain stock, but you are not entirely sure and you would also like to time your purchase well. So you wait a few days to see how the stock price moves. How would you react if your observed stock loses three days in a row? Maybe you would like to wait a little bit longer since you feel somewhat insecure about your purchase decision now? Or how would you react if the same stock went up for three days in a row? Now, maybe you would buy that stock immediately to avoid missing the trend entirely? These kinds of decision processes which rely on daily data of stock movements seem very natural for private investors. However, the effect of up-down-patterns on purchasing and selling decisions has to the best of our knowledge not been studied in the literature so far. Even though previous research found empirical evidence that investors react to past returns, the extent to which daily stock patterns have an impact on investors' decisions have been largely neglected. This lack of research is all the more surprising as most investors are constantly confronted with information of up-down-patterns: a short article in the local newspaper reporting that the stock market yesterday had its fourth day with losses this week or stock charts on various internet pages highlighting gains and losses are only two examples of the omnipresence of up-down-movements in investors' information flow. The frequent presence of information on up-down-movements suggests that investors consider them as a source of information. This conclusion would coincide with the findings of recent research (among others: Griffin, Nardari and Stulz 2007; Mussweiler and Schneller 2003), but contrasts sharply with the standard economic theory, which does not attach any importance to the past.

In order to understand why some private investors are buying stocks while at the same time other investors selling these stocks, it is important to comprehend the motivation of these investors for the respective transactions. The effect of up-down-movements had so far been overlooked. In this paper, we fill this gap and examine how private investors change their buy and their sell behavior in regard to market up- and downswings. In doing so, we rely on daily up-down patterns, which include the latest days before a transaction is taking place. We believe that these last days before a trade are important as many investors do not buy and sell stocks spontaneously but pre-choose a potential stock and observe it a certain time to be sure and to pick an appropriate moment for trade execution.

We find evidence for a distinct relationship between the form of the stock market pattern and the trading behavior of private investors. The more a pattern consists of positive days and the less this pattern is interrupted by negative days, the more investors trade – which is true for purchases and for sales. In the case of predominately rising market patterns it means that more investment decisions are triggered. This implies that a rising number of investors considers the stock price to be attractive (buyers) while at the same time a rising number of investors evaluates it as expensive (sellers). Although both, purchases and sales of private investors are increasing, we find that they do not rise by the same level: while private investors tend to sell relatively more stocks than they buy after positive market patterns, they purchase relatively more stocks following negative market patterns, leading to a changing transaction ratio.

Existing theories have severe difficulties to explain this link between market patterns and trade volume in combination with the imbalanced transaction ratio. To solve this puzzle, we introduce an approach that does not require the same decision process for all investors, but puts emphasis on the different perspectives on the buy and sell side of trading.

We explain our empirical findings by assuming that potential buyers and sellers who ponder about their decision observe the up-down-movements of the stock under consideration. These movements influence the confidence about their decision while at the same time influencing the potential future gain for buying (or loss for not selling). Our model (see Section 5) shows that this can explain the increase of buying *and* selling decisions after gains. Different confidence level between stock owners and potential buyers regarding their own forecast may explain the asymmetry in the trade ratio between both groups. Additionally, the well-known disposition effect (Barber and Odean 1999) increases this asymmetry further.

Our model supplements the results of Barber and Odean (2005) who found that private investors are net buyers following positive and negative one day market shocks – which they attribute to private investors' tendency of attention grabbing. In contrast, our results show that stock market patterns do not need to be attention inducing to trigger trades: the effect works even if the absolute returns are small and therefore unlikely to grab the attention of a private investor who hasn't looked at the stock previously already.

The paper is organized as follows: in the next section we review the empirical findings of the relationship between the past stock market development and a possible change in trading volume as well as its underlying theoretical explanations. In Section 3, we describe our data set and the methodology we employ. We report our empirical results in the following Section 4. We then present a formal model that can explain the observed pattern and discuss all of our results in Section 5. In Section 6 we conclude.

2 Current state of research

Standard economic theory suggests that prices at financial markets follow no specific pattern, but develop in a random way. In his efficient market theory, Fama (1965) described successive changes of prices as independent, identically distributed random variables. As prices have no memory, investors cannot use past quotations to predict the future in any meaningful way.

Rational actors – and in the economic standard theory, stock market investors are seen as these – do not need to take past prices into account.

This standard theory is in contrast to a range of empirical studies of recent years. According to these studies (and the obvious behavior of many practitioners), it seems as if investors are likely to see a link between prices of the past and prices of the future.Moreover, these studies show that these links are not random, but systematic which means that they can lead to market wide effects: for instance, Statman, Thorley and Vorkink (2006) find evidence for a strong positive correlation between past shocks in market return and market-wide trading activity. They observe a higher trading volume following the months after a bull market. In contrast, bear markets slow down trading activity in the following months considerably. The analysis of 46 global stock markets by Griffin, Nardari and Stulz (2007) confirms a strong positive relation between past market returns and trading volume. Investors increase trading activity significantly several weeks after positive return shocks, especially in developing countries.

However, slightly dissenting results are found by Gallant, Rossi and Tauchen (1992) and Chordia, Huh and Subrahmanyam (2006). Both analyses confirm that investors react to long term changes in market return but report increasing stock trading volume after very positive as well as very negative stock market developments. While Chordia, Huh and Subrahmanyam (2006) find that volume still increases stronger following positive market shocks, Gallant, Rossi and Tauchen (1992) provide evidence for a fairly symmetric effect after price declines and price rises. Barber and Odean (2005) also analyze the reactions of investors after strong market movements but limit their research to notable one day changes. Their outcome supports the results of Gallant, Rossi and Tauchen (1992) and Chordia, Huh and Subrahmanyam (2006) that investors react similar to positive and negative stock market shocks even though Barber and Odean (2005) refer only to the ratio of buy and sell transactions. They find evidence that private investors are net buyers of stocks that experience extreme one day returns. This applies for stocks with a considerable positive as well as with a considerable negative development.

As empirical findings differ in regard to the relation between past market development and following transaction patterns so do the theoretical explanations for this behavior. For Statman, Thorley and Vorkink (2006) and Glaser and Weber (2007) the main explanation of different reactions to bull and bear markets can be found in the overconfidence theory. According to this theory, investors are getting more self-confident after strongly positive stock market developments. This translates into an underestimation of future volatility of stock returns and as a consequence investors trade more frequently. Griffin, Nardari and Stulz (2007) point to a whole series of explanatory approaches that explain why the return-volume relation is different across countries. The explanation that is most consistent with their findings is investors' participation costs.

Barber and Odean (2005) show that individual investors react similar after positive and after negative one day shocks and thus offer another starting point for explaining the behavior following strong stock market changes. They argue that attention based decision making has implications on how private investors are trading stocks. When choosing stocks, these private investors are confronted with a vast number of possible equities to buy. As alternatives are plentiful and search costs are high, attention-grabbing stocks offer a quick shortcut through the search dilemma. Barber and Odean (2005) argue that stocks which exhibit pronounced one day shocks are able to catch the attention of private investors. Thus, stocks that show strong one day gains and losses are more likely to be purchased by private investors the next day than stocks out of the limelight. In contrast, private investors do not face the same search dilemma when selling stocks. Because private investors do typically own only a small subset of all available market stocks, they can choose the stocks to sell in their portfolio by their preferences with only little search costs. The authors show that the simplification attempt of the human brain for purchase transactions and the technical limitation for sell transactions might be the reason why private investors are net buyer of attention-grabbing stocks after severe one day shocks.

Our study differs from the above mentioned papers in the following two dimensions:

Firstly, we determine the *trading volume for sell and buy transactions* as well as the corresponding *imbalance* between both kinds of transactions. Measuring the absolute and the relative changes enables us to take a deeper look into the different behavior of private investors who purchase and private investors who sell stocks and thus helps us to derive potential specifics in motivation, commitment and risk evaluation on each side. Most previous studies do not examine the partially inverse behavior of buyers and sellers and implicitly assume identical psychological processes for both investor groups. One paper that perceives the existence of differences between sellers and buyers is Barber and Odean (2005). However, they only acknowledge the existence of technical trading limitations but do not consider the behavioral issues behind the sell and purchase transactions.

Secondly, we examine the *up-down-pattern of the last days before a transaction* is released. We believe that many investors do not buy and sell stocks spontaneously, but that they already plan some days before a transaction which stock they want to sell or buy. This means they have picked a certain stock and only wait to be sure or for the "right moment" to start the transaction. The seemingly right moment could be indicated by a certain up-down pattern. This sustained – probably several days lasting – decision process contrasts the view of Barber and Odean (2005) who limit their research to very significant changes at the last day before a transaction occurs.

While we do not claim that all private investors follow the behavior described above, we do think that it is natural to assume that a substantially large proportion of private investors will take several days for a final decision about buying or selling a stock and that they will watch stock prices during this time.

In these two dimensions, we can augment the previous models about further relevant behavior of private investors.

An additional advantage of day-to-day patterns might be the incorporation of further information into the decision process - at least in the eyes of private investors. Barber and Odean (2005) focus only on the latest stock market development which might consider the most prominent day in private investors' mind but misses to cover the short-term trend. For example, a one day gain of 1.5 percent might not be particularly remarkable for investors; however, four days in a row with 1.5 percent gains might arouse a more distinct interest. Thus, our work combines the examination of multi-day market patterns and the buy-sell trading-contrast to obtain a full understanding of the trading behavior of private market participants.

3 Data set and methodology

Our analysis is based on a data set provided from the Taiwan Stock Exchange (TWSE). It covers *all* orders submitted to the TWSE from January 2001 to December 2006. During this time roughly 4.7 billion stocks have changed ownership. The huge number of transactions and the complete coverage of a whole stock market allows us to draw reliable conclusions regarding the trading patterns of investors. – At the same time, it made the analysis technically demanding due to the large amount of data involved.

The data made available for us include the number of bought and sold stocks for each day and each investor during the referred period. For each investor it is know whether he or she is a private or institutional market participant and whether he or she is a foreign investor. Private investors are defined as investors who are investing on their own behalf. No further classification of institutional investors is provided. According to the numbers provided by TWSE almost 80 percent of the exchanged stocks are traded by private investors. Our analysis considers only transactions in stocks. Other financial instruments that could be used for hedging or diversification purposes are only taken into account when the underlying stock was traded at the stock exchange.

The TWSE sets the price of the Taiwan Capitalization Weighted Stock Index (TAIEX) which covers nearly all of the stocks traded in Taiwan. Over the covered period of six years the TAIEX realized a positive average annual return of nearly eight percent, but was subject to large price changes during this period, with a low of 3446 points and a high of 7824 points. This changing environment gives additional explanatory power to the results of our analysis as we are able to take investors' behavior during different market conditions into account.

We use the TAIEX as a benchmark for the general development of Taiwanese stocks. When stating a positive or negative day at the stock market we are referring to the TAIEX closing price of a certain trading day in comparison to the closing price of the previous trading day, as that would be the relevant number reported in the media.

To focus on domestic private investors that most probably use publicly available information and that have no extensive professional advice, we divide this investor subgroup according to their annual trading volume. We categorize private investors with an annual trading volume of 1 billion New Taiwan Dollar (around 30 million US-Dollar) as large private investors, following Chen et al. (2015, p.40). We believe, with such a high turnover, this subgroup of affluent investors is more probably seeking professional financial advice and is more likely to have better access to valuable information than private investors with less trading volume. Contrary, small private investors are defined by an annual trading of less than 30 million US-Dollar. We assume that this group of investors has most probably less professional advice than their institutional and large private counterparts. Also, their access to stock market related information is more limited due to financial and time restrictions.

According to this definition, out of the 80 percent stocks that were exchanged by domestic private investors at the TWSE, 65 percentage points are traded by small private investors and 15 percentage points are traded by large private investors. Altogether more than 3 million different small private investors are trading stocks at the TWSE in the analyzed time period.

For calculating the average number of buy and sell transactions in regard to a certain up-down-pattern we set t_0 as trade execution day. The days before t_0 are forming the up-down-pattern for which we examine the impact on the traded stock at t_0. We focus in this paper on the effect that the price movement of the most recent days (t_{-1} to t_{-4}) has on private investors' decisions at t_0. We do not consider the stock information of t_0, as the number of buy and sell decisions at this day affects the stock prices at the very same day.

To determine a potential transaction imbalance we use two-, three- and four-day patterns. For each pattern we calculate the imbalance as:

$$TI_p = \frac{\frac{\sum_{i=1}^{k_p} B_i}{n_p}}{\sum_{p=1}^{f} \frac{\sum_{i=1}^{k_p} B_i}{n_p}} - \frac{\frac{\sum_{i=1}^{k_p} S_i}{n_p}}{\sum_{p=1}^{f} \frac{\sum_{i=1}^{k_p} S_i}{n_p}}$$

where k_p is the number of different stocks that could be traded after the up-down-pattern p, B_i is the number of purchases of stock i one day after pattern p ends, S_i is the number of sales of stock i one day after pattern p ends, n_p is the number of times a certain pattern occurs and f is the number of different patterns. For each pattern we calculate the share of buy and the share of sell transactions that are executed the day after the pattern. These pattern specific buy and sell ratios cover all trades over the whole period of six years. To identify pattern-dependent transaction imbalances (TI_p) we subtract the share of sold stocks after pattern p from the share of bought stocks after the very same pattern. If private investors buy more stocks than they sell after a certain pattern, we get a positive transaction imbalance. If private investors are inclined to sell more stocks, we get a negative transaction imbalance.

4 Results

In the following, we examine the reaction of Taiwanese private investors to past up-down-movements. First, we focus on the relation between different patterns and their effects on the frequency of trading. In a subsequent step we examine the transaction imbalance after different types of market patterns.

4.1 The impact of up-down-patterns on the trading activity

If investors react to up-down-patterns, this is likely to have an effect on the number of trades executed. Our results (Table 1–4) confirm a distinct difference between three-day stock up-down-patterns with predominantly positive and three-day patterns with predominantly negative days. While primarily positive patterns trigger the purchase and sale of more stocks, a sequence of primarily negative days causes fewer transactions.[4]

We see the strongest discrepancy between the market index patterns of three days with gains (+++) and three days with losses (---), see Table 1: after the pattern +++ small private investors on average buy 50.5% more stocks and sell 60.7% more than after the pattern ---. After alternating market patterns without a distinct up- or downward trend investors tend to release only an average number of buy and sell transactions as can be seen for the patterns +-+- and -+-+. Employing the Tukey's range test confirms the significant difference between predominantly positive and negative stock market patterns.

While the same trend holds for large private investors, we do not find such a clear pattern for institutional investors (Table 2). This suggests that the driving force between this trade pattern are more likely private investors. We find, however, a pattern for foreign investors that is opposite to the pattern of private (domestic) investors.

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[4] Statistical significance of these results will be established using a more sophisticated regression analysis in the next section.

Small Private Investors						Large Private Investors					
Bought (in billions)		Sold (in billions)		Imbalance		Bought (in millions)		Sold (in millions)		Imbalance	
+++	2.599	+++	2.688	-++	-0.4%	+++	619.8	+++	624.5	+-+	-0.2%
-++	2.253	-++	2.355	+++	-0.4%	-++	544.8	-++	538.5	---	-0.2%
+-+	2.231	+-+	2.299	+-+	-0.2%	+-+	515.3	+-+	523.7	--+	-0.1%
++-	2.174	++-	2.183	--+	-0.1%	++-	498.3	++-	487.3	+++	-0.1%
--+	1.936	--+	1.970	++-	0.1%	--+	447.9	--+	453.7	+--	0.0%
-+-	1.930	-+-	1.914	-+-	0.2%	-+-	426.5	-+-	422.4	-+-	0.1%
+--	1.836	+--	1.798	+--	0.4%	+--	403.9	+--	404.4	-++	0.2%
---	1.727	---	1.673	---	0.4%	---	365.7	---	372.9	++-	0.3%

Table 1: Number of stocks traded on average after a certain up-down-pattern of the market index and trade imbalance between the proportion of shares bought after this pattern minus the proportion of shares bought after this pattern. The up-down-patterns are indicated by a sequence of + and –. The sequence –++, e.g., means one drop of the index followed by two positive days.

Foreign Investors						Institutional Investors					
Bought (in billions)		Sold (in billions)		Imbalance		Bought (in millions)		Sold (in millions)		Imbalance	
+++	0.390	++-	0.287	---	-2.8%	+++	400.7	+++	419.4	++-	-1.3%
-++	0.348	+--	0.284	+--	-2.2%	-++	370.8	++-	382.7	+--	-0.4%
+-+	0.338	-+-	0.281	-+-	-1.6%	+-+	363.1	-++	362.8	-+-	-0.2%
++-	0.332	+++	0.277	--+	-0.5%	++-	335.6	+-+	359.2	+++	-0.2%
--+	0.294	--+	0.271	++-	0.4%	--+	330.9	-+-	322.0	---	-0.1%
-+-	0.276	---	0.269	+-+	1.5%	-+-	306.1	+--	317.7	+-+	0.6%
+--	0.266	+-+	0.266	-++	2.2%	+--	297.2	--+	313.4	-++	0.7%
---	0.233	-++	0.260	+++	3.1%	---	278.9	---	290.6	--+	1.0%

Table 2: The same results as Table 1, but for institutional and foreign investors.

Small Private Investors						Large Private Investors					
Bought (in thousands)		Sold (in thousands)		Imbalance		Bought (in millions)		Sold (in millions)		Imbalance	
+++	105.5	+++	111.5	-++	-0.7%	+++	14.4	+++	15.4	+++	-1.0%
-++	102.4	-++	108.3	+++	-0.7%	-++	13.5	-++	14.3	-++	-0.8%
---	98.8	+-+	99.6	+-+	-0.5%	+-+	12.2	+-+	12.7	+-+	-0.5%
--+	96.7	--+	99.0	--+	-0.2%	--+	11.7	--+	12.0	--+	-0.4%
+-+	95.1	++-	91.0	++-	-0.1%	++-	10.8	++-	10.0	---	0.4%
+--	90.1	---	89.3	-+-	0.3%	-+-	10.0	-+-	9.4	+--	0.5%
++-	89.3	-+-	87.1	+--	0.7%	---	9.8	---	9.3	-+-	0.8%
-+-	88.5	+--	85.4	---	1.3%	+--	9.5	+--	9.1	++-	0.9%

Table 3: Average numbers of a stock bought or sold by private investors depending on its previous up-down-movements for private investors.

Foreign Investors						Institutional Investors					
Bought (in millions)		Sold (in millions)		Imbalance		Bought (in millions)		Sold (in millions)		Imbalance	
-++	7.1	---	9.0	---	-7.3%	+++	4.7	+++	5.2	---	-3.5%
+++	7.0	+--	6.7	+--	-3.1%	-++	4.6	-++	4.5	+--	-2.8%
--+	6.9	-+-	6.1	-+-	-2.2%	+-+	4.1	+-+	4.2	-+-	-1.4%
---	6.4	--+	5.8	++-	0.1%	--+	4.1	--+	4.1	++-	-1.0%
+-+	6.4	++-	5.1	--+	0.7%	---	3.9	---	4.0	--+	1.3%
+--	6.0	-++	4.6	+-+	2.8%	-+-	3.5	-+-	3.9	+-+	2.0%
++-	5.8	+-+	4.4	-++	3.8%	++-	3.5	++-	3.9	+++	2.6%
-+-	5.7	+++	4.0	+++	5.1%	+--	3.4	+--	3.7	-++	2.8%

Table 4: Same as Table 3, but for institutional and foreign investors.

When looking now at the up-down-pattern of individual stocks of the previous three days, we find very similar results (Table 3–4).

Moreover, we observe that not only the number of positive and negative days is important for the buy and sell decisions. Instead, we find that more recent trading days tend to be of higher importance.

In conclusion, our results indicate that investors are more willing to trade after patterns with predominantly positive days and that the trade imbalance for private investors is most negative in these cases while the other groups of traders (foreign and institutional) essentially counterbalance this.

We can also observe this general behavior when we consider two or four days (details on request). The effect is stable over time: when splitting our sample into two equally long timespans, roughly corresponding to bear and bull markets, the results are the same (details on request). The effect is not driven by a few highly traded stocks, as it is similar when restricting the sample to the 50% lowest trading volume stocks (Table A.1 in the appendix). It is also not driven by low volatility days, as it is similar when restricting to the 10% highest volatility days (Table A.1). We did also not find an effect of stock splits on our results (details on request). The results are finally also not driven my penny stocks, as the effect is similar when taking out all stocks with a share price below 5 NTD (the usual definition for penny stocks in Taiwan), compare Table A.2.

4.2 Up-down-patterns and transaction imbalance

In the following we want to take a closer look at buying, selling and the transaction imbalance of small private investors. Are the differences that we have observed in the Section 4.1 indeed significant or just a random result? Is it really the up-down-pattern that causes this imbalance or is it only the actual return or maybe the volatility (proxied by the absolute value of the return)? And is it really the sign of the return of the stock or is it rather the return of the stock market (with which the return of the stock is correlated)?

To test this, we conduct a number of regression analyses. Since the amount of data, particularly for small private investors, is huge, we needed to restrict the small private investors sample to a random subsample: for the buy and sell regressions we randomly selected 10% of the data entries (rounded to 88 000 observations), for the trade imbalance regressions we randomly selected 1% (rounded to 200 000 observations).

The empirical findings of the previous subsections suggested that buying and selling behavior is influenced by up-down-movements in a way that more recent movements count more. This leads us to define a variable that measures the weighted signs for a stock return over the past three days: for each past day, the value of the variable becomes larger if there is a positive return and smaller if there is a negative return, but the amount of this adjustment depends on how long that day has past. This corresponds essentially to a standard time discounting method. Using a discounting factor of 0.5 and using only the last three days, we arrive at the following formula for the weighted signs *WS*:

$$WS = \frac{4}{7}\left(\operatorname{sign}(r_t) + \frac{1}{2}\operatorname{sign}(r_{t-1}) + \frac{1}{4}\operatorname{sign}(r_{t-2})\right).$$

WS can take values between –1 (sequence ---) and +1 (sequence +++). We use this variable in the following regressions as predictive variable for the sum of bought or sold shares and for the trade imbalance. In all cases, we cluster standard errors for the investors and the stocks.

Table 5 shows that the weighted signs of the stock has a significant impact on the number of bought and sold stocks, even after controlling for the stock returns, the index return and the signs of the index return. Table 6 shows that the trade imbalance is also impacted by the weighted signs, even after controlling for a variety of other factors, including the stock returns (related to momentum), their absolute value (as proxy for volatility[5]) and these values for the index return (reflecting general market sentiment).

All in all, the results suggest that there is a clear relation between the price pattern of a stock and the subsequent decisions of potential buyers and sellers. The statistical significance is very high (mainly due to the extremely large dataset). The economic significance is also high: as we can see, adding controls reduces the coefficients, but still a noticeable portion of the effect observed in Table 3 is still attributed to the weighted sign variable.

The observed pattern is also robust to various controls, as we have seen. This shows that it is neither an artifact of volatility effects or market sentiment. It also cannot be explained by investors trading according to momentum or short-term reversal strategies, since in these cases only the actual returns and not their weighted signs should matter.

In the following section we will provide a simple model that can qualitatively predict the observed patterns. Other explanations might of course be possible.

[5] Christoffersen & Diebold (2006) have shown that volatility predictability implies return sign predictability. Thus, our results could (without this control) be also caused by volatility patterns influencing trading decisions.

	Sum of bought shares			Sum of sold shares		
Independent Variable	Model (1)	Model (2)	Model (3)	Model (1)	Model (2)	Model (3)
(Intercept)	725,038***	685,692***	654,026***	735,1***	679,755***	632,475***
	(13,597)	(13,257)	(12,149)	(13,573)	(13,102)	(11,985)
Weighted signs	211,92***	88,341***	87,242***	238,625***	61,382***	61,582***
	(13,339)	(6,621)	(6,608)	(13,9)	(5,098)	(5,19)
Return t-1		52,954***	53,265***		84,664***	89,084***
		(8,383)	(8,231)		(11,755)	(11,768)
Return t-2		27,381***	25,608***		27,26***	26,674***
		(7,41)	(6,792)		(6,941)	(6,748)
Return t-3		26,112***	30,969***		28,886***	32,558***
		(6,142)	(6,763)		(6,76)	(7,116)
Sign (index return t-1)			7,359			28,366
			(0,328)			(1,415)
Sign (index return t-2)			44.915			53,782*
			(1,778)			(2,26)
Sign (index return t-3)			11,386			15,436
			(0,637)			(0,899)
Index return t-1			-1,579			-27,439**
			(-0,192)			(-3,206)
Index return t-2			-0,614			-11,279
			(-0,055)			(-1,089)
Index return t-3			-23,961**			-20,592**
			(-3,156)			(-2,636)
N	88000	88000	88000	88000	88000	88000

Table 5: The weighted sign of the past days' returns is a significant factor for the subsequent buying and selling decisions of small private investors. T-values in parentheses.
* denotes p<0.05, ** denotes p<0.01 and *** denotes p<0.001.

	Transaction Imbalances			
Independent Variable	Model (1)	Model (2)	Model (3)	Model (4)
(Intercept)	-0,022***	-0,014***	-0,014***	-0,023***
	(-36,014)	(-19,506)	(-18,62)	(-9,915)
Weighted signs	-0,026***	-0,006***	-0,005**	-0,005**
	(-47,053)	(-4,008)	(-3,218)	(-3,067)
Return t-1		-0,006***	-0,004***	-0,005***
		(-10,487)	(-5,984)	(-7,994)
Return t-2		-0,005***	-0,006***	-0,006***
		(-15,677)	(-12,99)	(-12,277)
Return t-3		-0,004***	-0,003***	-0,003***
		(-14,252)	(-7,25)	(-5,845)
Index return t-1			-0,011***	-0,009***
			(-9,773)	(-8,103)
Index return t-2			0	0,001
			(0,291)	(0,684)
Index return t-3			-0,004***	-0,005***
			(-3,642)	(-4,072)
Absolute return t-1				0,006***
				(7,673)
Absolute return t-2				0
				(0,556)
Absolute return t-3				-0,003***
				(-4,432)
Absolute index return t-1				-0,002
				(-1,364)
Absolute index return t-2				-0,001
				(-0,44)
Absolute index return t-3				0,004**
				(3,083)
N	200000	200000	200000	200000

Table 6: The weighted signs of the past days' returns are a significant predictor for the trade imbalance of small private investors on the following day, even when controlling for a number of factors. T-values in parentheses.
* denotes p<0.05, ** denotes p<0.01 and *** denotes p<0.001.

4.3 Clusters of trading patterns

Not all investors are the same. In fact, a high degree of heterogeneity has to be expected in any data on investment strategies. The observed average pattern from the past section will therefore only apply to a certain (maybe even small) part of the small private investors. In order to shed some light on the distribution of certain trading patterns, we conducted a K-cluster analysis. To this aim we constructed a dataset with 1% of the subjects (randomly selected) and computed for each of them their average trade imbalance after each of the eight possible three-days patterns. We used the resulting eight variables for the computation of the clusters (restricted to investors who had bought or sold at least once after each of the eight trading patterns). We obtained four clusters that had some interesting and clear pattern (see Table 7). The first cluster corresponds to the observed average pattern: after three ups the trade imbalance is most negative, i.e. sales dominate. After three downs it is the other way around. Cluster B corresponds to the symmetric behavior. We will see in Section 5 how both patterns can be explained with a simple model.

Cluster C and D are more complex. They can be interpreted as signs of market timing: In Cluster C market participants tend to sell after the pattern --+. A reason could be that they perceive a general negative trend and want to sell the stock right after it made one positive day, seeing this as a good opportunity. In general, sales for this cluster of investors tend to follow positive days.

Pattern	WS	A	B	C	D
+++	1.00	-17%	19%	-1%	-3%
-++	0.86	-11%	5%	-7%	3%
+-+	0.71	-7%	0%	-4%	1%
--+	0.57	3%	-1%	-9%	4%
++-	0.43	-2%	-6%	4%	-1%
-+-	0.29	6%	-5%	4%	-1%
+--	0.14	9%	-6%	7%	-1%
---	0.00	21%	-6%	6%	-2%
	Females	54%	48%	56%	48%
	Subjects	4766	3426	5513	8927

Table 7: Investors clustered by their trade imbalances after each of the eight possible investment patterns. Highest deviations are marked in red. Cluster A corresponds to the average behavior that we have found before, Cluster B is the reverse behavior. Cluster C can be interpreted as an attempt to market timing for selling (sell after a general bad trend, broken by one positive day). Cluster D suggests a tendency to market timing for buying (wait for a cheap opportunity to buy).

Cluster D works again in a symmetric way to Cluster C: investors *buy* particularly after the pattern --+. Here the logic could be that investors perceive an underpricing of the stock, but they wait whether the stock becomes even cheaper. As soon as this negative trend stops, however, they think that it is now time to buy. We notice, however, that in Cluster D the imbalances tend to be smaller. This suggests that the cluster analysis put many investors into this category who did not follow a clear trading pattern regarding up and down movements. This can also explain why the number of investors in Cluster D is relatively high.

When looking at gender distribution we notice a certain surplus of female investors in Clusters A and C, while male investors are more frequent in Clusters B and D. Both effects are statistically significant ($p<0.01$) and we will come back to them later.

5 Interpretation of the results

5.1 Towards a model explaining reactions on up-down patterns

Our results from the previous section show primarily two findings:

- First, private investors react with different behavior to certain stock patterns. The examined Taiwanese investors trade more after predominantly positive patterns and reduce trading after negative patterns. This observation is true for stock purchases as well as for stock sales.
- Second, there is a difference between the execution of purchases and sales: while proportionally more stocks are sold than bought after patterns with mostly up days, patterns with mostly down days result in a disproportionally large share of purchases.

In the following, we present a model that could explain this behavior of private investors.

We assume that both potential buyers and sellers (i.e. private investors who contemplate about buying or selling a given stock) have a valuation of that stock which differs from the current price: in the case of potential buyers it will be higher, for sellers it will be lower. Let us denote this valuation by S. Their estimate, however, is risky. The standard error of the valuation at day t will be noted by $\sigma(t)$. We assume that this perceived risk about the valuation will become smaller when a price movement (a daily absolute return r_t) that fits the forecast occurs and it will become larger if the price movement contradicts this expectation. This essentially implies that private investors follow the hot (cold) hand fallacy called behavior.[6] More precisely, we assume that

$$\sigma(t+1) = \begin{cases} a\delta \cdot \sigma(t), & \text{if } \operatorname{sign}(r_t) \text{ aligned with expectation} \\ \frac{1}{a} \cdot \sigma(t), & \text{if } \operatorname{sign}(r_t) \text{ not aligned with expectation} \end{cases}$$

Where $a<1$ denotes the strength of the adjustment and δ denotes the potential amount of confirmation bias: investors often take information more important if it confirms their beliefs, but tend to ignore or downplay contradicting information. $\delta = 1$ corresponds to the "rational" case of no asymmetry between confirming and disconfirming outcomes, while smaller values correspond to a bias.[7]

Since investors who own a certain stock already, will on average feel more confident about their knowledge about this stock, we also assume that a is larger for potential sellers than for potential buyers. We denote these two different values by a_b for the buyer and a_s for the seller.

After a few days of observing the daily return r_t of the stock price S_t, the potential buyer or seller finally decides to buy if the expected gain with respect to the risk is sufficiently high, the minimum value denoted as m.

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[6] The hot (cold) hand fallacy describes the erroneous belief that the continuation of a trend has a higher probability though the sequence of the single elements of the trend is random.

[7] This classical idea has been already used by Daniel et al. (1998) as a model for the momentum effect.

The potential buyer decides to buy if

$$\frac{S - S_t}{\sigma(t)} \geq m$$

and the potential seller decides to sell if

$$\frac{S_t - S}{\sigma(t)} \geq m.$$

Let us take a look now on the impact of up-down-movements on the likelihood that a potential buyer or seller turns into an actual buyer or seller:

After a positive day the buying decision should become easier, as the perceived risk decreases. However, at the same time the price of the stock increased which reduces the potential gains. In the extreme case, the potential buyer might be really sure now that it *would have been* a good idea to buy, but *now* it's too late, as the price has already gone up!

We can derive a condition for the likelihood of buying to increase after a stock price increase:

$$\frac{S - S_t}{\sigma(t)} = \frac{S - S_{t-1} - r_t}{\sigma(t)} > \frac{S - S_{t-1}}{\sigma_{t-1}},$$

which we can transform into

(1) $$a_b \delta < \frac{S - S_{t-1} - r_t}{S - S_{t-1}}.$$

Analogously, for the potential seller we derive the following condition for increased selling propensity after a positive day:

(2) $$a_s > \frac{S - S_{t-1}}{S - S_{t-1} - r_t}.$$

After a negative day, using similar computations we find the same conditions, just that (1) is now the condition for potential sellers and (2) for potential buyers.

The stronger the adjustment of the perceived risk (captured by a) in relation to $|S - S_{t-1}|$, the more likely (1) will be satisfied rather than (2). Since $a_s > a_b$, inequality (1) can be satisfied for potential buyers and (2) for potential sellers, thus our model can predict an increase in buying *and* selling decisions after positive days.

Let us consider a numerical example:

Consider first a positive day and take S_{t-1}=100 and r_t=2. A potential buyer might estimate the target price with S=110, a potential seller with S=90. We also assume that most potential buyers have a value of a_b between 0.7 and 0.8, while most potential sellers have a larger value of a_s, say, between 0.9 and 1.0. We also assume for simplicity at first that $\delta = 1$.

Given our variable choices for S, S_{t-1} and r_t=2, inequality (1) and (2) become:

$$a_b < 0.8 \text{ and } a_s > 0.83.$$

Using the assumptions on a_s and a_b, we see that most potential buyers will satisfy the inequality and thus will have a higher tendency to buy after a positive return, but also most potential sellers will have a higher tendency to sell after a positive return. (The former, because they became even more optimistic, the latter because their expected loss for not selling increased.)

Assuming now a smaller value of δ makes it even more likely that investors buy after a positive return, but does not affect the propensity of selling.

A negative return leads to the opposite situations and then most people would neither like to sell nor to buy. Here, however, a smaller value of δ would make selling more likely, while it would not affect buying.

It is obvious, that in reality neither parameter ranges nor a strict implementation of this model will be observed, but if only *sufficiently many* private investors *sufficiently often* follow *approximately* this model, higher trading activity of private investors following up-movements will be the result. We also see that the trade imbalance between buying and selling will be directly affected by the value δ: if the asymmetry in adjustment between confirming and disconfirming outcomes is larger, i.e. δ is smaller, we will see a trend towards a positive trade imbalance after up movements. We finally add one more factor into our model: the disposition effect (Shefrin & Statman, 1985, Barber & Odean, 1999). Investors are in general reluctant to sell stocks if they are in the "loss zone", i.e. if their market prices are below the initial purchasing prices.

This effect does not erase the previously studied effect, but how does it modify our model for potential sellers? After a positive day, fewer potential sellers will be in the "loss zone" and thus selling will increase. After a negative day, however, some will enter the "loss zone", thus becoming reluctant to sell, and consequently their selling probability will decrease. In summary, this increases the impact of up- and down-movements on potential sellers, but of course not on potential buyers whose decisions are not influenced by the disposition effect. This can explain the negative transaction imbalance between buyers and sellers: after up-movements, selling by private investors increases even more than buying and vice versa.

To summarize our model assumes:

- Some investors wait a few days before they sell or buy.
- Price movements that are in the direction of their forecast increase their confidence in this forecast (confirmation bias). Contradicting price movements reduce it.
- An increase in confidence finally makes a subsequent buying or selling decision more likely, a decrease less likely.
- Independently of that, selling decisions are additionally subject to the disposition effect: a decrease of the price makes it therefore more likely that stocks fall below the initial buying price and thus are *not* being sold.

Based on these mechanisms, the model predicts:

- more trades after an up-movement,
- a positive trade imbalance when the confirmation bias is the dominating factor,
- a negative trade imbalance when the disposition effect dominates.

5.2 Verification of model predictions

Our model can explain all patterns observed in the previous data analysis, but of course, it would be great to have data on behavioral biases for the investors to verify this model directly. Such data, however, are not available. Alternatively, we might generate similar data in a financial market experiment, but this would suffer from a severely reduced external validity.

We have, however, at least some indication that the confirmation bias might be related to a more positive trade imbalance by looking at the gender distribution of our sample: males are on average more overconfident (Lundeberg, 1994) – a concept related to the confirmation bias. Additionally, females tend to have a higher disposition effect (Rau, 2014). Taken both effects together, our model predicts that the trade imbalance is significantly less negative for men and more negative for women. The data support this prediction very well: We have computed the difference of the trade imbalance between the two extreme patterns (+++ and ---) for every investor and also computed its correlation between trade imbalance and the weighted sign of returns (WS), as defined in Section 4.2. As expected, we found a negative difference of the trade imbalances and also a negative correlation between trade imbalance and WS. Both variables, however, were with high statistical significance *more* negative for females (Table 8). This can be attributed to the aforementioned gender differences in overconfidence and disposition effect and thus confirms the prediction of our model.

		Average	Std. error	N
Trade imbalance difference between +++ and ---	male	-7.4%	0.29%	14097
	female	-9.4%	0.29%	15222
Correlation between WS and trade imbalance	male	-10.9%	0.51%	11078
	female	-18.0%	0.48%	11554

Table 8: Female investors tend to have a significantly more negative trade imbalance. Our model would predict exactly this, based on well-known gender differences in confirmation bias and disposition effect.

When looking back now at the previous section and particularly on Table 7, we find some more evidence for our model: there were two distinct clusters of investors (Cluster A and B) that can now be understood as those for whom disposition effect dominates and those for whom confirmation bias dominates. As predicted, in the former one the proportion of women is higher, whereas the latter one has a larger share of men.

5.3 Extension of the model to general market movements

We now want to discuss a possible extension to our model: while the assumption that the perceived risk changes when up- or down-movements (supporting or contradicting the investor's forecast) occur seems reasonable, it seems reasonable, too, that not only the sign matters, but also the amount: a strong upwards movement is obviously confirming a positive forecast more than a small upwards movement. This effect might explain why in our regression results (Table 5) also the returns themselves are statistically significant for buys and sales. On the other hand, the disposition effect will obviously be more relevant when the absolute value of returns is large, since the probability of leaving or reaching the "loss zone" is in this case larger which could explain why the previous days' returns are statistically significant for the trade imbalance as well (Table 6).

The previous returns, however, are also related to, e.g., momentum strategies, therefore we do not want to claim that this explanation would be the only or best one to interpret these side observations.

6 Conclusion

The efficient market theory assumes that investors make their purchase and sell decisions on the basis of new additional information. While it is in general well-known that reality is different, in our paper we can show even more, namely that also seemingly irrelevant information on the sign of stock market returns can have a substantial impact on stock trading by private investors. We show that the more positive a past market pattern is, the more it encourages private investors to trade stocks. This applies to purchases and to sales. After a rather negative pattern the observed private investors had significantly fewer trades. We thus can confirm the general observations of Statman, Thorley and Vorkink (2006) for short-term stock patterns that the past stock market development has a strong impact on the decisions of private stock market investors and extend them to reactions on the price pattern of several days.

Additionally, we examine the buy-sell ratio after these up-down patterns to find further evidence for differing reactions to the patterns. Again, we see differences in regard to the various patterns. While private investors execute more sell than buy trades after patterns with predominantly positive days, we measure the opposite behavior after mainly negative patterns.

Our findings restrict, but also supplement the results of Barber and Odean (2005), who attribute the increased trading after positive and negative one-day return shocks to an attention-grabbing mechanism. The price patterns examined in this paper, however, generate no such attention, but are perceived only by those who have become aware of the stock anyway – because they either own it or want to buy it. The model we have proposed in the last section can in general explain the observed patterns.

Our research contributes to the understanding of decision processes in investors. We hope that this can be one more step towards a deeper understanding of the investors' decision processes that could ultimately help to provide private investors with more effective tools to cope with the challenges of long-term asset management.

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Appendix: robustness tests

stocks with the lowest trading volume (lowest 50%)						Days with highest volatility days (highest 10%)					
Bought (in thousands)		Bought (in thousands)		Imbalance		Bought (in thousands)		Bought (in thousands)		Imbalance	
+++	98.7	+++	104.8	-++	-0.8%	+++	25.8	+++	26.4	+++	-0.6%
-++	95.8	-++	101.9	+++	-0.8%	---	25.3	---	25.9	-++	-0.6%
+-+	89.0	+-+	93.6	+-+	-0.6%	-++	25.3	-++	23.0	+-+	-0.4%
--+	88.8	--+	91.3	--+	-0.3%	--+	22.9	--+	23.0	--+	-0.2%
---	88.3	++-	84.3	++-	-0.1%	-+-	21.2	-+-	20.4	++-	0.0%
++-	82.7	-+-	79.4	-+-	0.3%	++-	20.6	++-	20.2	-+-	0.3%
+--	82.2	---	78.8	+--	0.8%	+-+	19.7	+-+	20.1	+--	0.4%
-+-	81.0	+--	77.3	---	1.4%	+--	19.6	+--	18.7	---	1.1%

Table A.1: Robustness tests for the stocks with the lowest trading volume and for the days with the highest volatility.

Data without penny stocks (excluding stocks with price < 5 NTD)					
Bought (in thousands)		Bought (in thousands)		Imbalance	
+++	97.3	+++	103.6	+++	-0.7%
-++	96.8	-++	103.0	-++	-0.7%
--+	91.6	+-+	95.2	+-+	-0.5%
---	91.6	--+	94.2	--+	-0.2%
+-+	90.5	++-	86.2	++-	-0.1%
+--	85.5	-+-	82.9	-+-	0.3%
++-	84.5	---	82.4	+--	0.7%
-+-	84.3	+--	80.7	---	1.4%

Table A.2: Robustness test omitting all penny stocks.