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Herd behaviors in index futures trading: Driving factors and impact on market volatility

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Abstract

This study analyzes market index futures data on the Taiwan Futures Exchange to explore herd trading behaviors and their impact on the market. The study finds that herd behaviors are prevalent in all trading directions and that investor sentiment is a more direct explanation than information chasing. Herding in intraday trading increases market volatility on the same day but decreases it on the following day. Additional tests show that overnight trading has a weaker herding tendency and a less noticeable market correction on the following day, which can be attributed in part to the lower participation of retail traders in overnight sessions. The analysis using overnight trading reinforces the relevance of retail trading in explaining herd trading. Overall, the study offers new evidence and insights into herd behaviors in the derivatives market dominated by retail investors.

KEYWORDS

herd behaviors, index futures, information chasing, investor sentiment, market volatility, retail investors

1 | INTRODUCTION

Financial markets are inherently volatile and difficult to predict. Retail investors, in particular, often struggle to keep pace with the market due to time constraints, information disadvantages, and investor sentiments when compared to professional institutional investors (Barber & Odean, 2008; Grinblatt & Keloharju, 2000; Kaniel et al., 2008). This can lead to difficulties in executing their own investment strategies (Kumar & Lee, 2006). Without the ability to make personal evaluations of investment opportunities, retail investors may rely heavily on mainstream market information, which can result in herd behavior when trading (Merli & Rogerz, 2013; Nofsinger & Sias, 1999; Shleifer & Summers, 1990). This herd behavior occurs when investors buy or sell in accordance with the same information held by others in the market. Additionally, sentiment in the market can lead individual investors to be overly optimistic or pessimistic, which can result in sentiment-driven herd behavior in trading. According to the literature, both information chasing and investor sentiment are the foundation of herding bias. However, few studies have directly compared these two explanations to determine which driving factor is more relevant to herd behavior in trading activities. This study attempts to fill this gap in the literature by analyzing intraday trading data for index futures.

Specifically, we used the data of index futures contracts on the Taiwan Capitalization Weighted Stock Index (TXF) of the Taiwan Futures Exchange (TAIFEX), which is particularly suitable for our study, to determine which factor drives herd behaviors the most.[1] Unlike the US market, on the TAIFEX, the trading proportion of retail investors is

[1]The TXF is the main stock market index on the Taiwan Stock Exchange.

much higher than that of institutional investors. At one point in our sample period, monthly individual trading accounted for as much as 70% of the entire market. Although individual trading volume has declined slightly in recent years, the average proportion of monthly individual trading throughout the sample period remained greater than 60%. Considering that retail investors are usually viewed as irrational noise traders, a market like the TAIFEX provides an opportunity to examine herd behaviors that are mainly driven by retail investors.

In addition, using the data of the TXF provides another advantage in examining herd behavior. The market index usually reflects market-wide information, such as macroeconomic news, which is commonly viewed as public information. In cases where each trader within the same market has access to the same set of public information, it seems far less likely for specific types of investors to be in possession of private information at the market level. For example, Pan and Poteshman (2006) found no evidence of informed trading in three broad index derivative markets: the S&P 100, the S&P 500, and the NASDAQ-100 indices. Therefore, when it comes to TXF trading, individual traders may be less likely to possess an information advantage. Uninformed investors are sensitive to the general sentiment and are more likely to be led by the mainstream market information, resulting in the frequent herd behaviors seen in the market.

Moreover, in the examination of herd behavior in TXF trading, this analysis is free from the influence of firm characteristics, since the TXF index is an alternative proxy of the market index. The herd trading of index futures on the TAIFEX, if any, is thus more likely to be directly driven by investor sentiment or the tendency of information chasing than specific firm characteristics. In sum, the TAIFEX, with its trading activities of index futures, provides an ideal environment for an empirical analysis of herd behavior, which enables us to discover the causes and effects of herd trading among investors.

Herd behavior has been intensively studied in the literature. The measurement of herd behavior in trading can be classified into two dimensions: herd trading for specific firms or financial assets (firm level) and the intensity of herd trading in the market (market level). Therefore, prior researchers have developed proxies for different levels of herd behaviors. Herding proxies proposed by three seminal works are worth mentioning. First, the herding intensity measure developed by Lakonishok et al. (1992) (LSV) examines the tendency of retirement fund managers to buy or sell the same stock over a period of time. Second, Christie and Huang (1995) used the cross-sectional standard deviation (CSSD) of individual stock returns and stock market index returns to proxy for the level of herding of all investors in the market. Finally, Chang et al. (2000) applied the framework of the capital asset pricing model to transform the CSSD into the cross-sectional absolute deviation (CSAD) to provide international evidence of herd behaviors in trading. Previous studies have widely used the LSV, CSSD, and CSAD indicators to examine financial markets and document the existence of herd behaviors in trading activities.[2]

However, previous studies have mostly utilized lower-frequency observations, such as daily or quarterly data, to estimate the herding tendency. Low-frequency data are suitable for testing herd behaviors in portfolio rebalancing but could underestimate the herding tendency in high-frequency trading activities. Indeed, some studies have determined investors' intraday herding behavior, which cannot be precisely observed by daily or quarterly trading data, through high-frequency trading data (Blasco et al., 2012; Fei et al., 2019; Hsieh, 2013; Zhou & Lai, 2009). It is well known that retail investors are active in trading and characterized by irrationally high turnover ratios (Barber et al., 2009). To study herd behavior that is mostly caused by individual trading, therefore, we focused on the intraday herding tendency via the proxy proposed by Blasco et al. (2012) rather than the LSV, CSSD, or CSAD.[3]

The empirical analysis and corresponding findings of this study consist of several parts. First, we used the indicators developed by Blasco et al. (2012) to measure the tendency of herding for each day of our sample period. Notably, Blascos et al.'s indicators are based on the number of changes in trading price direction for each intraday interval in a specific trading day. An indicator with a lower value is associated with fewer direction changes in consecutive

[2]Celiker et al. (2015) used the LSV herding indicator to study the mutual funds herding phenomenon in the industry. Caglayan et al. (2021) used the LSV to study hedge funds' herding effect and its impact on industry returns. Deng et al. (2018) used the LSV herding indicator to study the impact of mutual fund herding behavior on stock price crashes. Chiang and Zheng (2010) used the CSSD and CSAD to analyze herding behavior in 18 markets around the world, and they found evidence of herding effects in Asian markets but not Latin American markets. Batmunkh et al. (2020) used the CSAD to analyze border countries, finding that herding behavior is more pronounced in small-capitalization stock groups.

[3]Blasco et al.'s (2012) measure is based on the actual number of changes in trading direction within a day. A smaller number of direction changes imply that investors continue to trade in a single direction and suggest investors' herding. We provide the definition and explanation of herding indicators in a later section.

transactions, which implies that investors keep trading the prices in the same direction. Therefore, the "daily" herding indicators in this study present the "intraday" herd behaviors of investors for each day.

Second, we explored which driving factor of herd behaviors is more relevant. As mentioned earlier, both investor sentiment and information-chasing tendency can lead to herd behaviors. To determine the roles of both factors, we regressed herding indicators on investor sentiment and information-chasing tendency.

Our results show that index futures' herding behavior on the TAIFEX is severe when market participants' sentiment in trading is strong. Investor sentiment was measured by the margin trading ratio and volatility index (VIX). Regardless of the proxies used, we found that investor sentiment affects the herding tendency. Interestingly, a higher ratio of leveraged trading usually indicates that investors are more optimistic, while a higher VIX reveals that investors are more pessimistic. The regression results, therefore, suggest that extreme sentiment, either positive or negative, leads investors to herd in trading.

Conversely, we found no evidence that the tendency of information-chasing activities is related to herd trading on the TXF of the TAIFEX. Hong and Yu (2009) found that stock trading volume is lower during the summer because investors are on vacation and pay less attention to their investments. Similarly, Schmittmann et al. (2015) suggested that the opportunity cost of paying attention to investments on days with nice weather is higher for retail investors since they are more likely to spend time planning their next vacations or off-work activities. In line with these studies, we can infer that on the eve of a holiday, assuming that people's thoughts are focused on the upcoming vacation, they may be unable to maintain the same level of concentration as before on their work or daily investment decisions (Kahneman, 1973). Therefore, we can expect that investors would be more likely to rely on publicly reported news or information to make investment decisions before holidays due to the decreased attention during such times. If this is the case, the tendency to chase mainstream information in the market is also the cause of herd trading, and the herding tendency among investors should be higher before holidays.

Unfortunately, we found that the herding tendency is not higher in the preholiday period, which implies that herd trading activities on the TAIFEX are less likely to be driven by the tendency of chasing market information.

After determining the driving factor of herd behavior on the TAIFEX, we examined how herd trading affects the market. Previous studies have suggested that the herding of investors on the stock market exacerbates price movements, destabilizes the market, and increases the vulnerability of financial systems (Iihara et al., 2001; Venezia et al., 2011).[4] Therefore, we examined whether the herd behaviors of investors on the TAIFEX also have a similar impact on market volatility. Our findings showed that intraday herding activities temporarily increase price pressure and hence lead to significant price fluctuations on the same day. This finding supports the research of Blasco et al. (2012) and Avramov et al. (2006), who suggested that herding trades are usually subject to noise traders and thus unavoidably show increased price variation.

Interestingly, in addition to the concurrent relationship between herd behaviors and market volatility, we further found that short-term price pressure driven by herding traders subsequently results in price reversals and reduces market volatility the following day. This finding implies that herding investors cause an overreaction effect in the market, which echoes our previous finding that herd behavior in trading is driven by investor sentiment and reveals the essential irrationality of herding bias.

It is worth noting that our current findings are based on trading data from regular sessions. However, after-hours trading sessions were launched on the TAIFEX in May 2017 to facilitate instant responses to news in the overnight period. As herding behaviors were observed in regular sessions, a question arises: Do investors exhibit stronger or weaker herding tendencies in overnight sessions? Additional findings from further tests, using trading data in overnight sessions, emerged. Herding has a weaker impact on volatility in overnight sessions than in regular sessions, and there is a less noticeable market correction on the following day. These results suggest a weaker tendency toward herding, which can be attributed in part to the lower participation of retail traders in overnight sessions. Our analysis of

[4]Iihara et al. (2001) classified Japanese market investors into domestic individual, institutional, and foreign investors and found that the herding behaviors of institutional and foreign investors have a much greater impact on stock prices than those of domestic individual investors and lead to increased stock price volatility for specific groups of stocks. Venezia et al. (2011) used the trading records of the largest Israeli banks between 1994 and 1997 to separate professional and amateur investors and explore their investment decisions to enter and exit the market. They found a higher correlation between amateur investors and market volatility, which suggests that amateur investors pose a greater threat to market stability than professional investors.

herding in overnight sessions reinforces the importance of retail trading, supporting our earlier findings from trading data in regular sessions.

Despite the numerous prior studies that have examined herd behaviors in the stock market or mutual fund investments, empirical evidence of herding activities for derivatives trading is sparse. This study contributes to the literature on the herd behaviors of traders in financial markets by examining the herd trading of index futures on the TAIFEX, where we can directly observe herd trading behaviors without concerning ourselves with the compounding influences of firm characteristics. Our analysis of herd behaviors is based on intraday trading data, and we constructed a daily proxy to examine the driving factor of herding and its instant impact on the market. Therefore, compared with most previous findings that have been based on lower-frequency data, our findings provide new insight into existing research and enrich our understanding of the nature of herding behaviors.

The rest of this paper is organized as follows: Section 2 introduces the samples, variables, and research methods used in this study, Section 3 presents the empirical results, and Section 4 concludes this paper.

2 | SAMPLES, VARIABLES, AND METHODS

2.1 | Samples

This study used intraday trading data of the TXF to analyze herd behavior. The sample period examined in this study was from January 1, 2005, to March 31, 2019, totaling 3414 trading days. The intraday trading data of the TXF were obtained from the TAIFEX. We also collected other required trading data from the *Taiwan Economic Journal* database, a leading financial data vendor in Taiwan.

The TXF is the most liquid and mature futures contract that underlies the representative stock market index of Taiwan on the TAIFEX. Regular trading sessions for the TXF on the TAIFEX are continuous from 8:45 a.m. to 1:45 p.m. Monday to Friday (excluding public holidays). Each trading day on the TAIFEX, six TXF contracts with different expiration months are available for trading, including the spot (current) month, the next two calendar months, and the next three quarterly months. Upon expiration of the near month, the new contract month is listed for trading beginning on the next regular trading session.[5] Generally, the TXF contract expiring in the spot month has the greatest trading volume. However, as trading days approach the settlement date of the current month, many futures traders may close out their open positions and place new positions in the TXF contract expiring in the next calendar month. Therefore, near the settlement date, the trading volume of the contract expiring in the next month is sometimes greater than that of the contract expiring in the current month. To avoid any bias caused by trading illiquidity, we considered the TXF contract with the largest daily trading volume on each day, regardless of its expiry month.

Table 1 reports the daily statistics of trading variables. As shown in the table, the average trading volume of the TXF was 179,953 contracts per day. The average buyer-initiated trading volume was 40,883 contracts, while the average seller-initiated trading volume was 23,738 contracts, and the average flat trading volume was 115,285 contracts. When a trade can be classified with a trading direction, the statistics in Table 1 show that the buyer-initiated trading volume was much greater than the seller-initiated one, suggesting a stronger tendency to place long positions than short positions among traders on the TAIFEX. The finding is similar to that of Hao et al. (2016), who showed a positive aggregated order imbalance (buyer-initiated trades minus seller-initiated trades) of the TXF on the TAIFEX in the sample period from 2003 to 2008. Since the data analyzed by Hao et al. (2016) could identify different investor types, their results also showed that the TXF order imbalance of retail investors is positive. As mentioned earlier, since the raw data used in this study consists of the intraday transaction prices of the TXF only, we followed the method of Blasco et al. (2012) to define the trading direction using the tick test approach. However, in line with the previous literature, we found that the trading volume initiated by buyers is greater than that initiated by sellers. Therefore, the results reported in Table 1 indicate that the tick test is reasonable and applicable in identifying the trading direction.

[5]The regular trading session on the last trading day for the delivery month contract is adjusted to 08:45 a.m.–1:30 p.m.

TABLE 1 Descriptive statistics of trading variables.

	Mean	Std.	Minimum	Q1	Median	Q3	Maximum
Trading_volume	179,953	88,525	4608	28,522	182,870	355,549	812,818
$Trading\_volume_{Buy}$	40,883	19,238	4762	8676	38,771	83,672	223,996
$Trading\_volume_{Sell}$	23,738	10,999	4182	6526	21,744	49,139	138,892
$Trading\_volume_{Zero}$	115,285	65,186	4608	12,036	120,679	238,414	496,340
TXF	8116	1475	3903	4349	8138	10,917	11,227
TXF_return %	0.024	1283	−7.714	−4.501	0.067	2.668	6.992

Abbreviation: TXF, Taiwan Capitalization Weighted Stock Index.

2.2 | Herding proxy

We followed the approach of Blasco et al. (2012) to calculate the herding tendency by intraday trading data. First, we used the tick test to determine the direction of each trade.[6] If the price of the current trade was higher than that of the previous trade, the current trade was an up-tick. Conversely, if the price of the current trade was lower than that of the previous trade, the current trade was a down-tick. For others, the trade was a zero-tick. Next, we calculated the number of changes in trading direction. Trading direction changes were defined by the switch between up-tick, down-tick, and zero-tick. For example, if a trade changed from a down-tick or zero-tick to an up-tick, we referred to the trading direction change as a buyer-initiated run (R_{buy}); if a trade changed from an up-tick or zero-tick to a down-tick, then we referred to the trading direction change as a seller-initiated run (R_{sell}); and when a trade changed from an up-tick or down-tick to a zero-tick, we referred to the trading direction change as a flat run (R_{zero}). Finally, the herding tendency in each trade type (buy, sell, and zero) was measured as follows:

$$x(i,t) = \frac{(R_{i,t} + 1/2) - np_s(1 - p_s)}{\sqrt{n}}, \quad i = buy, sell, zero, \tag{1}$$

where $x(i, t)$ is the herding tendency of index futures trading for trade type i on day t. $R_{i,t}$ is the number of runs for trade type i on day t, and 1/2 is the noncontinuous adjustment parameter. n is the total number of trades on day t, and $np_s(1 - p_s)$ is the expected value of $R_{i,t}$, assuming that the changes in trading direction appear uniformly. p_s is the ex-ante probability that a trading direction appears and was set to be 1/3, since theoretically, each direction has an equal probability ex-ante. We assumed that $x(i, t)$ follows a normal distribution with a mean of 0. Therefore, the standardized $H(i, t)$ was obtained using the following formula:

$$H(i,t) = \frac{x(i,t)}{\sqrt{\sigma^2(i,t)}} \overset{a.d.}{\rightarrow} N(0,1), \tag{2}$$

where $\sigma^2(i,t) = p_s(1-p) - 3p_s{}^2(1-3p_s{}^2)$. If the number of runs for a specific trade type was lower than the expected value, the changes in trading direction were infrequent and $H(i, t)$ tended to be negative. Infrequent changes in trading direction indicate that trade prices occasionally move in the same direction across more ticks; therefore, a smaller value of $H(i, t)$ is associated with a greater tendency of herding behavior in index futures trading.

[6]By exploiting the advantage of unique data sets containing detailed trading information, some previous studies were able to identify the trading direction without the need for any adaptation algorithm. For instance, Barber et al. (2009) were able to obtain a comprehensive set of trading data from the Taiwan Stock Exchange. However, most studies lacking such unique data sets must rely on classification algorithms to identify trading directions. Some commonly used approaches in the literature include the tick rule (TR), Lee–Ready approach, and bulk-volume classification algorithm, among others. The selection of a particular method depends on the available data variables. Given that our time-series intraday trading data are similar to the data set used by Blasco et al. (2012), we have followed their approach and used the TR to determine the direction of each trade, as described in Table 1. As mentioned, the results indicate the validity of the tick test approach.

2.3 | Regression model

The empirical analysis of this study consists of three parts. We introduce the regression models for each part of the analysis in the following subsections.

(1) *Effect of investor sentiment on herd behaviors in trading*

To determine whether investor sentiment drives herd trading on the TAIFEX, we conducted the following regression:

$$H_{i,t} = \alpha + \beta_1 H_{i,t-1} + \beta_2 sentiment_t + Year\ FE + Month\ FE + Weekday\ FE + \varepsilon_t, \tag{3}$$

where $sentiment_t$ indicates investor sentiment in the market on trading day t. We considered two proxies to measure investor sentiment: the margin trading ratio on the stock market and the VIX of the market. The margin trading ratio is calculated as the ratio of the balance of total margin purchase over the balance of total short sales.[7] The VIX is commonly regarded as the market's perception of future stock market volatility and is also known as the fear index.[8] Since herd behaviors could persist across days, we controlled $H_{i,t-1}$ in Equation (3). We expected the coefficient β_2 to be negative if investor sentiment mostly drove the tendency of herd trading.

(2) *Effect of investor attention on herd behaviors in trading*

When retail investors are unable to execute investment strategies based on their own set of information, they are more likely to follow the behaviors of other investors which result in herding. In other words, the opportunity costs of paying attention matter in this scenario for retail investors (Hong & Yu, 2009; Schmittmann et al., 2015). Therefore, we supposed that the tendency of herd behaviors in trading would increase before holidays, since during holidays, individual traders are more likely to allocate their time to holiday plans and pay less attention to investment decisions or information collection. To test this effect, we defined a preholiday dummy and conducted the following regression:

$$H_{i,t} = \alpha + \beta_1 H_{i,t-1} + \beta_2 preholiday_t + Year\ FE + Month\ FE + Weekday\ FE + \varepsilon_t, \tag{4}$$

where $preholiday_t$ is equal to 1 if trading day t is the day before a long holiday (i.e., at least 3 days off) and 0 otherwise. We did not consider regular 2-day weekend holidays since individuals are more likely to plan for a longer vacation when the day before a holiday that lasts three consecutive days or more falls on a trading day. If the eve of a long holiday does cause investors to pay less attention to the market and result in a stronger tendency of herd behaviors in trading, the coefficient β_2 should be negative.

(3) *Impact of herd trading behavior on market volatility*

The final part of our empirical analysis was the impact of herd trading behavior on market volatility. The regression model is as follows:

$$volatility_t = \alpha + \beta_1 H_{i,t} + \beta_2 TXF_t + \beta_3 volatility_{t-1} + \beta_4 return_t + Year\ FE + Month\ FE + Weekday\ FE + \varepsilon_t, \tag{5}$$

where $volatility_t$ refers to the market volatility, TXF_t is the closing price of the TXF on trading day t, and $return_t$ is the index return of the TXF on trading day t. It is well known that volatility can persist over time; thus, we controlled $volatilit_{t-1}$ in the model for persistence. If herding trades shake the market more (less), the coefficient β_1 is positive (negative).

Since our herding proxy was a daily indicator and captured the herding tendency across multiple trading intervals within a day, we used high–low price variation within a trading day (HLV_t) to measure market volatility to examine the

[7]On the Taiwan Stock Exchange, only individual investors can trade on margin. Therefore, the margin trading ratio is commonly used to represent a sentiment index of retail trading in the market. A higher margin trading ratio indicates that individual investors are more optimistic about the market and actively participate in trading; conversely, a lower margin trading ratio suggests that investors are more conservative about the market growth.

[8]The sample period of this study was from 2005 to the first quarter of 2019; however, the data of the VIX in Taiwan are only available from December 1, 2006. When using the VIX as a sentiment proxy, we shortened the sample period to match the availability of the VIX data.

TABLE 2 Descriptive statistics of main variables.

	Mean	Std.	Minimum	Q1	Median	Q3	Maximum
H_{buy}	−158.38	47.48	−351.21	−194.15	−162.97	−119.20	−53.09
H_{sell}	−158.31	47.46	−350.38	−194.14	−162.92	−119.03	−52.58
H_{zero}	−157.30	45.07	−339.90	−190.60	−161.10	−122.90	−51.50
HLV	1.30	0.56	0.17	0.72	1.05	1.55	12.52
Margin trading	2.26	0.41	1.47	1.95	2.20	2.51	4.08
VIX	19.63	8.51	7.82	13.62	16.91	23.25	60.41
Preholiday	0.02	0.15	0	0	0	0	1

Abbreviation: VIX, volatility index.

concurrent relationship between herding activities and the price variation in the market. The equation used to calculate HLV_t is as follows:

$$HLV_t = \frac{max_t - min_t}{TXF_{t-1}} \times 100\%, \tag{6}$$

where max_t refers to the highest price of the TXF on trading day t, min_t refers to the lowest price of the TXF on trading day t, and TXF_{t-1} refers to the closing price of the TXF on trading day $t-1$.

2.4 | Descriptive statistics of main variables

Table 2 shows the descriptive statistics of the main variables, including herding indicators, market volatility, investor sentiment, and preholiday dummy. As reported, the average buyer-initiated herding indicator was −158.38, while the average seller-initiated herding indicator was −158.31, and the average flat trading herding indicator was −157.30. According to Blasco et al. (2012), negative herding indicators suggest that the amount of the price direction change is lower than the expected value, which implies herding in trading. The statistics here suggest that herd behaviors are prevailing on the TAIFEX for both trading directions. Investors herd on buying, selling, and even flat trading. We also tested the differences between H_{buy}, H_{sell}, and H_{zero} and found no significant differences between the three indicators, which suggests that the herd behaviors of buying, selling, and flat trading for the TXF on the TAIFEX do not differ in their tendencies.[9] No particular trade type is more likely than other types to lead investors to herd in trading.

The average daily HLV was 1.3%, with a small standard deviation of 0.56%, showing that the TAIFEX is quite volatile on the intraday horizon. Considering that for most of the time during our sample period, the daily price limits (up or down) were only 7% on the TAIFEX, a variation of 1.3% between the highest and lowest prices is noteworthy.[10] The average values of daily sentiment proxies for the margin trading ratio and VIX were 2.26 and 19.63, respectively. The statistics show that retail investors on the Taiwanese stock market are actively engaged in margin trading; meanwhile, they tend to be more sentimental in trading, since the average VIX in the US market around the same period was 18.6 and was less volatile than that in Taiwan. The average value of preholidays was 0.02, which means that 2% of trading days in the sample were days before a long holiday.

To present the time variation of herd indicators across years, Table 2 shows the daily average of each herding indicator for each year. We also conducted a t test for the values, the results of which showed that the average value of each year's herding indicators, regardless of trade type, was significantly different from 0. From time to time, the tendency of herding in trading became stronger since the average values of herding indicators increased over the years. Given that the participation of institutional investors in the TAIFEX grew stably over the years in our sample period, having more rational investors does not seem to alleviate the tendency of herd trading.

[9]For brevity, the results of the difference tests on herding indicators are not reported in the table.
[10]The price limits on the TAIFEX were relaxed to 10% starting in August 2015.

TABLE 3 Annual averages of herding indicators.

Year	H_{buy}	H_{sell}	H_{zero}
2005	−85.10***	−85.10***	−85.53***
2006	−97.28***	−97.25***	−98.75***
2007	−98.39***	−98.24***	−101.95***
2008	−116.73***	−116.38***	−125.21***
2009	−134.81***	−134.73***	−138.27***
2010	−156.47***	−156.43***	−155.68***
2011	−178.59***	−178.41***	−178.72***
2012	−173.49***	−173.43***	−171.06***
2013	−166.96***	−166.98***	−163.98***
2014	−177.31***	−177.26***	−173.74***
2015	−195.22***	−195.13***	−191.22***
2016	−197.51***	−197.50***	−193.06***
2017	−203.55***	−203.55***	−199.11***
2018	−217.51***	−217.46***	−210.71***
2019	−191.44***	−191.53***	−185.34***

*, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

In sum, the statistics reported in Tables 1 and 2 offer a portrait of the TAIFEX in which index futures trading is volatile within a day and commonly subject to herd behaviors. Meanwhile, investors in this market can be quite sentimental in trading and occasionally affected by long holidays. All of these characteristics further support the suitability of the TXF data of the TAIFEX in examining herd behaviors (Table 3).

3 | EMPIRICAL RESULTS

3.1 | Driving factors of herd behaviors

Table 4 examines the first possible driving factor of herd behaviors: investor sentiment. The regression results are based on Equation (5) with two different sentiment proxies—margin trading ratio (Panel A) and VIX (Panel B).

As reported in the first three columns of Table 4, we found that regardless of the proxy used (Panels A and B), investor sentiment has a significant negative impact on the herding indicator for any trade direction. A higher VIX or greater margin trading ratio tends to drive more investors to herd in trading and decrease the value of herding indicators. To further examine whether the sentiment impact can last more than 1 day, we replaced $sentiment_t$ of Equation (5) with $sentiment_{t-1}$ and conducted the regression analysis again. The last three columns of Table 4 show that the reported coefficients of $sentiment_{t-1}$ are smaller than those of $sentiment_t$ but are still negative and statistically significant. These results suggest that both margin trading and VIX in the last trading day can still affect the current day's herding indicators, although the impact can decline over time.

Interestingly, even though both the margin trading ratio and VIX affect the herding tendencies of investors, a higher VIX and greater margin trading ratio relate to different types of investor sentiment. More margin trades imply that retail traders in the market are relatively optimistic and tend to buy more shares with leverage; on the contrary, a high VIX indicates that market investors are in a state of panic, thus driving up market uncertainty. Taken together, these findings show that extreme investor sentiments, whether positive or negative, can increase investors' tendency to herd on transactions. In short, the results of Table 4 suggest that investor sentiment is a driving factor of herding behaviors on the TAIFEX.

TABLE 4 Relationship between investor sentiment and herding behaviors.

Dependent	H_{buy}	H_{sell}	H_{zero}	H_{buy}	H_{sell}	H_{zero}
Panel A: Margin trading						
Constant	−37.169*** (4.067)	−37.560*** (4.061)	−34.279*** (4.125)	−43.662*** (4.076)	−43.781*** (4.068)	−40.976*** (4.136)
Margin trading$_t$	−11.739*** (1.804)	−11.565*** (1.799)	−13.455*** (1.840)			
Margin trading$_{t-1}$				−8.244*** (1.816)	−8.228*** (1.811)	−9.838*** (1.854)
$H_{i,t-1}$	0.269*** (0.016)	0.268*** (0.016)	0.269*** (0.016)	0.273*** (0.016)	0.272*** (0.016)	0.273*** (0.016)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Weekday FE	Yes	Yes	Yes	Yes	Yes	Yes
N	3413	3413	3413	3413	3413	3413
Adjusted R^2	0.803	0.803	0.773	0.801	0.802	0.771
Panel B: VIX						
Constant	−55.844*** (5.551)	−55.971*** (5.539)	−55.070*** (5.616)	−59.580*** (5.692)	−59.515*** (5.677)	−58.931*** (5.768)
VIX$_t$	−0.815*** (0.085)	−0.806*** (0.085)	−0.935*** (0.086)			
VIX$_{t-1}$				−0.549*** (0.086)	−0.552*** (0.086)	−0.653*** (0.088)
$H_{i,t-1}$	0.264*** (0.017)	0.263*** (0.017)	0.259*** (0.017)	0.272*** (0.017)	0.271*** (0.017)	0.268*** (0.017)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Weekday FE	Yes	Yes	Yes	Yes	Yes	Yes
N	2946	2946	2946	2946	2946	2946
Adjusted R^2	0.728	0.729	0.681	0.723	0.724	0.675

Abbreviations: FE, fixed effect; VIX, volatility index.

*, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

We next examined an alternative driving factor of herd behavior: the tendency of information chasing. As mentioned in Section 2, we considered the decreased investor attention before a long holiday to measure the tendency of information chasing. The regression analysis was based on Equation (6), and the results are reported in Table 5.

Although the coefficient of the preholiday dummy was statistically significant, the sign was positive, indicating that on trading days before long holidays, traders on the TAIFEX tend to be less subject to herding bias. Given that previous studies (e.g., Hong & Yu, 2009) have documented that vacations increase the opportunity costs of paying attention to investments and lead to price comovement of different stocks, the results of Table 5 imply that the tendency of information chasing does not serve as a main driving factor of the herding activities on the TAIFEX. Interestingly, given our failure to associate decreased investor attention with herd behaviors, the results of Table 5 may indirectly support the explanation of investor sentiment. Choi and Choi (2019) and Cheng et al. (2021) obtained similar results that during the holiday season, market participants become calmer and conduct fewer trading activities. In line with this finding, the preholiday effect reported in Table 5 may just serve as a reverse sentiment effect and cause a finding opposite to that in Table 4.

TABLE 5 Preholiday effect and herding behaviors.

Dependent	H_{buy}	H_{sell}	H_{zero}
Constant	−58.769*** (2.374)	−58.870*** (2.369)	−58.877*** (2.413)
$preholiday_t$	7.183*** (2.652)	7.044** (2.645)	7.049** (2.703)
$H_{i,t-1}$	0.284*** (0.016)	0.283*** (0.016)	0.288*** (0.016)
Year FE	Yes	Yes	Yes
Month FE	Yes	Yes	Yes
Weekday FE	Yes	Yes	Yes
N	3413	3413	3413
Adjusted R^2	0.800	0.801	0.770

Abbreviation: FE, fixed effect.

*, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

To further verify the above conjecture, we performed an additional analysis by regressing the logarithmic daily trading volume of the TXF (*Trading_volume*) on the preholiday dummy. The regression model is as follows:

$$Trading\_volume_t = \alpha + \beta_1 preholiday_t + \beta_2 TXF_{t-1} + \beta_3 return_{t-1} + \beta_4 Trading\_volume_{t-1} + Year\ FE + Month\ FE + Weekday\ FE + \varepsilon_t, \quad (7)$$

where $Trading\_volume_t$ is the logarithmic value of total TXF contracts traded on the TAIFEX on trading day t. Other variables are defined in previous equations. The regression results are reported in Table 6.

Table 6 shows that the TXF trading volume on trading days before long holidays is significantly lower than that on regular trading days. This finding supports the argument that the calmness before long holidays leads investors to trade less actively on the TAIFEX and therefore alleviates the tendency of herd trading behaviors. Taking the findings from Tables 4 to 6 together, it is evident that investor sentiment is a more likely driving factor of herd trading behavior than the tendency of information chasing, although previous studies suggested both factors as possible explanations of herding bias.

In economic terms, the finding that changes in investor sentiment are more likely than information chasing to drive herd behavior can be explained by the concept of social proof, the idea that individuals are more likely to conform to the actions of others when they are uncertain about what to do (Cialdini, 1984). In the context of investing, this means that investors may look to the actions of others for guidance when they are uncertain about the direction of the market. This can lead to a self-reinforcing cycle of positive or negative sentiment that drives herd behavior, even in the absence of new information.

For example, when investor sentiment is positive, investors may become more optimistic about the market and begin to buy into financial assets. As more investors buy, the market rises, which reinforces positive sentiment and encourages even more buying. This process can lead to a price bubble. Conversely, when investor sentiment is negative, investors may become fearful and start to sell their investments. As more investors sell, the market falls, which reinforces negative sentiment and encourages even more selling. This process can lead to a crash.

In contrast, the process of chasing information suggests that investors are looking for new or additional information to inform their investment decisions when they have limited time to collect personal information and make proper valuations. This process is more rational than emotional behavior, as investors are seeking to make informed decisions based on the available data. However, this process may not necessarily lead to herd behavior, as investors may interpret the available data differently and thus make different decisions.

In short, the uncertainty theoretically predicts emotional consistency, but investors who process the same information could still act differently. Our findings in Tables 4 and 5 support these arguments and indicate the main driving factor of herd trading on the TAIFEX.

TABLE 6 Preholiday effect and market trading volume.

Dependent	$Trading\_volume_t$
Constant	10.229*** (0.468)
$preholiday_t$	−0.112*** (0.033)
TXF_{t-1}	−0.335*** (0.048)
TXF_return_{t-1}	−0.020*** (0.004)
$Trading\_volume_{t-1}$	0.269*** (0.016)
Year FE	Yes
Month FE	Yes
Weekday FE	Yes
N	3413
Adjusted R^2	0.775

Abbreviations: FE, fixed effect; TXF, Taiwan Capitalization Weighted Stock Index.

*, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

3.2 | Impact of herd trading in the market

Finally, given the prevalence of herding bias among investors on the TAIFEX, we investigated whether the herding of investors can create a market-wide impact on market volatility. The regression analysis is based on Equation (7), and the results are reported in Table 7.

Table 7 reveals that, regardless of trading direction, herding indicators have a significant negative impact on market volatility on the same day, with smaller herding indicators (a stronger tendency of herding) leading to greater market volatility. Since retail investors as a group account for most of the trading activities on the TAIFEX, the market-wide impact from herd behaviors, if any, can be viewed as the impact caused by retail trading. Therefore, our findings in Table 7 echo those in previous studies: individual investors are mostly noise traders (Black, 1986; De Long et al., 1990), and herd trading increases noise trading and thus the price variation (Avramov et al., 2006). In short, the findings in Table 7 indicate that the intraday herd trading behavior on the TAIFEX aggravates the price variation of index futures. When most traders buy or sell index futures jointly or subsequently within a short time, the price pressure in the same direction rises significantly, thus making the market more volatile.

3.3 | Robustness tests

To provide further support for our findings, we utilized various robustness tests and discuss the results in this section. First, the analysis of Table 7 only considers the concurrent relationship between market volatility and herd behaviors. In an additional analysis, we incorporated the lagged herding indicators for up to 5 days into the model to control the persistence of herd behaviors and thus alleviate the influence of omitted variables. By doing so, we reexamined Table 7 and report the results in Table 8. Table 8 show the results for buyer-initiated, seller-initiated, and flat trading herd behaviors, respectively.

As reported, regardless of trading direction, herding indicators on trading day t still have a negative impact in the market volatility on the same day after lagged herding indicators are added to the model. Notably, herding indicators on trading day $t-1$ have a significant but positive impact in the market volatility on trading day t. For herding indicators on trading days $t-2$, $t-3$, $t-4$, and $t-5$, we found no significant impact on market volatility.

The results of Table 8 suggest that the impact of herd trading on market volatility is quite distinct and is driven by overreacting herding investors. Herd trading increases the same-day market volatility but decreases the market volatility of the next day, which reveals that the market corrects the overvariation that arises from the previous days' herd behaviors.

TABLE 7 Impact of herding behaviors on market volatility (HLV).

Dependent independent	HLV_t		
	H_{buy}	H_{sell}	H_{zero}
Constant	16.919*** (0.983)	16.924*** (0.983)	17.003*** (0.954)
$H_{i,t}$	−0.017*** (0.0005)	−0.017*** (0.0005)	−0.018*** (0.0004)
TXF_t	−1.996*** (0.112)	−1.996*** (0.112)	−2.012*** (0.109)
HLV_{t-1}	0.118*** (0.014)	0.119*** (0.014)	0.099*** (0.014)
TXF_return_t	−0.017** (0.008)	−0.023*** (0.008)	−0.015* (0.008)
Year FE	Yes	Yes	Yes
Month FE	Yes	Yes	Yes
Weekday FE	Yes	Yes	Yes
N	3413	3413	3413
Adjusted R^2	0.591	0.591	0.614

Abbreviations: FE, fixed effect; TXF, Taiwan Capitalization Weighted Stock Index.

*, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

As per our previous analyses, herd behaviors on the TAIFEX are apparently primarily driven by investor sentiment. Therefore, the findings of Table 8 can be interpreted as an emotional overreaction of investors. This finding is consistent with the longstanding argument in the behavioral finance literature that investors sometimes overreact to their sentiments and engage in irrational trading behaviors. This, in turn, leads to suboptimal investment outcomes that ultimately affect the market. For instance, investors, especially retail traders, may become excessively optimistic and greedy when they witness other investors making significant gains. Consequently, they feel positive about their decisions, which can result in a herd mentality where investors buy into a specific asset class because they believe that the market will continue to perform well, even when the fundamental signals suggest otherwise. To avoid cognitive dissonance, overoptimistic investors tend to pursue emotional consistency and ignore all contrary information. This positive reinforcement of emotions creates irrational expectations and can lead to financial markets being overpriced (Shiller, 2000).[11]

In the analyses of Tables 7 and 8, we used the HLV of the TXF as our market volatility proxy. However, the literature has used alternative proxies to measure market volatility. Next, we considered these proxies to reexamine Table 8 using robustness checks.[12]

Our first alternative proxy of market volatility is from Parkinson (1980) and suggests that under the assumption of a random walk of stock prices, volatility can be more efficiently tracked using the highest and lowest prices of an underlying asset over a period of time to measure the degree of price variation. We followed this approach to measure market volatility, which was calculated as follows:

$$\sigma_{p,t} = \frac{1}{2\sqrt{\ln 2}}\sqrt{\frac{1}{n}\sum_{t=1}^{n} P_t^2} \times 100\%, \tag{8}$$

where $P_t = \ln(max_t/min_t)$, max_t is the highest price of the TXF on trading day t, min_t is the lowest price of the TXF on trading day t, and n is the number of days in the calculation period. We chose 5 days as the period.

[11]Shiller (2000) has shown that such irrational exuberance can lead to market bubbles that eventually burst; for example, the dot-com bubble of the late 1990s.

[12]We skipped the reexamination of Table 7, as the analysis of Table 8 confirms that of Table 7.

Our second alternative proxy of market volatility is based on Garman and Klass (1980) and calculates volatility using the opening and closing prices rather than the highest and lowest prices. The equation is as follows:

$$\sigma_{GK,t} = \sqrt{\frac{1}{n}\sum_{t=1}^{n}\left[\frac{1}{2}P_t^2 - \left(2\ln 2 - 1\right)Q_t^2\right]} \times 100\%, \quad (9)$$

where $Q_t = \ln(C_t/O_t)$, C_t refers to the closing price of the TXF on trading day t, and O_t is the opening price of the TXF on trading day t. P_t and n are calculated in the same way as in Equation (8).

The reexamination results of Table 8 using Parkinson's (1980) and Garman and Klass's (1980) approaches are reported in Tables 9 and 10, respectively. In sum, the findings of Tables 9 and 10 are qualitatively similar to those of Table 8. Regardless of trading direction, herding indicators on trading day t have a negative impact on market volatility on the same day after lagged herding indicators are added to the model. In addition, herding indicators on trading day $t-1$ have a significant but positive impact in the market volatility on trading day t.

Overall, the impact of herd trading in the market volatility of the TAIFEX is not altered by alternative ways of estimating market volatility.

Finally, we reexamined the results of Tables 4 and 5. In addition to the margin trading ratio and VIX, we used the aggregated turnover rate on the stock market as an alternative investor sentiment proxy. As mentioned, the margin

TABLE 8 Impact of lagged herding behaviors on market volatility (*HLV*).

Dependent	***HLV_t***		
Independent	***H_{buy}***	***H_{sell}***	***H_{zero}***
Constant	15.905*** (0.980)	15.876*** (0.980)	15.908*** (0.954)
$H_{i,t}$	−0.019*** (0.0005)	−0.019*** (0.001)	−0.020*** (0.0005)
$H_{i.t-1}$	0.006*** (0.001)	0.006*** (0.001)	0.006*** (0.001)
$H_{i,t-2}$	0.001 (0.0005)	0.001 (0.0005)	0.001 (0.0005)
$H_{i,t-3}$	0.001 (0.0005)	0.001 (0.0005)	0.001 (0.0005)
$H_{i,t-4}$	0.0001 (0.0005)	0.0001 (0.0005)	0.0001 (0.0005)
$H_{i,t-5}$	−0.0001 (0.0005)	−0.0001 (0.0005)	−0.0001 (0.0005)
TXF_t	−1.837*** (0.112)	−1.833*** (0.111)	−1.846*** (0.109)
vol_{t-1}	0.218*** (0.017)	0.220*** (0.017)	0.203*** (0.017)
TXF_return_t	−0.013* (0.008)	−0.020** (0.008)	−0.012 (0.008)
Year FE	Yes	Yes	Yes
Month FE	Yes	Yes	Yes
Weekday FE	Yes	Yes	Yes
N	3409	3409	3409
Adjusted R^2	0.607	0.607	0.628

Abbreviations: FE, fixed effect; TXF, Taiwan Capitalization Weighted Stock Index.

*, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

TABLE 9 Impact of lagged herding behaviors on market volatility (σ_P).

Dependent	$\sigma_{p,t}$		
Independent	H_{buy}	H_{sell}	H_{zero}
Constant	9.528*** (0.593)	9.512*** (0.593)	9.531*** (0.577)
$H_{i,t}$	−0.011*** (0.0003)	−0.011*** (0.0003)	−0.012*** (0.0003)
$H_{i,t-1}$	0.004*** (0.0003)	0.004*** (0.0003)	0.003*** (0.0003)
$H_{i,t-2}$	0.0004 (0.0003)	0.0004 (0.0003)	0.0004 (0.0003)
$H_{i,t-3}$	0.0004 (0.0003)	0.0005 (0.0003)	0.0005 (0.0003)
$H_{i,t-4}$	0.0001 (0.0003)	0.0001 (0.0003)	0.00003 (0.0003)
$H_{i,t-5}$	−0.0001 (0.0003)	−0.0001 (0.0003)	−0.0001 (0.0003)
TXF_t	−1.101*** (0.068)	−1.098*** (0.068)	−1.106*** (0.066)
vol_{t-1}	0.220*** (0.017)	0.222*** (0.017)	0.205*** (0.017)
TXF_return_t	−0.019*** (0.005)	−0.023*** (0.005)	−0.018*** (0.005)
Year FE	Yes	Yes	Yes
Month FE	Yes	Yes	Yes
Weekday FE	Yes	Yes	Yes
N	3409	3409	3409
Adjusted R^2	0.607	0.606	0.627

Abbreviations: FE, fixed effect; TXF, Taiwan Capitalization Weighted Stock Index.

*, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

trading ratio and VIX measure positive and negative sentiment, respectively. Since either type of sentiment should drive investors to trade, the turnover rate is related to both sides of trading and could represent both types of investor sentiment. We conducted the regression analysis of Table 4 again and found that the results when using the turnover rate were qualitatively similar to those when using the margin trading ratio and VIX.

For the robustness check of Table 5, we adjusted the definition of long holidays to regular weekends, any holiday, 1-day holidays, and longer holidays up to 5 days. However, none of these changes affected our findings in Table 5.[13]

3.4 | Herding in overnight trading sessions

This study analyzed the trading data obtained from regular trading sessions. However, it is worth noting that the TAIFEX launched overnight trading sessions in May 2017 to enable derivatives investors to respond instantly to news from international financial markets.[14] Given that our previous findings showed herding behaviors to be observable in

[13]For brevity, we do not report the reexamination results of Tables 4 and 5 here. The results can be obtained upon request.

[14]The TAIFEX started to operate overnight trading sessions in May 2017, which allow market participants to trade beyond the regular trading hours. The overnight trading sessions in the TAIFEX are also known as the “After-Hours Futures Trading” sessions and run from 3:00 p.m. (day t) to 5:00 a.m. (day $t+1$).

TABLE 10 Impact of lagged herding behaviors on market volatility (σ_{GK}).

Dependent Independent	$\sigma_{GK,t}$ H_{buy}	 H_{sell}	 H_{zero}
Constant	9.405*** (0.566)	9.394*** (0.566)	9.406*** (0.551)
$H_{i,t}$	−0.010*** (0.0003)	−0.010*** (0.0003)	−0.011*** (0.0003)
$H_{i,t-1}$	0.003*** (0.0003)	0.003*** (0.0003)	0.003*** (0.0003)
$H_{i,t-2}$	0.0002 (0.0003)	0.0002 (0.0003)	0.0003 (0.0003)
$H_{i,t-3}$	0.0004 (0.0003)	0.0004 (0.0003)	0.0004 (0.0003)
$H_{i,t-4}$	−0.0002 (0.0003)	−0.0002 (0.0003)	−0.0002 (0.0003)
$H_{i,t-5}$	−0.00003 (0.0003)	−0.00004 (0.0003)	−0.0001 (0.0003)
TXF_t	−1.086*** (0.065)	−1.084*** (0.065)	−1.090*** (0.063)
vol_{t-1}	0.234*** (0.017)	0.236*** (0.017)	0.220*** (0.017)
TXF_return_t	−0.025*** (0.005)	−0.029*** (0.005)	−0.024*** (0.004)
Year FE	Yes	Yes	Yes
Month FE	Yes	Yes	Yes
Weekday FE	Yes	Yes	Yes
N	3409	3409	3409
Adjusted R^2	0.618	0.618	0.639

Abbreviations: FE, fixed effect; TXF, Taiwan Capitalization Weighted Stock Index.

*, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

regular trading sessions regardless of trading direction, a follow-up question arises: Do investors in overnight sessions exhibit stronger or weaker herding tendencies than investors in regular sessions?[15] If investors in overnight sessions are simultaneously affected by various information coming from the US market or the European markets, the effect could enhance the herding tendency among investors. However, overall trading volume in overnight sessions is much lower than that in regular sessions, indicating a lower market depth and weaker price continuation when trading.[16] In addition, the trading proportion of retail investors in overnight sessions is not as high as that in regular sessions.[17] Both characteristics may imply that the herding tendency among investors in overnight sessions will not be as strong as that in regular sessions.

To address the above question, we conducted an additional analysis using trading data from overnight sessions and calculated herding indicators for each trading direction according to Equation (2). Our untabulated results indicate that the mean (median) values of the herding indicator for buy, sell, and flat transactions are −152.34 (−150.18), −150.33 (−149.75), and −29.02 (−8.45). Compared with the findings in Table 2, the herding indicators in overnight sessions have higher values,

[15]We thank an anonymous referee for suggesting the analysis.

[16]Within our sample period, the average daily trading volume in overnight sessions is merely 21% of that in regular sessions.

[17]According to statistics based on the data reported by the TAIFEX, the TXF trading proportion of retail investors in overnight sessions is merely 45%, which is much lower than that in regular sessions.

TABLE 11 Impact of herding behaviors on concurrent market volatility—Overnight sessions.

Panel A:			
Dependent	***HLV_t***		
Independent	***H_{buy}***	***H_{sell}***	***H_{zero}***
$H_{i,t}$	−0.008*** (0.0005)	−0.008*** (0.0005)	−0.012*** (0.0006)
Other variables	Yes	Yes	Yes
N	455	455	455
Adjusted R^2	0.726	0.724	0.591
Panel B:			
Dependent	$\sigma_{p,t}$		
Independent	***H_{buy}***	***H_{sell}***	***H_{zero}***
$H_{i,t}$	−0.005*** (0.0002)	−0.005*** (0.0002)	−0.007*** (0.0006)
Other variables	Yes	Yes	Yes
N	455	455	455
Adjusted R^2	0.730	0.728	0.595
Panel C:			
Dependent	$\sigma_{GK,t}$		
Independent	***H_{buy}***	***H_{sell}***	***H_{zero}***
$H_{i,t}$	−0.004*** (0.0002)	−0.004*** (0.0002)	−0.006*** (0.0006)
Other variables	Yes	Yes	Yes
N	455	455	455
Adjusted R^2	0.748	0.746	0.603

*, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

suggesting a weaker tendency toward herding among investors, particularly for flat transactions. Although overnight sessions provide an alternative marketplace for local investors to react to other international markets, our results imply that investors in overnight sessions exhibit weaker herding behavior than those in regular sessions, which can be attributed to the relatively low trading activity and smaller proportion of retail trading in overnight sessions.

On the basis of these results, if investors in overnight sessions are less prone to herding bias in trading, how does herding behavior in overnight sessions affect market volatility? To further elucidate the impact of herding on market volatility during this period, we reexamined the results in Table 7 using trades in overnight sessions along with three different measures of volatility. The results are reported in Table 11.

The coefficients of the herding indicators in Table 11 show that a higher tendency toward herding, regardless of trading direction or volatility measure, leads to greater market volatility. Interestingly, the *HLV* coefficients in Table 11 (Panel A) are smaller than those in Table 7, indicating that herding has a weaker impact on market volatility in overnight sessions compared to regular sessions. These results suggest that although herding behaviors in overnight sessions also lead to more volatile markets, the impact is not as strong as that in regular sessions.

The previous findings in Tables 8–10 have shown that herd trading not only increases same-day market volatility but also decreases market volatility on the next day, suggesting that the market corrects the overvariation resulting from herd behaviors on previous days. As the impact of herd trading on volatility in overnight sessions is weaker, we wondered whether the same patterns observed in previous tables could be observed in overnight sessions. To investigate this, we conducted an analysis similar to that in Tables 8–10, and Table 12 reports the results of the impact of herding on market volatility while additionally controlling for

TABLE 12 Impact of herding behaviors on concurrent and next-day market volatility—Overnight sessions.

Panel A:			
Dependent	HLV_t		
Independent	H_{buy}	H_{sell}	H_{zero}
$H_{i,t}$	−0.008***	−0.008***	−0.012***
	(0.0004)	(0.0004)	(0.001)
$H_{i,t-1}$	0.0005	0.0005	0.0009
	(0.0006)	(0.0006)	(0.001)
Other variables	Yes	Yes	Yes
N	455	455	455
Adjusted R^2	0.726	0.725	0.590
Panel B:			
Dependent	$\sigma_{p,t}$		
Independent	H_{buy}	H_{sell}	H_{zero}
$H_{i,t}$	−0.005***	−0.005***	−0.007***
	(0.0003)	(0.0003)	(0.0008)
$H_{i,t-1}$	0.0003	0.0003	0.0005
	(0.0003)	(0.0003)	(0.0009)
Other variables	Yes	Yes	Yes
N	455	455	455
Adjusted R^2	0.730	0.728	0.595
Panel C:			
Dependent	$\sigma_{GK,t}$		
Independent	H_{buy}	H_{sell}	H_{zero}
$H_{i,t}$	−0.004***	−0.004***	−0.006***
	(0.0002)	(0.0002)	(0.001)
$H_{i,t-1}$	0.0006*	0.0005*	0.0003
	(0.0003)	(0.003)	(0.0007)
Other variables	Yes	Yes	Yes
N	455	455	455
Adjusted R^2	0.748	0.745	0.604

*, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

lagged herding indicators for up to 5 days.[18] Upon examination, Table 12 indicates that there is only weak evidence that herd trading in overnight sessions affects the market volatility of the next day, unlike the findings in regular sessions. Specifically, among the three different volatility proxies used, herding indicators only appear to have an intertemporal effect on σ_{GK} (Panel C), whereas Panels A and B do not show the same pattern.

In sum, the results of Table 12 support those of Table 11. In comparison to regular sessions, herding has a weaker impact on volatility in overnight sessions, and the subsequent market correction on the following day is less noticeable. These results indicate a weaker tendency toward herding, which is partially attributable to the lower number of retail traders participating in overnight sessions. Our additional analysis of herding in overnight sessions highlights the relevance of retail trading, further corroborating our prior findings from trading data in regular sessions.

[18]For brevity, we only report the regression coefficients of concurrent and 1-day lagged herding indicators since those of other lagged herding indicators, as shown in Tables 8 to 10, are statistically insignificant.

4 | CONCLUSION

In this study, we used the data of market index futures trading on the TAIFEX from January 2005 to March 2019 to explore the prevalence of herd trading behaviors. We particularly focused on the driving factors of herd behaviors and the market-wide impact caused by herding investors. Following Blasco et al.'s (2012) approach, we estimated the daily tendency of herd trading behaviors using intraday trading data. The daily herding indicators allowed us to examine the direct relationship between herd behaviors and other variables within a daily horizon, which has been relatively unexplored in previous studies. In addition, the TAIFEX, with its features of market index futures trading and market structure, which is dominated by retail investors, provided an ideal setting to study herd behaviors, as they present fewer concerns about potential problems of sample selection or omitted variables of firm characteristics.

Our empirical findings can be briefly summarized as follows. First, we found that herd behaviors in all trading directions (buy, sell, and flat) on the TAIFEX are prevalent among investors. Second, investor sentiment is a more direct explanation for herding behaviors than the tendency of information chasing, and past studies have suggested that both factors are possible channels.

Third, the results showed that herding behaviors in intraday trading can aggravate the market volatility on the same day. Herding investors trading in either direction within a short period temporarily increase the pressure on index prices, causing the market to fluctuate further. However, the effect of herd trading behaviors on market volatility induces a volatility reduction for the market on the following day, implying that herding investors may overreact to the sentiment causing herding bias, resulting in a price reversal following a more significant price variation.

Finally, after-hours trading sessions on the TAIFEX were launched in May 2017 to allow instant responses to news in the overnight period. We examined whether investors exhibit stronger (or weaker) herding tendencies in overnight sessions. Our findings showed that herding has a weaker impact on volatility in overnight sessions than in regular sessions, with less noticeable market correction on the following day. This weaker tendency toward herding is attributed to the lower participation of retail traders overnight. Our analysis reinforced the importance of retail trading in explaining herd trading, supporting our earlier findings from trading data in regular sessions.

Our findings survived various robustness tests and were not affected by alternative measures of market volatility, investor sentiment, or the tendency of information chasing. This study contributes to the literature by providing new evidence of herd trading behaviors in the derivatives market. In addition, our findings shed new light on the study of herd behaviors by clarifying the relevance of alternative driving factors of herding bias and verifying the market-wide impact of herding investors. We believe that the analysis results of this study enhance the overall understanding of not only herding behaviors but also the information content of a derivatives market that is dominated by retail investors.

On the basis of our findings, which have generated further interest in the literature, we suggest two possible directions for follow-up studies with research potential. First, previous studies on the TAIFEX, utilizing specific data sets, have discovered distinct trading patterns among various types of investors (e.g., Chuang et al., 2019). This study did not address the potential differences in herding tendencies between foreign and domestic institutional investors on the TAIFEX. Researchers who possess investor-type identity data could explore herding tendencies' association with different types of institutional trading. Second, our findings from the TAIFEX data suggest that investor sentiment is more likely to drive herd trading behavior than the tendency of information chasing. This discovery leads us to wonder whether other markets with similar characteristics to the TAIFEX (e.g., the Korean derivatives market) could also produce comparable results.[19] Such research would contribute to the development of the literature and enhance our understanding of the relationship between herding investors and market structure. Unfortunately, due to data limitations, we were unable to address these issues in our analysis. These valuable research questions are left for future studies.

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DATA AVAILABILITY STATEMENT

The data used in this study were obtained from a third-party data vendor and cannot be openly shared due to licensing restrictions. The original data set used for this study is not publicly available. However, the reported numbers in the

[19]The authors thank the reviewer for suggesting a valuable future research direction.

tables and the main content of the manuscript provide a comprehensive summary of the findings. Any requests for data access can be made to the data vendor, subject to their approval and licensing restrictions.

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