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Industry Herding, Spillover Index and Investment Strategy

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Abstract

This study investigates the spillover effects of the herding behavior of institutional investors in industries using the new spillover index. We further examine the lead-lag relationship between the herding spillover index and stock market. Finally, this paper furthers our understanding of the momentum strategy in industries. The empirical evidence indicates that industry herding in terms of semi-conductor manufacturing has had a significant impact on other types of industry herding. Second, since the industry herding spillover index and the selling industry herding spillover index have led to stock index returns, we conjecture that the industry herding spillover effect is a predicate to stock returns. Finally, the results support the claim that an institutional investor is an industry momentum trader. Moreover, we find that a long position in relation to higher or lower herding winners and a short position in relation to low herding losers yields good subsequent returns.

JEL classification numbers: G02; G23
Keywords: Industry herding, Spillover Index, Momentum

1 Introduction

Recent studies report evidence on institutional industry herding. This study examines whether institutional industry herding plays an important role, and has

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three primary objectives. First, this study uses institutional investor data to calculate the institutional industry herding spillover effect and to construct an institutional industry herding spillover index employing the new spillover approach proposed by Diebold and Yilmaz (2012). In particular, this paper defines "the institutional industry herding spillover effect" as the degree of cross-industry spillover captured by the share of cross-industries error variance in the variance decomposition relative to the total error variance of the markets examined. Second, this study examines the effect of institutional industry herding spillover index on the stock index return. Moreover, this study tests for asymmetry in the relationship between the buy and sell institutional industry herding spillover index, which contends that sell institutional industry herding spillover could send a stronger signal than buy institutional industry herding spillover on stock index returns. Finally, we examine the impact of industry herding on return momentum. Unlike most studies that use a CSSD or CSAD variable for herding, we consider the variable for herding put forward by Lakonishok, Shleifer and Vishny (1992, hereafter LSV). The CSSD or CSAD method uses market prices to estimate herding, but not precisely measure the herding behavior like the LSV method. Thus far the LSV method remains important when measuring herding, and for this reason this study uses the second method to analyze herding effects. We examine whether institutional industry herding is a successful signal for subsequent returns.

For the first issue, many studies employ the spillover index, which divides spillovers into those coming from (or to) a particular asset and, thus, identifies the main recipients and transmitters of shocks proposed by Diebold and Yilmaz (2009, 2012 and 2016) on the stock, exchange rate, real estate and commodities markets. However, they do not consider the spillover index of institutional industry herding. The spillover index of institutional industry herding is able to further our understanding of the contributions made by the spillovers of volatility shock across industries of institutional herding to the total forecast error variance. The spillover effect on herding behavior across industries is seldom investigated in the literature. Thus, this study first estimates the spillover index of industry herding proposed by Diebold and Yilmaz (2012) and then analyzes the inflow, outflow and net spillover effect across industry herding behaviors.

For the second issue, practitioners and investors are able to invest or hedge if they know the rotation across industries. Junhua (2008) reported sector rotation strategies that guide investment across the different industries during different rates of inflation. However, the identification of peaks and valleys using inflation information obtained from official government data can be only be confirmed after a wait of at least one year. However, investors cannot wait until after these turning points are announced to invest. Therefore, this study investigates whether the industry spillover of institutional herding predicts stock market returns. This paper uses the change on spillover index of institutional industry herding to measure whether the herding behavior of institutional investors is active or inactive in rotations across industries. When the herding behavior of institutional investors is active across industries, it will positively affect stock market movements. Jiang, Yao and Yu (2007) pointed out that industry rotation plays an important role in the investment strategies of funds, and found funds adjust asset allocations according to high (low) beta industries when expecting market upswings (downturns). Hong, Torous, and Valkanov (2007) pointed out that a significant number of industry returns are able to predict the stock market based on the US stock markets from 1946 to 2002, and argue that this finding is robust for the eight largest non-US stock markets from 1973 to 2002. Past studies focus on how returns of industry portfolios impact on stock market returns; however, it is unclear how returns of industry portfolios impact industry herding diffusion. There is even less work undertaken with the express purpose of investigating the predictability of aggregate stock returns based on the spillover index of institutional industry herding. Moreover, the change of the institutional industry herding spillover index is often measured without distinguishing whether the imbalance is on the buy or on the sell side. Thus, this paper extends the spillover of institutional industry herding measure to define the measures for buying and selling institutional industry herding spillover index (SBIH and SSIH) and investigates whether SBIH and SSIH predict stock market returns in order to thereby understand the buying and selling decisions of herding move stock prices.

Finally, we investigate whether return momentum is impacted on by institutional industry herding. Momentum refers to a strategy of buying stocks or other securities that have had high past returns and selling those that have had poor returns over the past n months; momentum strategies then secure positive returns for the following n months. Jegadeesh and Titman (1993) found that adopting momentum strategies ensures a profit for the following n months using US stock data from 1965 to 1989. Nofsinger and Sias (1999) found that institutional investors with positive-momentum trade more than individual investors. Moreover, Moskowitz and Grinblatt (1999) found evidence of industry momentum and find that momentum profits industry portfolios rather than individual stock portfolios. Before Celiker, et al. (2015) and Demirer, Lien, and Zhang (2015), the impact of industry herding on momentum returns were rarely noticed. Demirer, Lien, and Zhang (2015) found further asymmetry in the relationship between herding and momentum and yield positive returns depending on different industry herding effects using the CSAD and CSSD methods to measure herding in the Chinese stock market for the period January 1996 through December 2013. However, because Demirer, Lien and Zhang (2015) used the CSAD and CSSD methods, which do not accurately or precisely measure herding because they only use market price data; this paper uses LSV to measure herding by institutional investor behavior. Moreover, Jegadeesh and Titman (1993 and 2001) considered the price momentum of individual stocks in order to obtain superior returns by holding a zero-cost portfolio. Our paper further uses the zero-cost portfolio to examine whether the relationship between industry herding and momentum return is able to assemble an investment portfolio.

This paper fills a gap in the literature on the spillover effects of herding behavior of institutional investors in industries by the spillover index. Second, this study

examines the lead-lag relationship between the herding spillover index and stock markets. Finally, this paper further studies the momentum strategy in industries. Thus, our empirical study significantly contributes to this field of research and thereby fills a gap in the literature. The empirical evidence indicates that industry herding in the semi-conductor manufacturing industry has a significant impact on other industry herding. Second, since the industry herding spillover index and selling industry herding spillover index have lead to stock index returns, this study conjectures that industry herding spillover indices have predicate stock markets. Finally, the results clearly support the fact that institutional investors are industry momentum traders. Moreover, we see that taking a long position in high or low herding winners and a short position in low herding losers yields good subsequent returns, implying that the profitability of zero-cost industry momentum strategies depends on the level of industry herding. These findings are consistent with those of Demier Lien and Zhang (2015).
The remainder of this paper is organized as follows: Section 2 presents literature review, Section 3 briefly presents our methodology and data; Section 4 presents the results of the empirical analysis; Section 4 provides summary conclusions.

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2 Literature Review

2.1 Spillover index

Spillovers measure the identification of the interaction between assets. Diebold and Yilmaz (2012) considered the new spillover index by applying the Cholesky factor identification to examine whether forecast-error variance decompositions are variant, depending on the ordering of the variables and refined measures of directional spillovers and net spillovers. There are abundant studies that use the new spillover index proposed by Diebold and Yilmaz (2012). Studying the spillover effect in stock markets can be found in Diebold and Yilmaz (2009), Wang and Wang (2010), Zhou, Zhang and Zhang (2012), Tsai (2014) and Diebold and Yilmaz (2016); using the exchange rate to analyze the spillover effect (Bubák, Kocenda and Zikeš, 2011; Antonakakis, 2012); using the real estate market (Liow and Newell, 2012) and using stocks, bonds, currencies and commodities markets (Diebold and Yilmaz, 2012). Past literature, however, has seldom investigated the spillover effect on herding behavior across industries.

2.2 Herding measure review

Herding behavior refers to a group of investors from the same background making the same decision or behaving in the same way (Nofsinger and Sias, 1999). Herding measures have two different operational definitions in the literature. The first definition is investors' herding towards market returns using returns data to measure CSSD by Christie and Huang (1995) and CSAD by Chang, Cheng and Khorana (2002); that is, the market returns approach. The second definition considers institutional investors' herding towards particular stocks using the imbalance in the number of institutional investors from Lakonishok, Shleifer and Vishny (1992), Wermers, (1999) and Sias, (2004). Lakonishok, Shleifer and Vishny (1992) used the net trading of fund managers to determine buyer or seller to calculate herding, and also find herd behavior in small cap stocks. Wermers (1999), who extends LSV's measure to define buy and sell herding measures, find more funds in the United States exhibit herd behavior in relation to smaller stock trading. The first method uses market prices to estimate herding, but does not as directly or precisely measure herding behavior as the second method; the LSV method.

2.3 Industry herding

Industry herding is defined as a group of investors trading in the same direction into the same industry over a period of time (Choi and Sias, 2009). Industry herding can also parallel the two abovementioned descriptions of herding. The first definition refers to investors' industry herding towards market returns (Yan, Yan and Sun, 2012; Lee, Chen and Hsieh, 2013; Demirer, Lien and Zhang, 2015). Yan, Yan and Sun (2012) found that industry herding can predict future price movement and that the momentum effect is magnified when there is a low level of industry herding, using the CSSD and CSAD methods in the US stock market from January 1980 to December 2008. Lee, Chen and Hsieh (2013) found the existence of industry herding in both bull and bear markets and in China's A-share markets from the 17th of May 2001 to the 16th of May 2011. Demirer, Lien and Zhang (2015) identified the impact of industry herding on the industry momentum effect in the Chinese stock market from January 1996 through December 2013. The second definition considers institutional investors' herding towards particular industries (e.g. Voronkova and Bohl, 2005; Choi and Sias, 2009; Chen, Yang and Lin, 2012; Gavriilidis, Kallinterakis and Ferreirac, 2013; Celiker, Chowdury and Sonaer, 2015). Voronkova and Bohl (2005) found a higher degree of industry herding in relation to metal production, banking and computer services by Polish pension fund managers from 1999 to 2002. Choi and Sias (2009) identified institutional industry herding in the US market from 1983 to 2005. Chen, Yang and Lin (2012) found that foreign institutional investors herd in industries in the Taiwan market from January 2002 to January 2009. Gavriilidis, Kallinterakis and Ferreirac (2013) found that mutual funds herding in industries under examination underperform, and exhibited high volatility and high volume using the Spanish market from June 1995 to September 2008. Celiker, Chowdury and Sonaer (2015) found mutual funds herding in industries using mutual funds in the US market from 1980 to 2013.

Our data are generally non-stationary, daily returns defined as:

$$\mathrm{R_t} = (\ln \mathrm{P_t} - \ln \mathrm{P_{t-1}}) \times 100 \quad (1)$$

where $\mathrm{P_t}$ is the Brent oil price at time t, with $t = 1,2,\ldots,T$, and ln is the natural logarithm.

Kremer and Nautz (2013) defined herding as the tendency of traders to accumulate on the same side of the market in specific stocks at the same time. This study applies the measure of herding proposed by Lakonishok, Shleifer and Vishny (1992) to estimate the herding behavior of foreign institutional investors in Taiwan's stock market. The herding for a given stock in a given time t is defined as follows:

$$\mathrm{HM}_{i,t} = \left|Q_{i,t} - E(Q_{i,t})\right| - E\left|Q_{i,t} - E(Q_{i,t})\right| \quad (2)$$

where the first term captures the deviation of the buyer ratio in industry i at t from the overall buy probability at time t. $Q_{i,t}$ is the proportion of buy transactions out of foreign institutional investors in industry i during t. $Q_{i,t} = B_{i,t}/(B_{i,t} + S_{i,t})$, where $B_{i,t}$ is the number of foreign institutional investors who increase their holdings in the industry in the time (net buyers), and $S_{i,t}$ is the number of foreign institutional investors who decrease their holdings (net sellers). $\mathrm{E}(Q_{i,t})$ is the average proportion of foreign institutional investors buying in time t relative to the number of active buyers. The second term $\mathrm{E}\left|Q_{i,t} - E(Q_{i,t})\right|$ is an adjustment factor. However, $\mathrm{HM}_{i,t}$ measures herding without considering the direction of the trade. Moreover, Wermers (1999) modifies the LSV model by dividing it into buy-side herding (BHM) and sell-side herding (SHM):

$$\mathrm{BHM_{i,t}} = \mathrm{HM_{i,t}}|Q_{i,t} > Q_t \quad (3)$$

$$\mathrm{SHM_{i,t}} = \mathrm{HM_{i,t}}|Q_{i,t} < Q_t \quad (4)$$

where $\mathrm{BHM_{i,t}}$ is the measure of herding for foreign institutional investors on the buy-side, and $\mathrm{SHM_{i,t}}$ is the measure of herding for foreign institutional investors on the sell-side.

3.2 Measuring the Spillover Index

Considering covariance, the stationary N=13 industry herding variables $\mathrm{VAR}(p)$ model is set as follows:

$$H_t = \sum_{i=1}^{p} \Phi_i H_{t-i} + \varepsilon_t, \mathrm{t} = 1,2,\ldots,\mathrm{T} \quad (5)$$

where $H_t = (H_{1t}, H_{2t}, \ldots, H_{Nt})'$ is a$(N \times 1)$ vector of endogenous variables, Φ_i is a $(N \times N)$ parameter matrix, ε_t is the vector of error with zero mean and the covariance matrix $\sum$. Assuming H_t is covariance stationary, then there exists a moving average representation, which is given by

$$H_t = \sum_{i=0}^{\infty} A_i \varepsilon_{t-i}, \mathrm{t} = 1,2,\ldots,\mathrm{T} \quad (6)$$

where the $(N \times N)$ coefficient matrices A_i obey a recursion of the form

$$A_i = \Phi_1 A_{i-1} + \Phi_2 A_{i-2} + \cdots + \Phi_p A_{i-p}, \mathrm{i} = 1,2,\ldots \quad (7)$$

with $A_0 = I_n$ and if $A_i = 0$ for $i < 0$. Diebold and Yilmaz (2012) use the KPPS Z-step-ahead forecast error variance decomposition, which is computed as

$$\theta_{ij}^{g}(S) = \frac{\sigma_{ii}^{-1} \sum_{h=0}^{H-1}(e_i' A_h \Sigma e_j)}{\sum_{h=0}^{H-1} e_i' A_h \Sigma A_h' e_i}, \mathrm{i}, \mathrm{j} = 1,2, \ldots, \mathrm{N} \tag{8}$$

where Σ is the variance matrix for the error vector ε. σ_{ii} is the standard deviation of the error term of the *i*th industry, and e_i is an $(N \times 1)$ vector with one as the *i*th element and 0 elsewhere.[3] Diebold and Yilmaz (2012) define "own variance shares" which are indicated by the fraction of the Z-step ahead forecast error variances in forecasting H_i due to shocks in H_i, for i=1,2,…,N, and "cross variance shares", or spillovers, to be a fraction of the Z-step ahead error variances in forecasting H_i due to shocks to H_j, for $(i \neq j)$.[4]

Diebold and Yilmaz (2009) present three spillover indices, (total spillover, directional spillover and net spillover). The total spillover index is constructed as follows:

$$\mathrm{S}^{\mathrm{g}}(\mathrm{Z}) = \frac{\sum_{\substack{\mathrm{i,j}=1 \\ \mathrm{i} \neq \mathrm{j}}}^{\mathrm{N}} \tilde{\theta}_{\mathrm{ij}}^{\mathrm{g}}(\mathrm{Z})}{\sum_{\mathrm{i,j}=1}^{\mathrm{N}} \tilde{\theta}_{\mathrm{ij}}^{\mathrm{g}}(\mathrm{Z})} \times 100 = \frac{\sum_{\substack{\mathrm{i,j}=1 \\ \mathrm{i} \neq \mathrm{j}}}^{\mathrm{N}} \tilde{\theta}_{\mathrm{ij}}^{\mathrm{g}}(\mathrm{Z})}{\mathrm{N}} \times 100 \tag{10}$$

where the total index measures the contributions from the spillovers of shocks across herding variables on industries to the total forecast error variance. Second, directional spillover allows us investigate both the magnitude and direction of the spillover. Directional spillover is defined as:

$$\mathrm{S}_{\mathrm{j} \to \mathrm{i}}^{\mathrm{g}}(\mathrm{Z}) = \frac{\sum_{\substack{\mathrm{j}=1 \\ \mathrm{i} \neq \mathrm{j}}}^{\mathrm{N}} \tilde{\theta}_{\mathrm{ij}}^{\mathrm{g}}(\mathrm{Z})}{\sum_{\mathrm{j}=1}^{\mathrm{N}} \tilde{\theta}_{\mathrm{ij}}^{\mathrm{g}}(\mathrm{Z})} \times 100 \quad \text{and} \quad \mathrm{S}_{\mathrm{i} \to \mathrm{j}}^{\mathrm{g}}(\mathrm{Z}) = \frac{\sum_{\substack{\mathrm{j}=1 \\ \mathrm{i} \neq \mathrm{j}}}^{\mathrm{N}} \tilde{\theta}_{\mathrm{ij}}^{\mathrm{g}}(\mathrm{Z})}{\sum_{\mathrm{j}=1}^{\mathrm{N}} \tilde{\theta}_{\mathrm{ij}}^{\mathrm{g}}(\mathrm{Z})} \times 100. \tag{11}$$

where $\mathrm{S}_{\mathrm{j} \to \mathrm{i}}^{\mathrm{g}}$ ($\mathrm{S}_{\mathrm{i} \to \mathrm{j}}^{\mathrm{g}}$) is the directional spillover received (transmitted) by variable i (j) from all other variables j (i). Third, net spillover is the difference between the gross volatility shocks transmitted to $\mathrm{S}_{\mathrm{i} \to \mathrm{j}}^{\mathrm{g}}$ and those received $\mathrm{S}_{\mathrm{j} \to \mathrm{i}}^{\mathrm{g}}$ from all other industries. The net spillover is defined as:

$$\mathrm{S}_{\mathrm{i}}^{\mathrm{g}}(\mathrm{Z}) = \mathrm{S}_{\mathrm{i} \to j}^{\mathrm{g}}(\mathrm{Z}) - \mathrm{S}_{\mathrm{j} \to \mathrm{i}}^{\mathrm{g}}(\mathrm{Z}) \tag{12}$$

where $\mathrm{S}_{\mathrm{i}}^{\mathrm{g}} > 0$ ($\mathrm{S}_{\mathrm{i}}^{\mathrm{g}} < 0$)defines i industry as a net sender (receiver).

3.3 Granger causality test between returns and spillover indices

We then use the Granger causality test to identify the nature of causality between industry herding spillover and stock returns, i.e. to see if it is stock returns that cause industry herding spillover or if it is industry herding spillover

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[3] To obtain a unit sum of each row of the variance decomposition, each entry of the variance decomposition matrix is normalized, so that the construction of the decomposition, including own shocks in each market, is equal to one. According to the characteristics of generalized VAR,$\sum_{j=1}^{N} \theta_{\mathrm{ij}}^{\mathrm{g}}(\mathrm{Z}) \neq 1$, normalize each entry of the variance decomposition matrix by the row, as follows $\tilde{\theta}_{\mathrm{ij}}^{\mathrm{g}}(\mathrm{Z}) = \theta_{\mathrm{ij}}^{\mathrm{g}}(\mathrm{Z}) / \sum_{j=1}^{N} \theta_{\mathrm{ij}}^{\mathrm{g}}(\mathrm{Z})$, where $\sum_{j=1}^{N} \tilde{\theta}_{\mathrm{ij}}^{\mathrm{g}}(\mathrm{Z}) = 1$ and $\sum_{i,j=1}^{N} \tilde{\theta}_{\mathrm{ij}}^{\mathrm{g}}(\mathrm{Z}) = \mathrm{N}$.

[4] This study uses 13 industry herding variables; the optimal lag of the VAR model is based on AIC and SBC and 10-step-ahead forecasts.

that causes stock returns, using the regressions relating industry herding spillover and stock returns as follows:

$$R_t = \alpha_0 + \sum_{p=1}^{n} \alpha_p R_{t-p} + \sum_{q=1}^{n} \beta_q \mathrm{Spillover}_{t-q}^{i} + \varepsilon_t \quad (13)$$

$$\mathrm{Spillover}_t^{i} = \theta_0 + \sum_{p=1}^{n} \theta_p R_{t-p} + \sum_{q=1}^{n} \pi_q \mathrm{Spillover}_{t-q}^{i} + \varepsilon_t \quad (14)$$

where R_t is stock index return; $\mathrm{Spillover}_t^{i}$=($\mathrm{Spillover}_t^{HM}$, $\mathrm{Spillover}_t^{BHM}$ and $\mathrm{Spillover}_t^{SHM}$) is the change of spillover index (spillover index of herding, buying herding and selling herding). If $\beta_q \neq 0$ and $\theta_p = 0$ ($\theta_p \neq 0$ and $\beta_q = 0$), this means that the $\mathrm{Spillover}_t^{i}$ (R_t) will affect R_t ($\mathrm{Spillover}_t^{i}$). Second, $\beta_q \neq 0$ and $\theta_p \neq 0$ refer to the feedback relationship between the two series. Finally, if $\beta_q = 0$ and $\theta_p = 0$, then there is a non-causal relationship between the two series.

3.4 Industry momentum returns and Zero-cost momentum strategies at the level of industry herding

This paper investigates the industry momentum strategies and zero-cost momentum strategies at different industry herding levels in the Taiwanese stock market. As evidence for industry momentum strategies, we sort industries into five groups from higher return to lower return industries based on their past 60 daily returns i.e. t through t-60. Industries are then defined as winner (loser) industries if their past 60 returns are highest (lowest) across all industries. We calculate the portfolios return spread between winner and loser industry portfolios in subsequent 10, 20, 40 and 60 days, respectively. The portfolios return spread has a significant positive spread between winner and loser industry portfolios, implying the presence of industry momentum. Second, there is evidence for zero-cost industry momentum strategies for high and low herding levels. Independently, industry herding is also sorted into high (33.3%), intermediate (33.3%) and low (33.3%) groups over the most recent 3-month period.

This study investigates whether subsequent returns are different between high and low herding industries in winner and loser portfolios. Finally, we establish four zero-cost industry momentum strategies in subsequent 10, 20, 40 and 60 days to examine whether the profitability of zero-cost industry momentum strategies depends on the level of industry herding.

4 Data and Empirical Results

4.1 Data Description, Summary Statistics and Unit Root Test

The data employed in this study include the daily industries index prices and foreign institutional holding data from the Taiwan Economic Journal (TEJ) during the period January 2, 2004 through December 31, 2014. Industries are classified in this paper using the industry specifications of the Taiwan Stock Exchange. Appendix 1 presents the proportion of foreign institutional holdings on industry;

we select a proportion of total market value for foreign institutions holding at least higher than 1%. Given this, there are thirteen industries in our sample. Those thirteen take up 92 of the proportion of total foreign institutions holding value, the proportions ranging from high to low are Semiconductor (38.89%), Finance (9.58%), Other Electronic (7.53%), Computer & Per. (6.75%), Elec. Parts (4.73%), Plastics (4.4%), Optoelectronic (4.02%), Comm. Internet (3.45%), Others (3.08%), Trading & Cons. (1.62%), Foods (1.47%), Elec. Machinery (1.24%) and Automobile (1.22%). This study uses this sample to compute herding measures, buy-side herding measures and sell-side herding measures, as well as analyze herding spillovers on industries in Taiwan.

In the case of returns on Table 1, the average return ranges from a low of -0.0266 for the Optoelectronic industry (M2326) to a high of 0.0752 for the Foods industry (M1200), and the Optoelectronic industry (M2326 =1.9709) has the highest volatility value while the Others industry (M9900=1.1438) has the lowest volatility. In the case of herding, the average herding ranges from a low of 5.3568 for the Computer & Per. industry (M2325) to a high of 8.6496 for the Automobile industry (M2200), and the Finance industry (M2800=7.4445) has the highest volatility value while the Computer and peripheral industry (M2325=4.5000) has the lowest volatility. In the case of buy-side herding in Table 2, the average buy-side herding ranges from a low of 4.8930 for the Others industry (M9900) to a high of 8.6611 for the Automobile industry (M2200), and the Finance industry (M2800=7.1264) has the highest volatility value while the Others industry (M9900=4.3082) has the lowest volatility. In the case of sell-side herding, the average sell-side herding ranges from a low of 7.7977 for the Finance industry (M2800) to a high of 8.6496 for the Automobile industry (M2200), and the Finance industry (M2800=7.4445) has the highest volatility value while the Computer & Per. industry (M2325= 4.5000) has the lowest volatility.

Table 1: Descriptive statistics of returns and HM

Panel A: Return R_t						
Industry	Mean	Std. Dev.	Max.	Min.	Skewness	kurtosis
M2324	0.0254	1.5912	6.8979	-6.9060	0.0227	2.7329
M2800	0.0228	1.6429	6.8646	-6.8400	-0.0170	3.3548
M2331	0.0102	1.9420	6.8233	-6.7854	-0.0206	1.7882
M2325	0.0165	1.5440	6.8466	-6.3904	-0.1516	2.3424
M2328	0.0081	1.5736	6.7230	-6.4675	-0.3508	2.2938
M1300	0.0292	1.4069	6.9335	-6.8186	0.0681	3.2689
M2326	-0.0266	1.9709	6.7278	-6.8938	-0.2302	1.2477
M2327	0.0176	1.1752	6.1037	-6.3302	-0.2004	2.4815
M9900	0.0433	1.1438	6.1691	-6.8424	-0.3319	3.5555
M2900	0.0611	1.4939	6.5851	-6.8137	0.0154	2.2073
M1200	0.0752	1.6834	6.7201	-6.7682	-0.0293	2.3832
M1500	0.0383	1.2890	6.1808	-6.7054	-0.5557	3.0028
M2200	0.0498	1.7205	6.8810	-6.8993	0.1253	1.9902
rtindex	0.0264	1.2610	6.7422	-6.6789	-0.3066	3.5834
Panel B: Herding (HM_t)						
Industry	Mean	Std. Dev.	Max.	Min.	Skewness	kurtosis
M2324	6.2397	5.2043	41.1125	0.0122	1.4205	2.6697
M2800	8.1428	7.4445	65.9531	0.0022	2.2283	8.3941
M2331	6.5278	5.5015	44.6667	0.0034	1.4137	2.7260
M2325	5.3568	4.5000	33.7598	0.0084	1.6027	3.8982
M2328	5.7417	5.0439	37.7228	0.0059	1.6418	3.6784
M1300	6.0773	5.2403	35.4102	0.0011	1.4992	2.7405
M2326	6.3254	5.2202	38.0175	0.0003	1.4124	2.6045
M2327	6.4645	5.2966	40.9673	0.0121	1.3340	2.1791
M9900	5.2948	4.7031	48.7318	0.0054	1.7446	5.2466
M2900	7.4662	6.2969	45.1138	0.0004	1.5271	3.1997
M1200	7.6963	6.6450	44.2127	0.0017	1.5156	2.8833
M1500	5.8780	4.9090	39.7850	0.0020	1.5520	3.6739
M2200	8.6496	6.8605	45.9410	0.0032	1.3192	2.4808

Note: M2324 is the code of Semiconductor, M2800 is the code of Finance, M2331 is the code of Other Electronic, M2325 is the code of Computer & Per., M2328 is the code of Elec. Parts, M1300 is the code of Plastics, M2326 is the code of Optoelectronic, M2327 is the code of Comm. Internet, M9900 is the code of Others, M2900 is the code of Trading & Cons., M1200 is the code of Foods, M1500 is the code of Elec. Machinery, M2200 is the code of Automobile. R_t is stock index return. HM_t is thee measure of herding by Lakonishok, Shleifer and Vishny (1992) to estimate the herding behavior of foreign institutional investors in Taiwan stock market. *T*=2735 (2004/1/2–2014/12/31).

Table 2: Descriptive statistics of BHM and SHM

Panel A: Buy-side herding (*BHM*)						
Industry	Mean	Std. Dev.	Max.	Min.	Skewness	kurtosis
M2324	5.9722	4.8724	28.2828	0.0168	1.3040	1.9175
M2800	8.1136	7.1264	65.9531	0.0022	2.2398	9.2834
M2331	6.6102	5.5625	42.6400	0.0135	1.3684	2.3833
M2325	5.4332	4.5335	33.7598	0.0084	1.6121	4.0147
M2328	5.6175	4.9771	35.4889	0.0073	1.6440	3.8991
M1300	6.1556	5.0584	31.3248	0.0045	1.3247	1.9677
M2326	6.1489	5.1407	33.2013	0.0003	1.3864	2.2160
M2327	6.4275	5.3433	40.9673	0.0121	1.3852	2.5670
M9900	5.6370	4.9908	48.7318	0.0054	1.8246	5.9622
M2900	7.2732	6.1350	45.1138	0.0023	1.6121	3.7928
M1200	7.6972	6.5808	44.2127	0.0017	1.3711	2.2273
M1500	5.7710	4.9831	36.8790	0.0067	1.6421	3.9879
M2200	8.6388	6.8082	45.9410	0.0032	1.2172	1.7820
Panel B: Sell-side herding (*SHM*)						
Industry	Mean	Std. Dev.	Max.	Min.	Skewness	kurtosis
M2324	6.4802	5.4759	41.1125	0.0122	1.4646	2.9096
M2800	8.1740	7.7977	63.8859	0.0076	2.2064	7.5333
M2331	6.4457	5.4405	44.6667	0.0034	1.4618	3.1085
M2325	5.2711	4.4608	29.5435	0.0187	1.5934	3.7758
M2328	5.8631	5.1055	37.7228	0.0059	1.6404	3.4905
M1300	6.0055	5.4023	35.4102	0.0011	1.6333	3.2845
M2326	6.4760	5.2837	38.0175	0.0032	1.4335	2.9017
M2327	6.4996	5.2532	30.6097	0.0182	1.2847	1.7981
M9900	4.8930	4.3082	26.6160	0.0091	1.5129	2.9488
M2900	7.6592	6.4511	41.0729	0.0004	1.4480	2.7018
M1200	7.6953	6.7127	42.0991	0.0028	1.6572	3.5172
M1500	5.9662	4.8449	39.7850	0.0020	1.4768	3.4199
M2200	8.6611	6.9174	45.2160	0.0096	1.4228	3.1805

Note: M2324 is the code of Semiconductor, M2800 is the code of Finance, M2331 is the code of Other Electronic, M2325 is the code of Computer & Per., M2328 is the code of Elec. Parts, M1300 is the code of Plastics, M2326 is the code of Optoelectronic, M2327 is the code of Comm. Internet, M9900 is the code of Others, M2900 is the code of Trading & Cons., M1200 is the code of Foods, M1500 is the code of Elec. Machinery, M2200 is the code of Automobile. R_t is stock index return. *BHM* is the measure of herding for foreign institutional investors on the buy-side. *SHM* is the measure of herding for foreign institutional investors on the sell-side. *T*=2735 (2004/1/2–2014/12/31).

4.2 Empirical Implementation of the Spillover Index

4.2.1 Industry herding Spillovers

We investigate whether herding in one industry has a spillover effect into other industries, and so look at spillovers across the Top 13 industries in Taiwan. The results of the degree and direction of herding spillover within and across industries are shown in Table 3. The total spillover index, given in the lower right hand corner of each panel, is computed as the average of the herding spillovers from all other industries. This indicates that in the full sample, approximately 17.70% of the forecast error variance comes from industry herding spillovers, implying that industry herding spillovers appear to be quantitatively pronounced on average.

Table 3 presents herding spillovers. We find that the Semiconductor industry (M2324) is the most affected by other industries (36.1%). Moreover, the semiconductor industry is affected by the electronic industries (M2331, M2325, M2328 M2326 and M2327) at 32.7% (3.3+12+3.9+10.7+2.8=32.7) and was affected by the non-electronic industries (M2800, M1300, M9900, M2900, M1200, M1500 and M2200) at 3.4% (0.4+0.5+0.5+0.3+1.2+0.4+0.1=3.4). In addition, the Optoelectronic industry (M2326) has large herding spillover to the Semiconductor industry at about 10.7%.

Table 3: industry Herding spillovers (HM)

	M2324	M2800	M2331	M2325	M2328	M1300	M2326	M2327	M9900	M2900	M1200	M1500	M2200	From Others(E)	From Others(NoE)	From Others
M2324	63.9	0.4	3.3	12.0	3.9	0.5	10.7	2.8	0.5	0.3	1.2	0.4	0.1	32.7	3.4	36.1
M2800	0.4	92.2	0.3	1.6	0.6	0.6	0.8	0.4	0.5	0.5	0.6	1.0	0.5	3.7	4.1	7.8
M2331	4.2	0.3	78.1	3.9	5.0	0.3	2.6	1.9	1.2	0.3	1.0	1.0	0.3	13.4	8.6	22.0
M2325	13.2	0.8	3.0	65.5	2.4	0.8	9.0	3.3	0.5	0.3	0.6	0.4	0.4	17.7	17.0	34.7
M2328	3.7	0.2	4.4	2.4	78.2	0.9	2.6	2.4	1.3	0.3	2.1	0.9	0.4	11.8	9.8	21.6
M1300	1.3	0.5	0.5	1.1	0.6	90.0	0.6	0.6	1.4	1.3	1.5	0.5	0.3	3.4	6.8	10.2
M2326	12.0	0.4	2.2	9.3	2.7	0.5	67.6	3.0	0.6	0.3	0.9	0.3	0.2	17.2	15.2	32.4
M2327	3.9	0.3	2.2	4.1	2.8	1.0	4.1	79.1	1.0	0.2	0.3	0.4	0.5	13.2	7.6	20.8
M9900	0.6	0.5	1.4	0.5	1.2	1.0	0.7	0.7	88.4	1.6	1.3	1.5	0.5	4.5	7.0	11.5
M2900	0.4	0.3	0.5	0.1	0.5	0.9	0.4	0.1	2.1	92.0	0.9	1.3	0.3	1.6	6.2	7.8
M1200	1.3	0.7	1.3	0.8	1.1	0.6	0.4	0.3	1.3	1.1	90.4	0.7	0.1	3.9	5.8	9.7
M1500	1.0	1.1	1.5	0.7	1.2	0.6	0.3	0.5	1.7	0.6	0.8	89.8	0.3	4.2	6.1	10.3
M2200	0.2	0.7	0.3	0.6	0.6	0.3	0.4	0.7	0.5	0.3	0.3	0.3	94.8	2.6	2.6	5.2
to others (E)	37.0	2.4	15.1	31.7	16.8	4.0	29.0	13.4	5.1	1.7	6.1	3.4	1.9			
to others(NoE)	5.2	3.8	5.8	5.4	5.8	4.0	3.6	3.3	7.5	5.4	5.4	5.3	2.0	Total spillover index =17.70%		
to others	42.2	6.2	20.9	37.1	22.6	8.0	32.6	16.7	12.6	7.1	11.5	8.7	3.9			
including own	106.1	98.4	99.0	102.6	100.8	98.0	100.2	95.8	101.0	99.1	101.9	98.5	98.7			

Note: M2324 is the code of Semiconductor, M2800 is the code of Finance, M2331 is the code of Other Electronic, M2325 is the code of Computer & Per., M2328 is the code of Elec. Parts, M1300 is the code of Plastics, M2326 is the code of Optoelectronic, M2327 is the code of Comm. Internet, M9900 is the code of Others, M2900 is the code of Trading & Cons., M1200 is the code of Foods, M1500 is the code of Elec. Machinery, M2200 is the code of Automobile.to others (E), to others(NoE) and to others denoted the i industry effects on electronic industry, non-electronic and other industry. From others (E), From others (NoE) and From others denoted the I industry was affect from electronic industry, non-electronic and other industry.

We find that the Semiconductor industry (M2324) most affects other industries (42.2%). The semiconductor industry effects the electronic industries (M2331, M2325, M2328 M2326 and M2327) at about 37% (4.2+13.2+3.7+12.0+3.9=37.0) and affects the non-electronic industries (M2800, M1300, M9900, M2900, M1200, M1500 and M2200) at about 5.2% (0.4+1.3+0.6+0.4+1.3+1.0+0.2=5.2). Thus, the Semiconductor industry has a major effect on the electronic industries. In addition, the Computers and Computing Peripheral Equipment industry (M2325) receive large herding from the Semiconductor industry, at about 13.2%.

Hence, the results show that the Semiconductor industry is not only the dominant industry in terms of herding transmission, but also that it is the dominant industry in receiving herding from all other industries. Moreover, the Automobile industry's (M2200) own-industry spillovers are very high (94.8%). Given the above, we find that the Semiconductor industry plays an important role across industries when it comes to institutional herding information.

4.2.2 Industry buy-side and sell-side herding Spillovers

The results of the degree and direction of buying herding spillover within and across industries are shown in Table 4. The buying industry herding spillover index is approximately 24.6% of the forecast error variance in Table 4. Panel A in Table 4 presents buying herding spillovers; we find that the Semiconductor industry (M2324) is the most affected by others industries (54.4%), followed by the Optoelectronic industry (M2326), which has a large herding spillover to the Semiconductor industry at about 14.2%. We find that in terms of affecting other industries (M9900) the most important role is played by the Semiconductor industry (68.8%), and then the Computers and Computing Peripheral Equipment industry (Optoelectronic industry and Other Electronic industries) receive the first (second and third) largest herding from the Semiconductor industry at about 17.6% (15.4% and 10.5%). Our results of the degree and direction of buying herding spillover within and across industries, as shown in Table 4, remain similar to the results shown in Table 3.

The selling industry herding spillover index is approximately 22.2% of the forecast error variance in Table 5. Our results of the degree and direction of buying herding spillover within and across industries in Table 5 remain similar to the results in Tables 3 and 4. Based on all of the results, the semiconductor industry is not only the dominant industry in terms of herding transmission, but is also the dominant industry in terms of receiving herding from all other industries.

4.2.3 Industry net herding Spillovers and Rolling spillover indices

Table 6 presents the net spillovers for herding, buying herding and selling herding. Panel A shows that the Semiconductor industry has the most positive total net spillovers for herding, buying herding and selling herding (6.1, 14.4 and 15.3). The Internet communications (Other Electronic) industry has the most negative total net spillovers for herding and buying herding (selling herding). Thus, the Semiconductor industry has a dominant spillover effect on other industries, and the Internet communications and Other Electronic industries are the industries most affected by others.

This paper estimates the time-varying measure using a 60-day rolling sample and Fig. 1 presents the dynamic behavior of the stock index return and industry herding spillover index. The correlation between the stock index return and industry herding spillover index of HM (BHM and SHM) is 0.9857 (0.9618 and 0.98678).

4.4 Granger causality test between returns and spillover indices

Table 7 reports the results of unit root testing. This study used unit root by ADF and PP. These tests are designed to indicate whether the returns and change of spillover index are non-stationary. The ADF method with intercept (with intercept and trend.) model of the $\mathrm{R_t}$, $\mathrm{Spillover_t^{HM}}$, $\mathrm{Spillover_t^{BHM}}$ and $\mathrm{Spillover_t^{SHM}}$ are -49.4531, -59.0547, -56.9546 and -49.4531 (49.4446, -59.0434, -56.9460 and -49.4446), respectively. The PP method with intercept (with intercept and trend.) model of the $\mathrm{R_t}$, $\mathrm{Spillover_t^{HM}}$, $\mathrm{Spillover_t^{BHM}}$ and $\mathrm{Spillover_t^{SHM}}$ are -49.4429, -60.2711, -57.5595 and -49.4429 (-49.4434, -60.3477, -57.6550 and -49.4434), respectively. Hence, the null hypothesis of a unit root is rejected at the 1% significance level, indicating that $\mathrm{R_t}$, $\mathrm{Spillover_t^{HM}}$, $\mathrm{Spillover_t^{BHM}}$ and $\mathrm{Spillover_t^{SHM}}$ are stationary.

We apply the Granger causality test to examine the lead-lag relationship between returns and spillover indices. As mentioned earlier, the lag length is selected to be one or three in our model based on AIC and SBC methods. Table 8 shows the estimated results of the Granger causality test between returns and spillover indices. Those in the lagged one-period return impact on the current return in three models. Those in the lagged one-period spillover index of industry herding impact on the current return in both HM and SHM models. F values (R) are 2.411 and 3.997 and are significant in both HM and SHM regressions. F values (S) are insignificant in HM, BHM and SHM regressions. Thus, the spillover indices of HM and SHM lead to stock index returns. Consequently, the information of institutional industry herding that gradually diffuses across industries and leads to price movements, could also be useful in devising strategies.

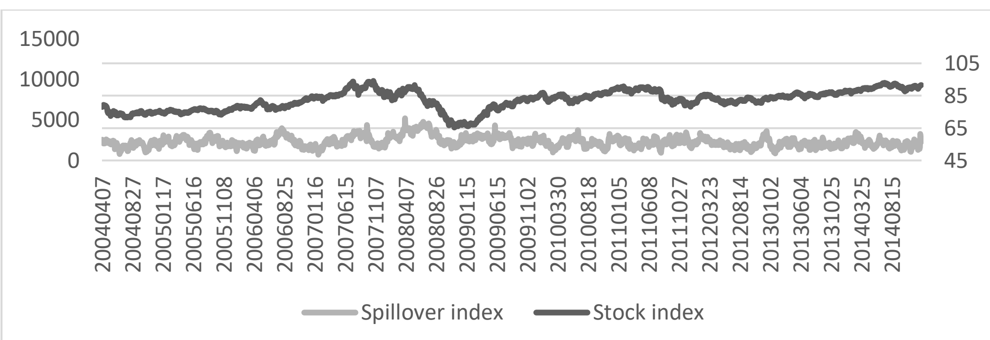

Fig. 1: Spillover index and stock index plot

Table 4: industry Herding spillovers (BHM)

	M2324	M2800	M2331	M2325	M2328	M1300	M2326	M2327	M9900	M2900	M1200	M1500	M2200	From Others(E)	From Others(NoE)	From Others
M2324	45.4	1.2	8.3	16.2	5.7	0.5	14.2	6.8	0.2	0.0	1.2	0.0	0.1	51.2	3.2	54.4
M2800	2.5	88.4	0.4	2.9	0.1	1.5	0.8	0.3	0.0	0.6	0.8	0.8	0.9	4.5	7.1	11.6
M2331	10.5	0.2	59.3	7.8	8.0	0.1	7.0	5.9	0.2	0.1	0.6	0.2	0.1	28.7	12.0	40.7
M2325	17.6	1.4	6.6	48.0	4.9	0.5	13.3	6.1	0.0	0.1	1.0	0.1	0.4	30.9	21.1	52.0
M2328	8.0	0.0	8.4	6.3	61.5	0.3	8.2	5.5	0.0	0.1	0.4	0.3	0.9	28.4	10.0	38.4
M1300	1.5	1.6	0.4	1.4	0.4	92.3	0.8	0.3	0.2	0.0	0.1	0.1	0.8	3.3	4.3	7.6
M2326	15.4	0.5	6.1	13.5	6.6	0.3	50.9	5.5	0.2	0.1	0.7	0.2	0.1	31.7	17.5	49.2
M2327	9.9	0.2	6.2	7.9	5.4	0.0	7.1	62.1	0.4	0.0	0.6	0.2	0.1	26.6	11.4	38.0
M9900	0.4	0.1	0.2	0.0	0.0	0.2	0.2	0.5	96.9	1.0	0.2	0.1	0.1	0.9	2.1	3.0
M2900	0.1	0.7	0.2	0.1	0.2	0.1	0.1	0.1	1.0	96.4	0.4	0.3	0.2	0.7	2.8	3.5
M1200	2.3	0.9	0.9	1.9	0.6	0.1	1.2	0.6	0.0	0.2	90.9	0.2	0.2	5.2	3.9	9.1
M1500	0.5	0.9	0.8	0.2	0.4	0.3	1.1	0.3	0.3	0.4	0.3	94.0	0.5	2.8	3.2	6.0
M2200	0.1	1.5	0.2	0.7	1.4	1.1	0.1	0.1	0.3	0.2	0.2	0.5	93.7	2.5	3.9	6.4
to others (E)	61.4	3.5	35.6	51.7	30.6	1.7	49.8	29.8	1.0	0.4	4.5	1.0	1.7	Total spillover index =24.60%		
to others(NoE)	7.4	5.7	3.1	7.2	3.1	3.3	4.3	2.2	1.8	2.4	2.0	2.0	2.7			
to others	68.8	9.2	38.7	58.9	33.7	5.0	54.1	32.0	2.8	2.8	6.5	3.0	4.4			
including own	114.2	97.6	98.0	106.9	95.2	97.3	105.0	94.1	99.7	99.2	97.4	97.0	98.1			

Note: M2324 is the code of Semiconductor, M2800 is the code of Finance, M2331 is the code of Other Electronic, M2325 is the code of Computer & Per., M2328 is the code of Elec. Parts, M1300 is the code of Plastics, M2326 is the code of Optoelectronic, M2327 is the code of Comm. Internet, M9900 is the code of Others, M2900 is the code of Trading & Cons., M1200 is the code of Foods, M1500 is the code of Elec. Machinery, M2200 is the code of Automobile. to others (E), to others(NoE) and to others denoted the i industry effects on electronic industry, non-electronic and other industry. From others (E), From others (NoE) and From others denoted the I industry was affect from electronic industry, non-electronic and other industry.

Table 5 industry Herding spillovers (SHM)

	M2324	M2800	M2331	M2325	M2328	M1300	M2326	M2327	M9900	M2900	M1200	M1500	M2200	From Others(E)	From Others(NoE)	From Others
M2324	48.8	1.1	5.9	15.2	6.9	0.3	14.1	5.8	0.1	0.3	1.0	0.2	0.2	47.9	3.2	51.1
M2800	2.8	89.2	0.0	2.5	0.1	0.5	1.3	0.2	0.2	1.2	0.4	0.6	1.0	4.1	6.7	10.8
M2331	8.2	0.2	65.7	7.2	6.6	0.1	5.7	4.8	0.1	0.1	0.7	0.1	0.5	24.3	10.0	34.3
M2325	17.3	1.3	5.3	51.1	4.2	0.4	12.3	6.0	0.2	0.0	1.2	0.1	0.4	27.8	20.9	48.7
M2328	8.8	0.3	6.4	4.7	67.4	0.6	4.9	5.0	0.1	0.1	0.9	0.2	0.7	21	11.7	32.7
M1300	0.8	0.4	0.1	0.6	0.7	95.6	0.7	0.2	0.2	0.3	0.1	0.1	0.2	2.3	2.1	4.4
M2326	16.9	0.6	4.5	13.1	4.3	0.2	53.9	5.4	0.2	0.1	0.8	0.2	0.1	27.3	19.1	46.4
M2327	8.2	0.1	4.0	8.0	4.8	0.3	6.8	66.8	0.1	0.0	0.6	0.2	0.1	23.6	9.6	33.2
M9900	0.2	0.1	0.2	0.3	0.1	0.3	0.3	0.1	97.3	0.5	0.2	0.3	0.1	1.0	1.7	2.7
M2900	0.6	1.5	0.2	0.5	0.0	0.3	0.4	0.0	0.9	95.0	0.1	0.2	0.2	1.1	3.8	4.9
M1200	2.2	0.6	1.3	2.2	1.3	0.1	1.4	1.0	0.2	0.2	89.1	0.4	0.2	7.2	3.9	11.1
M1500	0.3	0.8	0.1	0.0	0.3	0.6	0.1	0.1	0.3	0.2	0.5	96.3	0.2	0.6	2.9	3.5
M2200	0.1	1.2	0.5	0.7	1.0	0.2	0.1	0.1	0.1	0.2	0.4	0.2	95.2	2.4	2.4	4.8
to others (E)	59.4	3.6	26.1	48.2	26.8	1.9	43.8	27.0	0.8	0.6	5.2	1.0	2.0	Total spillover index =22.20%		
to others(NoE)	7.0	4.6	2.4	6.8	3.5	2.0	4.3	1.7	1.9	2.6	1.7	1.8	1.9			
to others	66.4	8.2	28.5	55.0	30.3	3.9	48.1	28.7	2.7	3.2	6.9	2.8	3.9			
including own	115.2	97.4	94.2	106.1	97.7	99.5	102.0	95.5	100.0	98.2	96.0	99.1	99.1			

Note: M2324 is the code of Semiconductor, M2800 is the code of Finance, M2331 is the code of Other Electronic, M2325 is the code of Computer & Per., M2328 is the code of Elec. Parts, M1300 is the code of Plastics, M2326 is the code of Optoelectronic, M2327 is the code of Comm. Internet, M9900 is the code of Others, M2900 is the code of Trading & Cons., M1200 is the code of Foods, M1500 is the code of Elec. Machinery, M2200 is the code of Automobile.to others (E), to others(NoE) and to others denoted the i industry effects on electronic industry, non-electronic and other industry. From others (E), From others (NoE) and From others denoted the I industry was affect from electronic industry, non-electronic and other industry.

Table 6: presents the net spillovers for each pair of variables.

	HM			BHM			SHM		
Industry	To	From	Net	To	From	Net	To	From	Net
M2324	42.2	36.1	6.1	68.8	54.4	14.4	66.4	51.1	15.3
M2800	6.2	7.8	-1.6	9.2	11.6	-2.4	8.2	10.8	-2.6
M2331	20.9	22.0	-1.1	38.7	40.7	-2.0	28.5	34.3	-5.8
M2325	37.1	34.7	2.4	58.9	52.0	6.9	55.0	48.7	6.3
M2328	22.6	21.6	1.0	33.7	38.4	-4.7	30.3	32.7	-2.4
M1300	8.0	10.2	-2.2	5.0	7.6	-2.6	3.9	4.4	-0.5
M2326	32.6	32.4	0.2	54.1	49.2	4.9	48.1	46.4	1.7
M2327	16.7	20.8	-4.1	32.0	38.0	-6.0	28.7	33.2	-4.5
M9900	12.6	11.5	1.1	2.8	3.0	-0.2	2.7	2.7	0.0
M2900	7.1	7.8	-0.7	2.8	3.5	-0.7	3.2	4.9	-1.7
M1200	11.5	9.7	1.8	6.5	9.1	-2.6	6.9	11.1	-4.2
M1500	8.7	10.3	-1.6	3.0	6.0	-3.0	2.8	3.5	-0.7
M2200	3.9	5.2	-1.3	4.4	6.4	-2.0	3.9	4.8	-0.9

Note: M2324 is the code of Semiconductor, M2800 is the code of Finance, M2331 is the code of Other Electronic, M2325 is the code of Computer & Per., M2328 is the code of Elec. Parts, M1300 is the code of Plastics, M2326 is the code of Optoelectronic, M2327 is the code of Comm. Internet, M9900 is the code of Others, M2900 is the code of Trading & Cons., M1200 is the code of Foods, M1500 is the code of Elec. Machinery, M2200 is the code of Automobile.

Table 7: Unit root test for returns and spillover indices

	Model	R_t	$Spillover_t^{HM}$	$Spillover_t^{BHM}$	$Spillover_t^{SHM}$
ADP	C	-49.4531**	-59.0547**	-56.9546**	-49.4531**
	C&T	49.4446**	-59.0434**	-56.9460**	-49.4446**
PP	C	-49.4429**	-60.2711**	-57.5595**	-49.4429**
	C&T	-49.4434**	-60.3477**	-57.6550**	-49.4434**

Note: R_t is stock index return; $Spillover_t^i$=($Spillover_t^{HM}$ $Spillover_t^{BHM}$ and $Spillover_t^{SHM}$) is the change of spillover index (spillover index of herding, buying herding and selling herding). C is model with intercept and C&T is model with intercept and trend. *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

Table 8: Granger causality test between returns and spillover indices

Panel A: Estimated results						
Variable	R_t	$Spillover_t^{HM}$	R_t	$Spillover_t^{BHM}$	R_t	$Spillover_t^{SHM}$
R_{t-1}	0.052***	0.038	0.0528***	-0.0037	0.0404**	0.0239
	(0.020)	(0.031)	(0.020)	(0.029)	(0.020)	(0.024)
R_{t-2}	0.001	-0.060*				
	(0.020)	(0.031)				
R_{t-3}	-0.007	0.017				
	(0.020)	(0.031)				
$Spillover_{t-1}^i$	0.026**	-0.149***	-0.0070	-0.1384***	-0.0260**	-0.2070***
	(0.012)	(0.019)	(0.014)	(0.020)	(0.013)	(-0.207)
$Spillover_{t-2}^i$	-0.002	-0.054***				
	(0.012)	(0.020)				
$Spillover_{t-2}^i$	0.019	-0.149***				
	(0.012)	(0.019)				
Constant	0.010	-0.001	0.0173	0.0073	0.0081	0.0139
	(0.025)	(0.039)	(0.025)	(0.037)	(0.025)	(0.014)
Panel B: Granger causality test						
F value (R)	2.408*	1.764	7.0289***	0.0162	4.2341**	0.6785
F value (S)	2.411*	38.266***	0.2580	47.9406***	3.9971**	115.9747***

Note:
1. R_t is stock index return; $Spillover_t^i$=($Spillover_t^{HM}$ $Spillover_t^{BHM}$ and $Spillover_t^{SHM}$) is the change of spillover index (spillover index of herding, buying herding and selling herding).
2. Model: $R_t = \alpha_0 + \sum_{p=1}^{n} \alpha_p R_t + \sum_{q=1}^{n} \beta_q Spillover_t^i + \varepsilon_t$ and $Spillover_t^i = \theta_0 + \sum_{p=1}^{n} \theta_p R_t + \sum_{q=1}^{n} \pi_q Spillover_t^i + \varepsilon_t$.
3. F value (R_t): a joint test whose H0: α_p or H0: θ_p.F value ($Spillover_t^i$): a joint test whose H0: β_q or H0: π_q.
4. *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.( ) is t value.

4.5 The industry momentum returns and Zero-cost momentum strategies at the level of industry herding

This paper investigates the industry momentum strategies and zero-cost momentum strategies at different industry herding levels in the Taiwanese stock market over the subsequent 2 weeks and 1, 2, and 3 months. Table 9 presents the evidence for industry momentum over the subsequent 2 weeks as well as 1, 2, and 3 months. We report the winner portfolio, loser portfolio and spread portfolio between winner and loser industry portfolios. We find that there is a -0.045 and not significant difference in the industry herding between winner and loser portfolios, but the buying or selling industry herding between winner and loser portfolios is significantly different. We also find that there is large BHM (SHM) in winner (loser) portfolios, implying that institutional investors may be industry momentum traders. Given the past 3 months returns, we use 60 daily returns to proxy for 3 months, which is 12.45% (-9.459%) in winner (loser) portfolios. In terms of subsequent returns, we find 0.363% to 1.949% (0.137% to 0.968%) from 2 weeks to 3 months in winner (loser) portfolios, indicating that winner industries tend to outperform loser industries in subsequent returns. In terms of industry momentum, we use spread portfolio between winner and loser industry portfolios to observe significant and positive spread in subsequent returns, which are 0.226%, 0.407%, 0.788% and 0.981% for the subsequent 2 weeks, 1, 2 and 3 months, respectively. This finding clearly supports the claim that an institutional investor is an industry momentum trader.

Table 9: Momentum strategies

				Past returns	Subsequent returns			
	herd	BHM	SHM	3 months	2 weeks	1 month	2 months	3 months
winner	7.486***	7.588***	7.376***	12.450***	0.363***	0.679***	1.356***	1.949***
t value	(132.026)	(95.249)	(91.453)	(119.681)	(7.885)	(10.209)	(13.960)	(15.915)
loser	7.531***	7.309***	7.730***	-9.459***	0.137***	0.272***	0.568***	0.968***
t value	(128.446)	(86.310)	(95.219)	(-81.193)	(3.001)	(4.122)	(5.734)	(7.871)
Difference	-0.045	0.279***	-0.354***	21.909***	0.226***	0.407***	0.788***	0.981***
t value	(-0.554)	(2.392)	(-3.095)	(140.694)	(3.481)	(4.338)	(5.678)	(5.641)

Note:
1. Each day between January 2 2004 and December 31 2014, industries are grouped into portfolios based on their momentum returns using the past 3-month returns.
2. Industries are defined as winner (loser) industries if their momentum returns (monthly) are above (below) the median momentum returns.
3. Portfolios are rebalanced. 2 weeks, 1-month, 2-month, and 3-month returns and indicated a spread between the average returns to winner and loser industries over the subsequent 2 weeks and 1, 2, and3 months.
4. *, ** and *** indicate significance at 10%, 5% and 1%, respectively. ( ) is t value.

Based on the industry momentum shown in Table 9, we proceed to investigate whether subsequent returns are different between high and low herding industries in winner or loser portfolios. Table 10 reports the winner or loser portfolios under high and low herding industries. We find that a high degree of herd, BHM and SHM are significantly larger than low degrees of herd, BHM and SHM and we observe significant differences between high and low herding industries in winner or loser portfolios. The past 3 month returns are 13.027% and 12.76% (-9.258% and -9.181%) for high and low herding industries in winner (loser) portfolios. The difference between high and low herding industries in winner portfolios is positively significant, but there is no significance found in the loser portfolio. The subsequent returns on 2 weeks, 1, 2 and 3 months for high (low) herding industries in winner portfolios are 0.306% to 1.982% (0.518% to 1.684%) and in loser portfolios are 0.257% to 1.334% (0.180% to 0.405%). We find that there are no significant differences between high and low herding in winner portfolios, except for 2 weeks subsequent returns, which are weakly significant at 10%. The subsequent returns on 2 and 3 months are significantly different between high and low herding in loser portfolios. Our finding is the return spread between low and high herding levels in winners or losers, implying an asymmetry between different herding industries in winner and loser portfolios.

Table 10: The impact of herding on return momentum

				Past returns	Subsequent returns			
	herd	BHM	SHM	3 months	2 weeks	1 month	2 months	3 months
Panel A: Winner								
High herding	14.411***	14.474***	14.340***	13.027***	0.306***	0.557***	1.251***	1.982***
t value	(134.055)	(95.352)	(94.345)	(67.496)	(3.600)	(4.540)	(7.111)	(8.977)
Low herding	1.945*	1.974**	1.916*	12.276***	0.518***	0.701***	1.159***	1.684***
t value	(91.329)	(64.104)	(65.403)	(63.444)	(6.095)	(5.699)	(6.566)	(7.439)
Difference	12.466***	12.500***	12.424***	0.750***	-0.212*	-0.144	0.092	0.298
t value	(111.699)	(77.399)	(80.886)	(2.745)	(-1.763)	(-0.828)	(0.370)	(0.942)
Panel B: Loser								
High herding	14.209***	14.206***	14.212***	-9.258***	0.257***	0.381***	0.881***	1.334***
t value	(138.224)	(90.946)	(104.043)	(-44.857)	(3.165)	(3.274)	(5.106)	(6.219)
Low herding	1.852***	1.848***	1.857***	-9.181***	0.180**	0.270**	0.246	0.405*
t value	(84.963)	(58.651)	(61.483)	(-42.720)	(2.105)	(2.137)	(1.293)	(1.708)
Difference	12.357***	12.358***	12.356***	-0.078	0.077	0.111	0.635***	0.929***
t value	(111.126)	(76.807)	(80.126)	(-0.261)	(0.653)	(0.648)	(2.476)	(2.910)

Note: Each day between January 2 2004 and December 31 2014, industries are grouped into portfolios based on their momentum returns using the past 3-month returns. Industries are defined as winner (loser) industries if their momentum returns (monthly) are above (below) the median momentum returns. Independently, industry herding is also sorted into top (33.3%), intermediate (33.3%) and bottom (33.3%) groups over the most recent 3-month period. Portfolios are rebalanced. 2 weeks, 1-month, 2-month, and 3-month returns and indicted a spread between the average returns to high and low industry herding under different winner and loser industries over the subsequent 2 weeks and 1, 2, and 3 months. *, ** and *** indicate significance at 10%, 5% and 1%, respectively. ( ) is t value.

Table 11 reports the zero-cost momentum strategies at different industry herding levels. There are four portfolios constructed: long high herding winner and short high herding losers (strategy 1), long high herding winner and short low herding losers (strategy 2), long low herding winner and short high herding losers (strategy 3), and long low herding winner and short low herding losers (strategy 4). We find that the zero-cost industry momentum strategy yields highly significant maximal subsequent returns for 0.338% of strategy 4 in 2 weeks, 0.431% of strategy 4 in 1 month, 1.005% of strategy 3 in 2 months and 1.576% of strategy 3 in 3 months. We see that taking a long position in high or low herding winners and a short position in low herding losers yields good subsequent returns, implying that the profitability of zero-cost industry momentum strategies depends on the level of industry herding.

Table 11: Zero-cost industry momentum strategies

Subsequent returns	2 weeks	1 month	2 months	3 months
Panel A: long high herding winners and short high herding losers				
Average returns	0.049	0.176	0.370	0.648**
t value	(0.417)	(1.041)	(1.499)	(2.102)
Panel B: long low herding winner and short high herding on loser				
Average returns	0.261**	0.320*	0.278	0.350
t value	(2.221)	(1.892)	(1.124)	(1.121)
Panel C: long high herding winners and short low herding on losers				
Average returns	0.126	0.287*	1.005***	1.576***
t value	(1.039)	(1.625)	(3.874)	(4.860)
Panel D: long low herding winners and short low herding losers				
Average returns	0.338***	0.431***	0.913***	1.278***
t value	(2.795)	(2.442)	(3.517)	(3.895)

Note: Each day between January 2, 2004 and December 31, 2014, industries are grouped into portfolios based on their momentum returns using the past 3-month returns. Industries are defined as winner (loser) industries if their momentum returns (monthly) are above (below) the median momentum returns. Independently, industry herding is also sorted into top (33.3%), intermediate (33.3%) and bottom (33.3%) groups over the most recent 3-month period. Portfolios are rebalanced 2 weeks, 1-month, 2-month, and 3-month returns and indicate a spread between the average returns of high and low industry herding under different winner and loser industries over the subsequent 2 weeks and 1, 2, and 3 months. ( ) is t value.

5 Conclusion

This study examines industry herding spillover effects among industries and captures an industry herding spillover index to analyze the lead-lag relationship between the industry herding spillover index and the stock index return. Finally, this paper investigates industry momentum strategies and zero-cost momentum strategies at different industry herding levels over 2 weeks and 1, 2, and 3 months.

The paper provides evidence that in terms of industry herding, the semiconductor industry is not only the dominant net sender, but is also the dominant net receiver; thus, foreign institutional investors herd on the semiconductor industry, which plays an important role across industries in relation to institutional herding information. Second, the spillover indices of HM and SHM lead to stock index returns, implying that the spillover indices of HM and SHM are good predictors of stock index returns. Finally, this study supports the claim that an institutional investor is an industry momentum trader and that the profitability of zero-cost industry momentum strategies indeed depends on the level of industry herding.

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