Thailand and The World Economy
P-ISSN: 2630-0931
E-ISSN: 2651-0529
Homepage : https://www.tci-thaijo.org/index.php/TER
Vol. 43, No.1, January – April 2025 Page [155- 163]

The Relationship of Aggregate Herd Behavior and Retail Investor Attention: A Multinomial Logistic Regression

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Received 15 December 2023, Received in revised form 27 June 2024,
Accepted 30 August 2024, Available online 6 January 2025.

Abstract

This paper investigates the relationship between aggregate market herding and investor attention in seven selected equity markets over the period of 2004-2019. The multinomial logistic regression employed in this study provides a more direct, comprehensive, and straightforward test than other methodologies found in existing studies, as it demonstrates a true occurrence of herding. Investor attention is positively (negatively) related to (anti-)herd behavior, in which information obtained from internet searches is associated with rational and unintentional herding. Thus, internet search improves stock market efficiency. Nonetheless, the role of investor attention is weaker during negative market returns and global financial crisis periods because investors are less attentive to their psychological discomfort explained by the Ostrich effect. The results call for policymakers to gear to the digital economy.

Keywords: herd behavior; behavioral finance; investor attention; Google search index; Ostrich effect
JEL Classifications: G14; G15; G40; G41

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1. Introduction

Roles of retail investor attention on stock market activities are well established in international equity markets (Mondria et al., 2010; Vozlyublennaia, 2014; Tantaopas et al., 2016; Padungsaksawasdi et al., 2019); however, those of imitating trades are scant. As attention is scared cognitive resource and internet search for an individual's investment is ubiquitous, a linkage between these factors is intuitively built up. Surfing the internet provides necessary information to investors, which is used for their investment decisions. This is supported by Kunte (2015) documenting that herd behavior is the most influential behavioral bias influencing investment decisions. Herd behavior is a group trait resulting in a correlated action, which can be categorized into two forms. First, investor-type herding utilizes specific data such as trading orders, analyst recommendations, and management decisions (Lakonishok et al., 1992; Sias, 2004) in order to detect mimicking trading decisions. Second, aligning with the rational asset pricing model, herd behavior at the aggregate level demonstrates a relationship between market return and return dispersion (Christie & Huang, 1995; Chang et al., 2000). In a different perspective, we also categorize herd behavior into spurious (or unintentional) and intentional herding. As enquirers use an identical internet search keyword, they are likely to get the same information, subsequently leading to a similar decision. This action is associated with spurious or unintentional herding. Conversely, lack of similar information is a source of uncertainty, which drives intentional herding. Peltomäki & Vahamaa (2015) employed a vector autoregressive model to capture dynamic relationship between aggregate herd behavior measured by return dispersion and investor attention proxied by Google Trends among the European banking sectors. However, the return dispersion is not a true measure of herd behavior in the spirit of Christie & Huang (1995) and Chang et al. (2000). Wanidwaranan & Padungsaksawasdi (2022), modifying the models of Chang et al. (2000), found a positive relationship between investor attention and herd behavior in 21 equity markets. Relying on the intuition of herd behavior models suggested by Chang et al. (2000), existence of herding is determined by the level of statistical significance of the nonlinear term in the model, which is ambiguous. Bogdan et al. (2022) used a logistic regression model to estimate the relationship between investor attention related to COVID-19 and herd behavior in Europe by employing stock market indices. This reduces the number of observations and neglects a movement of individual stock prices, which ultimately affects an accuracy of herding detection. Recently, Carvalho et al. (2024) detected an association between aggregate market herding and search volume in the Brazilian equity market. Focusing on investor-type herding in Taiwan, Hsieh et al. (2020) documented a significantly positive relationship between herd behavior and investor attention. The same study is explored by Philippas et al. (2020) and Wanidwaranan & Termprasertsakul (2024) in cryptocurrency markets. In summary, we investigate the association between (anti-)herd behavior and retail investor attention by using multinomial logistic regression in order to challenge the herding detection model of Chang (2000).

The contributions are as follows: First, as few investigate the role of investor attention on herd behavior, we fill the gap in prior literature by using international sample data. In addition, we propose and discuss the existence of anti-herd behavior, which is typically overlooked in prior literature. Second, the multinomial logistic regression is chosen for our study, as it demonstrates an exact occurrence of herding evidence. Most past studies focus on the statistical significance of estimated market return squared coefficients in Changet al.'s (2000) model for herding detection. Moreover, as prior studies did not pay much attention to the existence of anti-herd behavior, the multinomial logistic model allows us to explore both the relationship between investor attention and herd behavior as well as between investor attention and anti-herd behavior. Thus, our proposed methodology is straightforward, easy to interpret, and appropriate for herding detection. Third, we adopt a time-varying model framework to demonstrate the relationship, which better reflects the actual behavior of investor attention and herding than most existing studies in a static framework.

We find a positive intertemporal relationship between herding and investor attention and a negative intertemporal relationship between anti-herding and investor attention. Thus, internet search provides useful information to investors' decision making, amplifying imitating trades and curtailing individuals' trades. This evidence supports the existence of unintentional or spurious herd behavior, pressuring stock prices to be more efficient. However, the influential role of retail investors' attention diminishes in downward stock markets, especially during the global financial crisis. We relate these results to the Ostrich effect when investors lose attention because of their psychological discomfort during unfavorable periods. In general, our findings are consistent with Wanidwaranan & Padungsaksawasdi (2022).

2. Data Description and Methodology

We use internet search intensity from Google Trends as a proxy of retail investor attention (Da et al., 2011) and follow the principle suggested by Wanidwaranan & Padungsaksawasdi (2022) for choosing search keywords for each market. As English is the global language, all markets offer English as an alternative language in their trading platforms or websites. Moreover, an individual stock ticker symbol practically presents in English. Thus, we choose English as the search language in all stock exchanges. In addition, we compare five alternatives of search keywords that potentially represent an entire stock market. The highest average usage is selected as appropriate selected search keywords in this study. We also confirm the relevancy of the selected keyword by checking with the first page search results. All of them directly represent the respective chosen market. The selected search keywords are shown in Table 1. Our sample includes selected seven equity markets and employs daily available stock prices from the Refinitiv Eikon, covering from 2004 to August 13, 2019.[2]

Google search volume index ($GSVI$) is a relative index value ranging from zero to 100. Google Trends provides search volume on a daily basis for the inquiry horizon with less than a six-month period. In order to create a daily $GSVI$ over the entire sample period (Franz, 2018), we employ the monthly index data over the period of the full 15-year timespan download as

$$Adjusted\ daily\ GSVI = \frac{Actual\ daily\ GSVI\ from\ a\ 6\text{-}month \times Actual\ monthly\ GSVI\ from\ the\ 15\text{-}year\ period}{100} \tag{1}$$

[2] The results of basic statistics are available upon request.

Table 1: Search Keyword Selection

Country	Brazil	Canada	China	France	Hong Kong	Thailand	United States
Exchange	Sao Paulo Stock Exchange	Toronto Stock Exchange	Shanghai Stock Exchange	Euronext Paris	Stock Exchange of Hong Kong	Stock Exchange of Thailand	New York Stock Exchange
ALT#1	BOVESPA	S&P/TSX COMPOSITE	Shanghai Stock Exchange	CAC 40	HANG SENG	SET Index	NYSE
ALT#2	BVSP	S&P/TSX	Shenzhen Stock Exchange	CAC40	HSI	SET100	S&P500
ALT#3	IBX50	S&P/TSX 60	CSI 1000	CAC Index	Hang Seng Index	SET50	NASDAQ
ALT#4	IBrX	Toronto Stock Exchange	Shanghai Composite	EuroNext 100	Stock Exchange of Hong Kong	Thailand SET	DJIA
ALT#5	Ibovespa	Canada Stock Market	SZSE Component	SBF 120	Hong Kong Stock Exchange	Stock Exchange of Thailand	RUSSEL
Keyword	BOVESPA	Toronto Stock Exchange	Shanghai Stock Exchange	CAC 40	HANG SENG	SET Index	NYSE
1st page Relevancy	100%	100%	100%	100%	100%	100%	100%

Source: Authors' own work

Chang et al.'s (2000) herding detection model with the time-varying framework is

$$CSAD_t = \frac{1}{N}\sum_{i=1}^{N}\left|R_{i,t} - R_{m,t}\right| \quad (2)$$

$$CSAD_t = \alpha + \gamma_1\left|R_{m,t}\right| + \gamma_2\left(R_{m,t}\right)^2 + \varepsilon_t \quad (3)$$

where $CSAD_t$ is a cross-sectional absolute deviation of stock returns, N is a number of individual stocks, $R_{i,t}$ is a daily return of stock i, which is $100 \times \left(ln(P_{i,t}) - ln(P_{i,t-1})\right)$, $R_{m,t}$ is an equal-weighted market return, $P_{i,t}$ is an individual stock price i, t refers to day, and ε_t is an error term. γ_1 or γ_2 is expected to be significantly negative, representing herd behavior. However, when γ_2 is significantly positive, showing anti-herd behavior. Sharma et al. (2015), Bohl et al. (2016), and Ngene et al. (2017) documented that herding is intertemporal behavior, evolving over time as investors are not fully rational at all times and possess heuristic bias in trading decisions. In order to capture time-varying herd behavior, we detect aggregate market herding by using the 100-trading day rolling window with a one-day rolling step.

Herd behavior is more present during a highly volatile condition, such as during the negative market return periods. Investors feel more unsecured, panic, and fear when uncertainty amplifies (Vo & Phan, 2019; Wanidwaranan & Padungsaksawasdi, 2022). We follow the methodology suggested by Wanidwaranan & Padungsaksawasdi (2020) to assign a dummy variable for asymmetric herding and herding during the financial crisis period as below.

$$CSAD_t = \alpha + \gamma_1 D_d + \gamma_2\left|R_{m,t}\right| + \gamma_3 D_d\left|R_{m,t}\right| + \gamma_4\left(R_{m,t}\right)^2 + \gamma_5 D_d\left(R_{m,t}\right)^2 + \varepsilon_t \quad (4)$$

$$CSAD_t = \alpha + \gamma_1 D_c + \gamma_2\left|R_{m,t}\right| + \gamma_3 D_c\left|R_{m,t}\right| + \gamma_4\left(R_{m,t}\right)^2 + \gamma_5 D_c\left(R_{m,t}\right)^2 + \varepsilon_t \quad (5)$$

where D_d and D_c are dummy variables for negative market return dates and for the financial crisis period (March 1, 2008 to March 31, 2009), respectively, which are assigned to be one and zero otherwise. Likewise, γ_3 and γ_5 are expected to be significantly negative, indicating asymmetric herding and herding during the financial crisis period shown in Equations (4) and (5), respectively. If γ_5 is significantly positive, it confirms the existence of asymmetric anti-herding. In all cases, we use 5% statistical significance to test the presence of herding and anti-herding.

After identifying the existence of aggregate herding in each market by employing Equations (3) to (5) under each circumstance, we investigate the relationship between the Google search volume index and imitating trade by using the multinomial logistic regression suggested by Bogdan et al. (2022) as follows.

$$\Pr(H_t = -1) = \frac{e^{GSVI_t\beta^{(-1)}}}{e^{GSVI_t\beta^{(-1)}} + e^{GSVI_t\beta^{(0)}} + e^{GSVI_t\beta^{(1)}}} \quad (6)$$

$$\Pr(H_t = 0) = \frac{e^{GSVI_t\beta^{(0)}}}{e^{GSVI_t\beta^{(-1)}} + e^{GSVI_t\beta^{(0)}} + e^{GSVI_t\beta^{(1)}}}$$

$$\Pr(H_t = 1) = \frac{e^{GSVI_t\beta^{(1)}}}{e^{GSVI_t\beta^{(-1)}} + e^{GSVI_t\beta^{(0)}} + e^{GSVI_t\beta^{(1)}}}$$

where H_t is the dependent variable, representing herd behavior and assigning to be -1, 0, and +1 given the existence of anti-herding, no-herding, and herding on day t, respectively. Using Equations (3) to (5) allows us to identify an occurrence of herding in each condition, which is later assigned to the multinomial logistic regression as shown in Equation (6). No herd behavior refers to the base outcome for the analysis. A significant and positive (negative) coefficient of the Google search volume suggests that investor attention induces (anti-)herd behavior.

3. Results

Table 2: Herding and Anti-Herding

Panel A: Herd behavior

	Brazil	Canada	China	France	Hong Kong	Thailand	United States
$Intercept$	-3.877***	-3.150***	-1.707***	-3.330***	-2.962***	-4.149***	-6.058***
	(-23.71)	(-27.79)	(-24.56)	(-31.11)	(-24.39)	(-24.99)	(-15.42)
$GSVI_t$	0.0172	-0.0221	-0.216	0.0615***	0.0137***	0.0979***	0.0679***
	(1.01)	(-1.37)	(-1.38)	(8.96)	(3.99)	(7.46)	(6.09)
χ^2	3.165	21.650	3.485	68.650	16.490	52.390	91.310
$Pseudo\ R^2$	0.0009	0.0051	0.0006	0.0248	0.0042	0.0132	0.0229

Panel B: Anti-herd behavior

	Brazil	Canada	China	France	Hong Kong	Thailand	United States
$Intercept$	-1.366***	-1.095***	-0.180***	-2.627***	-1.640***	-1.061***	-0.617***
	(-24.21)	(-23.84)	(-4.64)	(-30.98)	(-22.90)	(-23.90)	(-9.93)
$GSVI_t$	-0.0112	-0.0277***	-0.0357	-0.0009	-0.0017	-0.0143	-0.0283***
	(-1.41)	(-4.15)	(-0.88)	(-0.09)	(-0.68)	(-1.30)	(-7.16)
χ^2	3.165	21.650	3.485	68.650	16.490	52.390	91.310
$Pseudo\ R^2$	0.0009	0.0051	0.0006	0.0248	0.0042	0.0132	0.0229

*Note: *** indicates 1% statistical significance.*

Source: Authors' own work

Panels A and B of Table 2 present the relationship between herding and investor attention, as well as anti-herding and investor attention, respectively. As shown in Panel A, investor attention is significantly positively associated with herd behavior in four selected markets: France, Hong Kong, Thailand, and the United States. Thus, when investors search for more information, imitating trades increases. As Google search is free, easily to access, public, and informative, an increase in mimicking trades among these countries is rational and unintentional, driving stock prices to be more efficient. Similar evidence is also found in the relationship of anti-herd behavior, as shown in Panel B, where the anti-herding-investor attention association is significantly negative in two countries : Canada and the United States. As anti-herd behavior decreases, given a large investors' search, it is promising of a likelihood of an increase in imitating trades because investors hold the same set of available information. In terms of economic significance, a one-unit increase of search index enhances a probability of herd behavior by 1.0138 ($e^{0.0137}$) and 1.1029 ($e^{0.0979}$) times in Hong Kong and Thailand, respectively, as shown in Panel A, while that of search index reduces a probability of anti-herd behavior by 0.9721 ($e^{-0.0283}$) and 0.9727 ($e^{-0.0277}$) times in Canada and the U.S., respectively.

Table 3: Asymmetric Herding and Anti-Herding

Panel A: Herd behavior

	Brazil	Canada	China	France	Hong Kong	Thailand	United States
$Intercept$	-1.7240***	-1.4890***	-1.9180***	-1.2360***	-2.1130***	-2.2800***	-1.7960***
	(-29.15)	(-29.84)	(-33.99)	(-24.96)	(-25.62)	(-34.99)	(-21.70)
$GSVI_t$	0.0301***	-0.0031	0.1330**	0.0120**	0.0016	0.0165	-0.0117**
	(4.48)	(-0.53)	(2.18)	(2.44)	(0.60)	(1.46)	(-2.34)
χ^2	20.2600	0.8820	17.0900	7.5620	13.1300	3.0130	5.8020
$Pseudo\ R^2$	0.0067	0.0003	0.0053	0.0019	0.0054	0.0014	0.0023

Panel B: Anti-herd behavior

	Brazil	Canada	China	France	Hong Kong	Thailand	United States
$Intercept$	-4.789***	-7.574***	-3.028***	-4.013***	-5.647***	-5.261***	-5.285***
	(-16.38)	(-7.57)	(-29.63)	(-21.80)	(-14.93)	(-18.09)	(-12.99)
$GSVI_t$	-0.0458	-3.762	-1.102**	-0.0287	0.0315***	-0.111	0.0043
	(-0.82)	(-0.01)	(-2.23)	(-1.10)	(3.70)	(-0.79)	(0.20)
χ^2	20.260	0.882	17.090	7.562	13.130	3.013	5.802
$Pseudo\ R^2$	0.0067	0.0003	0.0053	0.0019	0.0054	0.0014	0.0023

*Note: *** and ** indicate 1% and 5% statistical significance, respectively.*

Source: Authors' own work

Panels A and B of Table 3 suggest an asymmetric effect of herding and anti-herding during negative market return periods, respectively. The results show a less significantly positive impact of investor attention on herd behavior, in which the effect is prevalent in Brazil, China, and France. Interestingly, the effect of investor attention on anti-herding disappears. Only China demonstrates the significantly negative effect. Overall, it seems that investor attention plays fewer roles in determining mimicking trades during the negative market returns periods. We relate our results to the Ostrich effect, as suggested by Waniwaranan & Padungsaksawasdi (2022), that investors are less attentive, experiencing discomfort during downward markets, and inducing more emotional trades than rational trades obtained from the search. The evidence is strongly reinforced under the financial crisis period, as shown in Panels A and B of Table 4, for which there is no statistical significance in all cases.[3]

Table 4: Herding During the Global Financial Crisis

Panel A: Herd behavior

	Brazil	Canada	China	France	Thailand	United States
$Intercept$	-5.1820***	-4.0630***	-5.0240***	-5.1420***	-4.0510***	-5.9680***
	(-17.38)	(-26.65)	(-22.20)	(-17.57)	(-25.82)	(-9.73)
$GSVI_t$	-0.0024	-0.0197	0.0112	-0.0955	-0.2450	-0.0249
	(-0.06)	(-0.87)	(0.08)	(-1.44)	(-1.92)	(-0.60)
χ^2	0.1260	4.0930	0.0059	5.4600	12.2000	4.1490
$Pseudo\ R^2$	0.0003	0.0062	0.0001	0.0256	0.0118	0.0393

[3] We do not observe herd and anti-herd behavior of Hong Kong and China, respectively, during the financial crisis; thus, estimations are abolished in Table 4.

Panel B: Anti-herd behavior

	Brazil	Canada	France	Hong Kong	Thailand	United States
$Intercept$	-5.3180***	-5.5140***	-6.8370***	-6.9120***	-3.8430***	-6.1890***
	(-16.07)	(-17.00)	(-9.66)	(-6.91)	(-27.61)	(-6.19)
$GSVI_t$	-0.0168	-0.1850	-15.8100	-5.2830	-0.0954	-6.5350
	(-0.33)	(-1.11)	(-0.01)	(-0.00)	(-1.59)	(-0.01)
χ^2	0.1260	4.0930	5.4600	2.2580	12.2000	4.1490
$Pseudo\ R^2$	0.0003	0.0062	0.0256	0.1250	0.0118	0.0393

*Note: *** indicates 1% statistical significance.*

Source: Authors' own work

4. Conclusion

This paper attempts to investigate the intertemporal relationship between aggregate (anti-)herding and retail investor attention in international equity markets. The results of the multinomial logistic regression demonstrate a positive (negative) role of investor attention on herding (anti-herding), confirming an important role of information obtained from internet searches. Thus, the herd behavior is unintentional or spurious. Nevertheless, the effect disappears during downward and financial crisis periods due to raised investors' psychological discomfort explained by the Ostrich effect.

In addition, our results call attention to policymakers. As the Google search volume index is a proxy of investor attention, an increase in internet search activity improves the quality of investors' information. Similar trading decisions are expected to happen when investors utilize the same sets of information, promoting spurious or unintentional herd behavior and improving market efficiency. Therefore, policymakers should develop financial information infrastructure by boosting internet penetration, online databases, and information disclosure. Speed and quality of internet access are two of the key trading performances.

Even though our paper attempts to address a weakness of the popular herding detection model suggested by Chang (2000) by proposing a multinomial logistic regression model for better interpretation of the results, a limitation of this study still exists, which stems from the fact that herd behavior is time-varying and dependent on market development. More advanced continuous time finance is an alternative venue to address this issue, as well as an expansion of selected sample countries would better help validate the findings. In-depth analysis in different categories of market development provides insights to policymakers, regulators, and traders. In addition, Google is prohibited in China, which makes it more difficult for international comparison, though China is the second-largest economy in the world. These leave for further research.

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