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Do Investors Herd in Emerging Stock Markets?: Evidence from the Taiwanese Market

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Abstract

This paper has two contributions to the literature on investor herds. First, it extends investor herding studies to an emerging yet relatively sophisticated Taiwanese stock market by using firm level data. Second, it employs different testing methodologies designed to test the existence of investor herds and compares the robustness of inferences. We find that the linear model based on cross sectional standard deviation (CSSD) testing methodology yields no significant evidence of herding among Taiwanese investors. However, the non-linear model proposed by Chang et al. (2000) and the state space based models of Hwang and Salmon (2004) lead to consistent results indicating strong evidence of herd formation in all sectors. We also find that the herding effect is more prominent during down movements of the market. Further research is necessary to see whether similar findings hold for other emerging markets.

JEL Classification Code: G14, G15

Keywords: Herd behavior, Equity return dispersion, Taiwan Stock Exchange, Non-Linear and State Space models.

1. Introduction

Formation of investor herds has been proposed as an alternative explanation of how investors process information and make investment choices. Herding is simply defined as an investment strategy based on mimicking other investors' actions or the market consensus (e.g., Bikhchandani and Sharma, 2000).[1] One of the main contributions of this study is to extend herding tests to the Taiwanese stock market. The second main contribution is to employ different herding methodologies proposed in the literature and to provide robustness tests.

We select the Taiwanese stock market for several reasons. First, as shown in Table 1, domestic investors, mostly individual, account for the highest percentage of total investment amount in all sectors with the exception of electronics. So, this is a market dominated by domestic individual investors, rather than institutional and foreign investors. However, the table also suggests an increasing interest by foreign investors over the past six years, especially in electronics. Unlike investment trusts, foreign investors, and security dealers, most individual investors tend to have less professional knowledge and cannot access information accurately and easily. In a market dominated by domestic individual investors with limited access to information, one might argue that the resulting information asymmetry may lead these individual investors to follow the actions of other investors including more informed institutional and foreign investors. For this reason, one might expect the formation of investor herds in this market dominated by the less informed domestic individual investors. For this purpose, it is especially interesting to examine whether herd formation exists in the Taiwanese market with this unique characteristic.

[1] Prior studies differ in their explanation to what might trigger such behavior. Devenow and Welch (1996) use the arguments of investor psychology where investors feel a sense of security in following the crowd. Another view suggests that the actions of more informed traders may reveal useful information which may not be accessible to individual investors (Chari and Kehoe, 1999, Calvo and Mendoza, 1998, and Avery and Zemsky, 1998). Finally, a third approach focuses on the principal-agent relationship where fund managers might want to imitate others as a result of the incentives provided by the compensation scheme or in order to maintain their reputation (Scharfstein and Stein, 1990, Rajan, 1994, and Maug and Naik, 1996).

Second, despite being an emerging market, the Taiwanese stock market is highly developed. The ratio of average stock market total value to GDP, a commonly used measure of stock market development, in Taiwan during the period from 1975 to 2006 was 1.65, which is greater than that of the U.S. (1.25) and ranked first among 75 countries during this period.[2] If the results indicate evidence of herding, this suggests that herding may take place in a relatively developed yet still an emerging stock market like Taiwan.

Third, there is limited and conflicting evidence on herding behavior in the Taiwanese stock market. To our best knowledge, there are only two empirical studies of herding behavior in the Taiwanese stock market. Using one of the methodologies employed in this paper, Chang et al. (2000) analyze daily equally-weighted index return data from January 1976 to December 1995 and find significant evidence of herding in this market. However, their study examines firm level return data within the market portfolio without classifying individual firms into specific sectors. As Bikhchandani and Sharma (2000) suggest, herd formation would be more likely to occur at the level of investments in a group of stocks such as stocks in an industry where investors face similar decision problems and can observe the trades of others in the group. Lin and Swanson (2003) also study herd behavior of investors in the Taiwanese stock market during 1996-2003 period again using one of the methodologies we employ here, but they focus only on foreign investors and the most liquid stocks without classifying them into sector groups. They find no evidence that foreign investors herd in this market. Overall, we can conclude that there is no study of herding behavior in Taiwan covering the more recent period and the available studies produce conflicting findings. As Table 1 shows, studying the more recent period is important due to the increase participation of foreign investors.

Given different findings and limited work on Taiwan and the interesting institutional characteristic of this market (i.e., a large number of domestic individual investors with a small

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[2] See Beck, Demirguc-Kunt and Levine (2000).

but growing number of foreign investors), we extend the earlier studies in three significant aspects by (i) providing sector-specific evidence, (ii) employing different testing methodologies, and (iii) providing evidence using recent daily data from January 1995 to December 2006.

We employ two major different testing methodologies based on the dispersions of returns and factor sensitivities, and compare the inferences from each model using a large scale data. The findings have implications for the robustness of different herding tests used in the literature. Previous studies hypothesize that herding behavior may be captured by either return dispersions or relative dispersion of the time-varying betas for assets. For the former, we employ linear and non-linear models based on "return dispersions" among individual firms; more specifically, cross sectional standard deviations (CSSD) and cross sectional absolute deviations (CSAD) across a particular sector. For the latter, we employ models based on a state space model specification proposed by Hwang and Salmon (2004). These two sets of models differ in the sense that the first two focus on the cross-sectional variability of returns, whereas the last two focus on the cross-sectional variability of factor sensitivities. Understanding which models yield herding behavior may provide information about the ways in which investors herd. These models are summarized in Section 3.

Looking forward, we find no significant herding behavior based on the linear model. This is consistent with our finding of significant non-linear effects in the data, making the inferences from the linear model spurious. However, the non-linear model and the state space based models lead to consistent results, indicating strong evidence of herd formation in all sectors analyzed, suggesting that herding behavior may be captured by examining either cross-sectional return dispersions in a *non-linear* fashion or beta dispersions.

In Section 2, we briefly summarize previous studies on tests of investor herds as well as a summary of market efficiency studies on the Taiwanese stock market. Section 3 provides the details of different testing methodologies employed and data description. Section 4 presents empirical results and a comparison of the findings from the return dispersion based models and state space models. Finally, Section 5 concludes the paper and proposes further research.

2. Previous Studies on Investor Herds

Different methodologies have been suggested in the literature to test the existence of investor herds. Testing methodologies based on return dispersions among a group of securities focus on cross sectional standard (or absolute) deviations of returns. Prior studies include Christie and Huang (1995) on U.S. equities, Chang, Cheng and Khorana (2000) on international equities, Gleason, Lee and Mathur (2003) on commodity futures traded on European exchanges, Gleason, Mathur and Peterson (2004) on Exchange Traded Funds, and Demirer and Kutan (2006) and Tan et al. (2008) on Chinese stocks. With the exception of Tan et al. (2008), prior studies generally provide results in favor of the rational asset pricing theories and conclude that herding is not an important factor in determining security returns during periods of market stress. In a limited study using sixty highest capitalization stocks held by foreign investors in Taiwan, Lin and Swanson (2003) employ the cross sectional standard deviation based methodology and find no evidence that foreign investors herd in this market.

A different testing methodology based on cross sectional variability of factor sensitivities, instead of returns, is suggested by Hwang and Salmon (2004). Their analysis of daily stock returns in the South Korean market provides support for herd formation in this market. Extending the study to futures markets, Weiner and Green (2004) employ both parametric and non-parametric methodologies and find little evidence of herding in heating oil and crude-oil futures. In a more recent study, Uchida and Nakagawa (2007) use the LSV herding measure of Lakonishok, Shleifer, and Vishny (1992) to test herd behavior in the domestic loan market for Japanese banks and find evidence of herd behavior among regional banks and among geographically proximate banks.

The efficient market hypothesis (EMH) suggests that asset prices reflect all available information processed by rational investors who make investment decisions based on their independent research of these assets. In that sense, formation of investor herds can be considered as an alternative investment behavior which might lead to an inefficient market where asset prices show significant deviations from what one would expect in an efficient market. This clearly is a significant concern for not only traders in the market but also for policy makers as such behavior would lead to unnecessary volatility and more frequent extreme observations. The efficiency of the Taiwanese stock market has been the topic of several studies in the literature. Lee et al. (2004) classify this market as a semi-strong efficient market, observing that institutional investors and informed investors can earn excess returns when they receive private signals. In an earlier study, using Sherry's (1992) non-parametric methods to examine the efficiency of six Asian stock markets, Los (2001) concludes that Taiwan's stock market lacks at least one of the two required fair game attributes, and accordingly, the efficient market hypothesis must be rejected for this market. Separately, Yu and Huang (2004) examine the statistical properties of volatility among New York and five stock markets in Asia and find that Taiwan is the most volatile market among the six stock markets studied.

In an earlier study, Titman and Wei (1999) compare Korean and Taiwanese stock markets and find that the Taiwanese market has been the more volatile one despite the similarities between these the two markets. They note the higher trading volume in the Taiwanese market and link the high volatility in this market to the volatile nature of underlying fundamentals. Although their analysis rejects the notion that excessive speculation is the source of high volatility in this market, they acknowledge that stock prices may have deviated from fundamental values at selected times. Consistent with these findings, Leung, Daouk and Chen (2006) characterize the Taiwanese market as highly volatile, having relatively smaller capitalization, and less price efficient. Finally, Lim, Brooks, and Hinich (2007) utilize the bi-correlation statistics of Hinich (1996) and find that the Taiwan Stock Exchange weighted index has no clear trend towards higher efficiency as predicted by the classical efficient market hypothesis.

Overall, the empirical evidence summarized above indicates that Taiwan's stock market is not yet informationally efficient as defined by the EMH. Our study, in that respect, can be viewed as an extension of market efficiency studies in this market as the existence of herd formation would clearly indicate violation of the assumptions for an efficient market in which prices fully and instantaneously reflect all available information.

3. Methodology

We employ two testing methodologies: return dispersion based models and state space models. This section summarizes the methodology for each testing methodology.

3.1 Return Dispersion Models

The first two testing methodologies employed are based on cross sectional standard deviations (CSSD) and cross-sectional absolute standard deviations (CSAD) among individual firm returns within a particular group of securities. Christie and Huang (1995) use CSSD as a measure of the average proximity of individual asset returns to the realized market average in order to test herd behavior. Chang et al. (2000) use CSAD in a non-linear regression specification in order to examine the relation between the level of equity return dispersions and the overall market return.

The first return dispersion methodology employed in this study is based on return dispersions as measured by CSSD. This methodology has been used by Christie and Huang (1995), Chang, Cheng, and Khorana (2000), Gleason, Lee and Mathur (2003), Lin and Swanson (2003), Gleason, Mathur and Peterson (2004), and Demirer and Kutan (2006). Cross-sectional standard deviations (CSSD), used as a measure of return dispersion, is formulated as follows:

$$CSSD_t = \sqrt{\frac{\sum_{i=1}^{N}(r_{i,t} - r_{p,t})^2}{N-1}} \quad \textbf{(1)}$$

where *n* is the number of firms in the aggregate market portfolio, $r_{i,t}$ is the observed stock return on firm *i* for day *t* and $r_{p,t}$ is the cross-sectional average of the *n* returns in the market portfolio for day *t*. This measure can be regarded as a proxy to individual security return dispersion around the market average.

The main idea in this methodology is based on the argument that the presence of herd behavior would lead security returns not to deviate far from the overall market return. The rationale behind this argument is the assumption that individuals suppress their own beliefs and make investment decisions based solely on the collective actions of the market. On the other hand, rational asset pricing models offer a conflicting prediction suggesting that dispersions will increase with the absolute value of market return since each asset differs in its sensitivity to the market return.

This methodology also suggests that the presence of herd behavior is most likely to occur during periods of extreme market movements, as they would most likely tend to go with the market consensus during such periods. Hence, we examine the behavior of the dispersion measure in (1) during periods of market stress and estimate the following linear regression model:

$$CSSD_t = \alpha + \beta_D D_t^L + \beta_U D_t^U + \varepsilon_t \quad \textbf{(2)}$$

where D_t^L = 1, if the return on the aggregate market portfolio on day *t* lies in the *lower* tail of the return distribution; 0 otherwise, and D_t^U = 1, if the return on the aggregate market portfolio on day *t* lies in the *upper* tail of the return distribution; 0 otherwise. Although somewhat arbitrary, in the literature, an extreme market return is defined as one that lies in the one (and five) percent lower or upper tail of the return distribution.

The dummies in equation (2) aim to capture differences in return dispersions during periods of extreme market movements. As herd formation indicates conformity with market consensus, the presence of negative and statistically significant β_D (for down markets) and β_U (for up markets) coefficients would indicate herd formation by market participants.

The second return dispersion methodology employed in this paper is suggested by Chang et al. (2000) and uses the cross-sectional absolute deviation of returns (CSAD) as a measure of return dispersion. CSAD is expressed as

$$CSAD_t = \frac{1}{N}\sum_{i=1}^{N} | r_{i,t} - r_{m,t} | \quad \textbf{(3)}$$

Chang et al. (2000) challenge the CAPM assumption that return dispersions are an increasing function of the market return and that this relation is linear. If there are significant non-linear effects, then the results based on the cross sectional standard deviations of returns would not be valid. The authors suggest that during periods of market stress, one would expect the relation between return dispersion and market return to be non-linearly increasing or even decreasing. Therefore, they propose a testing methodology based on a general quadratic relationship between $CSAD_t$ and $r_{m,t}$ of the form:

$$CSAD_t = \alpha + \gamma_1 |r_{m.t}| + \gamma_2 r_{m.t}^2 + \varepsilon_t \quad \textbf{(4)}$$

According to this methodology, herding would be evidenced by a lower or less than proportional increase in the cross-sectional absolute deviation (CSAD) during periods of extreme market movements. As a result, if herding is present, then the non-linear coefficient, γ_2 will be negative and statistically significant; otherwise a statistically positive γ_2 would indicate no evidence of herding.

3.2 State Space Models

The next testing methodology we employ is suggested by Hwang and Salmon (2004). Rather than returns, Hwang and Salmon (2004) focus on the cross-sectional variability of factor sensitivities. Considering a one factor model with the factor being the market return, they formulate a herding measure based on the relative dispersion of the betas for all assets in the market. Next, we briefly explain this methodology. Consider the following CAPM in equilibrium,

$$E_r(r_{it}) = \beta_{imt} E_t(r_{mt}) \tag{5}$$

where r_{it} and r_{mt} are the excess returns on asset i and the market at time t, respectively, β_{imt} is the systematic risk measure, and $E_t(\cdot)$ is conditional expectation at time t. In equilibrium, we only need β to price an asset i. When herding behavior is present, investors disregard the equilibrium relationship of Equation (5) and trade in such a way that matches individual asset returns with that of the market. When that happens, the β term and the expected rate of return present a bias which reflects this matching of individual asset returns with that of the market. So, considering CAPM again, when herding behavior is present, real β coefficient obeys the following relation which replaces equation (5):

$$\frac{E_t^b(r_{it})}{E_t(r_{mt})} = \beta_{imt}^b = \beta_{imt} - h_{mt}(\beta_{imt} - 1), \tag{6}$$

where $E_t^b(r_{it})$ and β_{imt}^b are the market's biased short run conditional expectation on the excess returns of asset i and its beta at time t, and h_{mt} is a latent herding parameter that changes over time, $h_{mt} \leq 1$, and conditional on market fundamentals. In general, when $(0 < h_{mt} < 1)$, one could argue that some degree of herding exists in the market determined by the magnitude of h_{mt}.

Since the form of herding we discuss represents market-wide behavior and Equation (6) is assumed to hold for all assets in the market, the level of herding is estimated using all assets in the market rather than a single asset, thereby removing the effects of idiosyncratic movements in any individual β_{imt}^b. The standard deviation of β_{imt}^b is then formulated as

$$Std_c(\beta^b_{imt}) = \sqrt{E_c((\beta_{imt} - h_{mt}(\beta_{imt} - 1) - 1)^2)}$$

$$= \sqrt{E_c((\beta_{imt} - 1)^2)}(1 - h_{mt})$$

$$= Std_c(\beta_{imt})(1 - h_{mt})\,, \qquad \textbf{(7)}$$

where $E_C(\cdot)$ represents the cross-sectional expectation. Taking the logarithm of Equation (7) and assuming that $Std_c(\beta^b_{imt})$ can be time-varying over a time interval in response to the level of herding in the market, we rewrite Equation (7) as

$$\log[Std_c(\beta^b_{imt})] = \mu_m + \upsilon_{mt}$$

where $\mu_m = E[\log[Std_c(\beta_{imt})]]$ and $\upsilon_{mt} \sim iid(0, \sigma^2_{m\upsilon})$. *State Space Model 1* is then estimated as

$$\log[Std_c(\beta^b_{imt})] = \mu_m + H_{mt} + \upsilon_{mt}\,, \qquad \textbf{(8)}$$

$$H_{mt} = \phi_m H_{mt-1} + \eta_{mt}\,, \qquad \textbf{(9)}$$

where $H_{mt} = \log(1 - h_{mt})$ and $\eta_{mt} \sim iid(0, \sigma^2_{m\eta})$. Equations (8) and (9) are the standard state-space model with Kalman filter estimation. In this methodology, we only focus on the dynamic pattern of movements in the latent state variable, H_{mt}, the state equation. When $\sigma^2_{m\eta} = 0$, there is no herding which implies that $H_{mt} = 0$ for all t. The model allows herding, H_{mt}, to evolve over time and follow a dynamic process. A significant value of $\sigma^2_{m\eta}$ can be interpreted as the existence of herding and a significant ϕ supports this particular autoregressive structure.

An alternative, augmented model can be formulated when we add to Equation (8) market volatility, $\log\sigma_{mt}$, and return , r_{mt}, as independent variables. This leads to *State Space Model 2* formulated as

$$\log[Std_c(\beta^b_{imt})] = \mu_m + H_{mt} + c_{m1}\log\sigma_{mt} + c_{m2} r_{mt} + \upsilon_{mt}\,. \qquad \textbf{(10)}$$

Similarly, a significant value of $\sigma^2_{m\eta}$ can be interpreted as the existence of herding and a significant ϕ supports this particular autoregressive structure.

4. Data and Empirical results

4.1 Data

The data set used in this study contains daily returns for 689 Taiwanese stocks traded on the Taiwan Stock Exchange over the January 1995–December 2006 period. Data are obtained from the *Taiwan Stock Exchange Corporation* (TSEC). Herding tests in the literature are based on the suggestion that a group is more likely to herd if it is sufficiently homogeneous, i.e., each member faces a similar decision problem, and each member can observe the trades of other members in the group (Bikhchandani and Sharma, 2000). Prior studies have, therefore, applied the tests on groups of stocks categorized on the basis of industry classification (e.g., Christie and Huang, 1995), exchange or country assignment (e.g. Gleason, Mathur and Peterson, 2004 and Chang, Chen, and Khorana, 2000). Following these studies, we assign each of the 689 firms to one of eighteen sector groups including Cement, Food, Plastics, Textile, Electrical Appliances, Wire & Cable, Chemicals, Glass & Ceramics, Pulp & Paper, Steel, Rubber, Automobile, Electronics, Construction, Transportation, Tourism, Banking & Securities, and Retailing. We then calculate portfolio returns based on an equally weighted portfolio of all firms in each sector classification.

Table 2 provides summary statistics for average daily log returns, return dispersions, and the average number of firms used to compute these statistics for each sector. Since the number of stocks in a sector does not stay constant over time, we report the average number of firms over the sample period in the second column of Table 2. Examining Table 2, we observe that the average daily returns for all sectors are positive and electronics and construction sectors have the highest average daily volatility. Panel B in Table 2 reports summary statistics for daily cross sectional standard deviations within each sector. Consistent with the findings from Panel A, we observe the highest cross sectional volatility in Electronics followed by Construction.[3]

4.2 Results of return dispersion models

Table 3 presents estimation results for the CSSD based model in Equation 2. Given the significant variation in dispersions and strong correlation, all estimations are done using the Newey-West heteroskedasticity and autocorrelation consistent standard errors[4]. We use the Taiwan Stock Exchange Composite Index to represent the market and use the upper and lower one and five percentiles of the market return to represent periods of market stress. For a majority of the sectors analyzed, we do not find any evidence in favor of herd formation during periods of large market swings. This finding is consistent with Lin and Swanson (2003) who tested whether foreign investors herd in the Taiwanese stock market using the same methodology. Similar to their findings, our regressions yield statistically significant and positive β estimates indicating that equity return dispersions increase during periods of large price changes as predicted by CAPM. However, estimations across sector groups indicate that the only exception to this is Electronics where we observe significantly lower return dispersions when market is in the upper or lower one percentile, indicating herd formation during extreme moves of the market index.

Table 4 presents estimations results for the non-linear CSAD based model in Equation 4. Following Chang et al. (2000), we run three separate regressions for each sector: one using the whole sample, and two restricting the data to up (or down) movements of the market index. Running separate models in this manner allows us to examine whether there is any asymmetric effect of herd behavior. Our findings with the non-linear model lead to completely different results than the first methodology.

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[3] Over the past few years, the electronics sector has shown rapid growth. According to the annual report of Taiwan Stock Exchange Corporation, this sector accounts for 60% and 70% of the total volume and value of the Taiwan stock market, respectively. Regarding the construction sector, the government of Taiwan has executed different policies frequently to stimulate growth in the housing market. Such governmental intervention policy might have led to the higher returns and corresponding higher volatility in this sector.

[4] We also estimated the models using GARCH models; the results were qualitatively the same.

Focusing on Table 4, we first note that the nonlinear term (γ_2) is statistically significant almost in all cases, suggesting that inferences from the linear model reported in Table 3 are spurious. We therefore heavily rely on the non-linear tests reported in Table 4 to make inferences about herding. Indeed, we find evidence to herd formation in Table 4 in all sectors, except for Tourism and Automobile. The regressions yield statistically significant and negative γ_2 estimates indicating a non-linear and decreasing relation between equity return dispersions and the market return. However, when we examine regression results run with data restricted to up and down markets separately, we observe that herding effect is mostly prominent during market losses. The results suggest that t is more likely to observe herd formation during periods of market losses.[5]

4.3 Results of state space models

Table 5 presents estimation results for State Space Model 1. Consistent with our findings from the non-linear model, the results indicate strong evidence of herding through H_{mt}. We observe that H_{mt} is highly persistent with large and significant values of $\hat{\phi}_m$. More importantly, the estimates for $\sigma_{m\eta}$ are highly significant providing support for herd behavior.

Table 6 presents estimation results for State Space Model 2. Compared with State Space Model 1, Model 2 contains two market variables – market volatility and market return. The addition of these two variables in the measurement equation allows us to analyze the degree of herding, given the state of the market. Our findings are similar to those we observe with the first state space model results in Table 5. Once again, taking into account the level of market volatility and return this time, we find that the term H_{mt} is still significant when these two explanatory variables are included. This finding suggests that changes in the volatility of factor sensitivities, $Std_c(\beta^b_{imt})$, could be explained by herding rather than changes in fundamentals.

[5] This finding is consistent with some of the behavioral finance literature suggesting the concept of loss aversion. According to this theory, investors' utility function is formed in such a way that investors have a greater tendency towards avoiding losses than acquiring gains (see for example Kahneman and Tversky, 1979 and Tversky and Kahneman, 1991). Therefore, the finding that investors herd during periods of market losses can be due to investor psychology leading to asymmetric responses to up and down markets.

Furthermore, we estimate significant and negative coefficients for the term $\log\sigma_{mt}$ for Plastics, Electrical App., Chemicals, Pulp, Steel, Automobile, Tourism, and Retailing sectors, indicating that the volatility of factor sensitivities, $Std_c(\beta^b_{imt})$, decreases with market volatility. These results are consistent with previous studies which suggest that herding is more likely to occur during periods of market stress, i.e. highly volatile periods.

However, in the case of Cement, Food, Textile, Wire & Cable, Glass, Electronics, and Banking & Securities sectors in Table 6, our findings suggests that the volatility of factor sensitivities, $Std_c(\beta^b_{imt})$, increases as market volatility rises since the coefficients for the market volatility term ($\log\sigma_{mt}$) have significant and positive values. Interestingly, the majority of these sectors where factor sensitivities increase with market volatility also have relatively higher foreign shareholding percentage (Table 1). Thus, we believe that investors in these sectors may exhibit herding behavior regardless of the level of market conditions, as signals from a significant body of foreign investors in these sectors may be stronger or more visible to domestic individual investors.

Furthermore, comparing the estimates for $\hat{\phi}_m$ across sectors we notice that the effect of herd behavior in Electronics is relatively higher compared to other sectors. Once again, examining Table 1, we note that Electronics sector stands out among other sectors with the strongest presence of foreign investors. It is also interesting to note that the Electronics sector is the largest sector with 307 firms (Table 2), accounting for 60% and 70% of the total volume and value of the entire Taiwan stock market, respectively.

5. Conclusions and suggestions for further research

There are scant studies on herding behavior in Taiwan and they produce conflicting inferences and do not provide evidence at the sector level. In this paper, we extend tests of investor herds to the Taiwan Stock Exchange, using firm level data on 689 firms classified into 18 different sectors. Also, we employ different herding models simultaneously using a large data set to compare and contrast inferences under different approaches to testing the formation of investor herds.

The linear model proposed by Christie and Huang (1995) provides no evidence of investor herds, except for the Electronics sector. However, we find that the assumption of linearity between return dispersions and the market return in this methodology yields unreliable results as our tests of the non-linear model suggests significant non-linear effects. Extending our tests to the non-linear model proposed by Chang et al. (2000), which assumes that return dispersion and market return to be non-linearly related, indicates herding in all sectors analyzed. We find significant non-linear effects, suggesting that inferences from the Chang et al. (2000) model yields more reliable inferences on herding. Our tests of factor sensitivities using the state space based models proposed in Hwang and Salmon (2004) further support the results of the non-linear model, indicating robust evidence of herd formation in Taiwan across all sectors. This is the initial study comparing the inferences from different empirical models of herding. It would be interesting to see whether similar results would hold when the same tests are applied to different emerging markets or developing and developed markets..

Our results, which are based on dispersions of returns and factor sensitivities, should be interpreted cautiously, however, as there are other tests of herding formation. It would be interesting to compare our findings with those from different herd-formation methodologies such as those on trading data.

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Table 1. Shareholding Percentage of Market Participants by Sector (%)

Year	Domestic Individual	Domestic Institution	Foreign Investor	Domestic Individual	Domestic Institution	Foreign Investor	Domestic Individual	Domestic Institution	Foreign Investor
	Cement			**Food**			**Plastics**		
1996	90.33	0.87	8.80	90.13	0.63	9.24	81.58	0.47	17.95
2001	94.63	0.80	4.57	92.62	0.55	6.83	81.89	0.52	17.60
2006	75.42	0.91	23.67	74.99	0.90	24.11	82.54	0.53	16.93
	Textiles			**Electrical App.**			**Wire & Cable**		
1996	88.49	1.09	10.43	86.02	2.03	11.96	85.84	0.57	13.59
2001	85.87	1.47	12.67	89.93	1.93	8.15	90.67	0.55	8.78
2006	81.50	0.97	17.53	81.26	2.42	16.32	77.43	0.66	21.91
	Chemicals			**Glass**			**Pulp & Paper**		
1996	89.24	1.91	8.85	90.83	0.33	8.84	86.67	0.75	12.58
2001	94.74	3.17	2.09	95.64	0.72	3.64	93.29	0.40	6.31
2006	80.94	1.58	17.49	94.39	0.28	5.33	88.64	0.83	10.53
	Steel			**Rubber**			**Automobile**		
1996	92.38	0.11	7.51	89.19	1.77	9.04	71.63	0.54	27.83
2001	87.58	0.18	12.24	93.66	2.19	4.16	76.39	0.66	22.95
2006	77.33	1.08	21.59	87.97	2.00	10.03	74.44	1.44	24.12
	Electronics			**Construction**			**Transportation**		
1996	80.46	1.32	18.22	91.90	1.46	6.64	83.43	0.39	16.18
2001	74.94	2.49	22.57	95.73	0.55	3.72	84.89	0.59	14.52
2006	57.57	0.59	41.84	87.80	1.89	10.31	79.63	1.19	19.18
	Tourism			**Banking & Securities**			**Retailing**		
1996	89.66	0.17	10.17	94.71	0.78	4.52	90.66	1.13	8.21
2001	89.28	0.12	10.61	90.52	0.89	8.59	77.97	1.07	20.96
2006	76.52	1.97	21.52	73.26	1.06	25.68	71.95	0.81	27.24
	Others								
1996	85.85	2.17	11.98						
2001	85.98	2.97	11.05						
2006	72.95	1.45	25.61						

Table 2. Summary Statistics: Average Daily Returns and Cross-Sectional Standard Deviations.

Industry	# Firms	# Obs.	Mean	Std. Dev.
	Panel A: Average Daily Return			
Cement	8	3154	0.016%	2.457%
Food	18	3154	0.026	2.404
Plastics	20	3154	0.028	2.735
Textiles	47	3154	0.014	2.773
Electrical App	36	3154	0.040	2.506
Wire & Cable	14	3154	0.021	2.670
Chemicals	35	3154	0.035	2.476
Glass and Ceramics	7	3154	0.003	3.019
Pulp & Paper	7	3154	0.017	2.707
Steel	24	3154	0.043	2.827
Rubber	9	3154	0.044	2.723
Automobile	5	3154	0.056	2.212
Electronics	307	3154	0.056	3.106
Construction	34	3154	0.051	3.183
Transportation	18	3154	0.049	2.641
Tourism	6	3154	0.039	2.486
Banking & Securities	45	3154	0.019	2.426
Retailing	10	3154	0.040	2.433
Others	39	3154	0.049	2.498
	Panel B: Cross-Sectional Standard Deviation			
Cement			1.558%	0.811%
Foods			1.868	0.705
Plastics			1.895	0.725
Textile			2.119	0.608
Electrical App			2.015	0.648
Wire and Cable			1.956	0.790
Chemicals			1.923	0.638
Glass and Ceramics			2.299	1.084
Pulp and Paper			1.690	0.815
Steel			1.917	0.736
Rubber			1.914	0.843
Automobile			1.405	0.888
Electronics			2.433	0.920
Construction			2.324	0.730
Transportation			1.868	0.731
Tourism			1.655	0.843
Banking & Securities			1.644	0.639
Retailing			1.845	0.778
Others			2.073	0.590

Table 3. Regression Coefficients for $CSSD_t = \alpha + \beta_D D_t^L + \beta_U D_t^U + \varepsilon_t$ (t-ratios in parentheses).

Return Dispersions	Market return in the extreme upper/lower 1% of the return distribution			Market return in the extreme upper/lower 5% of the return distribution		
Industry	α	β_D	β_U	α	β_D	β_U
Cement	1.553%	0.245%	0.294%**	1.527%	0.353%***	0.269%***
		(1.532)	(2.053)		(5.057)	(4.563)
Food	1.857	0.699***	0.442***	1.824	0.541***	0.351***
		(4.812)	(4.004)		(8.979)	(7.005)
Plastics	1.893	0.168	0.026	1.857	0.498***	0.260***
		(1.019)	(0.314)		(7.580)	(5.704)
Textile	2.116	0.146	0.149*	2.090	0.339***	0.242***
		(1.014)	(1.840)		(6.507)	(6.433)
Electrical App.	2.009	0.243*	0.304***	1.980	0.402***	0.285***
		(1.646)	(3.449)		(6.727)	(6.954)
Wire and Cable	1.955	0.089	0.016	1.928	0.322***	0.238***
		(0.512)	(0.117)		(4.530)	(4.001)
Chemicals	1.919	0.379***	0.043	1.890	0.476***	0.193***
		(2.649)	(0.629)		(8.739)	(4.764)
Glass and Ceramics	2.296	0.089	0.186	2.262	0.331***	0.403***
		(0.334)	(0.899)		(3.394)	(4.313)
Pulp and Paper	1.691	-0.0002	-0.073	1.670	0.307***	0.099
		(-0.001)	(-0.523)		(4.245)	(1.612)
Steel	1.914	0.086	0.165	1.881	0.404***	0.313***
		(0.724)	(1.488)		(6.770)	(5.814)
Rubber	1.916	0.061	-0.219*	1.886	0.456***	0.113*
		(0.277)	(-1.661)		(5.214)	(1.902)
Automobile	1.395	0.392*	0.569***	1.367	0.479***	0.285***
		(1.947)	(3.423)		(5.777)	(3.920)
Electronics	2.330	-0.389***	-0.485***	2.319	0.069	-0.012
		(-3.111)	(-5.340)		(1.245)	(-0.260)
Construction	2.319	0.217	0.274**	2.299	0.257***	0.257***
		(1.424)	(2.388)		(4.441)	(5.262)
Transportation	1.862	0.426**	0.197*	1.828	0.514***	0.283***
		(2.541)	(1.945)		(8.813)	(5.951)
Tourism	1.641	0.838***	0.542***	1.609	0.564***	0.344***
		(3.574)	(4.162)		(6.480)	(5.384)
Banking & Securities	1.639	0.320**	0.135	1.610	0.359***	0.326***
		(2.559)	(1.090)		(6.306)	(7.047)
Retailing	1.841	0.350**	0.100	1.811	0.448***	0.249***
		(2.497)	(1.177)		(7.214)	(5.435)
Others	2.067	0.348***	0.210***	2.041	0.418***	0.221***
		(3.019)	(2.418)		(9.346)	(5.410)

(***, **, and * denote statistical significance at 1%, 5%, and 10%, respectively)

Table 4. Regression Coefficients for $CSAD_t = \alpha + \gamma_1 |r_{m.t}| + \gamma_2 r_{m.t}^2 + \varepsilon_t$ (t-ratios in parentheses).

Absolute Deviation	**Whole Sample**			**Down Market (R_m<0)**			**Up Market (R_m>0)**		
Industry	α	γ_1	γ_2	α	γ_1	γ_2	α	γ_1	γ_2
Cement	1.016	0.162***	-0.018***	1.002	0.217***	-0.029***	1.036	0.095**	-0.003
		(5.993)	(-2.691)		(6.050)	(-3.637)		(2.373)	(-0.263)
Food	1.196	0.193***	-0.013**	1.173	0.265***	-0.024***	1.221	0.117***	0.0004
		(7.913)	(-2.050)		(8.051)	(-3.030)		(3.240)	(0.044)
Plastics	1.211	0.304***	-0.043***	1.188	0.381***	-0.056***	1.236	0.221***	-0.029***
		(11.281)	(-6.643)		(10.103)	(-6.143)		(6.373)	(-3.728)
Textile	1.393	0.229***	-0.030***	1.370	0.281***	-0.039***	1.421	0.169***	-0.018***
		(9.322)	(-4.774)		(8.065)	(-4.392)		(5.593)	(-2.606)
Electrical App.	1.324	0.206***	-0.022***	1.308	0.258***	-0.032***	1.345	0.144***	-0.009
		(7.944)	(-3.291)		(7.018)	(-3.393)		(4.843)	(-1.298)
Wire & Cable	1.296	0.195***	-0.027***	1.277	0.258***	-0.039***	1.321	0.122***	-0.013
		(7.033)	(-4.059)		(6.836)	(-4.573)		(2.993)	(-1.195)
Chemicals	1.234	0.242***	-0.030***	1.209	0.320***	-0.042***	1.260	0.161***	-0.018***
		(10.459)	(-5.398)		(9.789)	(-5.291)		(5.364)	(-2.604)
Glass & Ceramics	1.545	0.201***	-0.023**	1.551	0.246***	-0.034**	1.544	0.145***	-0.009
		(4.725)	(-2.073)		(4.025)	(-2.078)		(2.712)	(-0.692)
Pulp & Paper	1.123	0.203***	-0.036***	1.105	0.257***	-0.044***	1.143	0.146***	-0.027***
		(7.887)	(-6.058)		(7.301)	(-5.561)		(3.954)	(-3.156)
Steel	1.253	0.231***	-0.029***	1.255	0.302***	-0.043***	1.255	0.149***	-0.011
		(8.772)	(-4.593)		(8.505)	(-5.418)		(3.855)	(-1.148)
Rubber	1.248	0.271***	-0.045***	1.231	0.347***	-0.057***	1.266	0.194***	-0.033***
		(9.607)	(-6.644)		(8.809)	(-6.383)		(4.731)	(-3.147)
Automobile	0.923	0.125***	-0.008	0.881	0.224***	-0.028***	0.978	0.002	0.020**
		(4.028)	(-0.954)		(5.470)	(-2.854)		(0.051)	(1.984)
Electronics	1.597	0.275***	-0.058***	1.577	0.293***	-0.060***	1.617	0.258***	-0.057***
		(12.534)	(-11.953)		(9.692)	(-9.514)		(7.737)	(-7.063)
Construction	1.588	0.196***	-0.025***	1.570	0.238***	-0.033***	1.610	0.145***	-0.014
		(7.027)	(-3.635)		(6.103)	(-3.552)		(3.847)	(-1.525)
Transportation	1.205	0.233***	-0.027***	1.187	0.310***	-0.039***	1.227	0.150***	-0.012
		(8.669)	(-3.929)		(8.258)	(-4.146)		(4.244)	(-1.439)
Tourism	1.096	0.137***	0.000	1.095	0.178***	-0.006	1.097	0.094**	0.008
		(4.042)	(0.042)		(3.662)	(-0.467)		(2.339)	(0.805)
Banking & Securities	1.023	0.218***	-0.025***	0.999	0.257***	-0.032***	1.050	0.175***	-0.017*
		(9.637)	(-4.496)		(8.310)	(-4.576)		(4.958)	(-1.774)
Retailing	1.218	0.188***	-0.021***	1.174	0.257***	-0.029***	1.263	0.120***	-0.012*
		(7.105)	(-3.262)		(6.718)	(-3.142)		(3.519)	(-1.656)
Others	1.346	0.192***	-0.018***	1.326	0.237***	-0.024***	1.365	0.147***	-0.012*
		(8.020)	(-2.907)		(6.818)	(-2.648)		(4.957)	(-1.664)

(***, **, and * denote statistical significance at 1%, 5%, and 10%, respectively)

Table 5. State Space Model 1 (t-ratios in parentheses)

$\log[Std_c(\beta^b_{imt})] = \mu_m + H_{mt} + \upsilon_{mt}$ and $H_{mt} = \phi_m H_{mt-1} + \eta_{mt}$

Industry	μ	ϕ_m	$\sigma_{m\upsilon}$	$\sigma_{m\eta}$
Cement	-0.685***	0.940***	0.085***	0.099***
	(-20.667)	(125.420)	(20.057)	(20.354)
Food	-0.635***	0.930***	0.019***	0.091***
	(-26.858)	(133.023)	(3.173)	(35.052)
Plastics	-0.580***	0.945***	0.048***	0.091***
	(-19.496)	(153.061)	(11.752)	(27.420)
Textile	-0.647***	0.958***	0.040***	0.068***
	(-20.535)	(144.139)	(10.893)	(18.509)
Electrical App.	-0.698***	0.913***	0.053***	0.113***
	(-28.868)	(116.803)	(11.126)	(28.401)
Wire and Cable	-1.456***	0.927***	0.015***	0.064***
	(-25.168)	(708.846)	(2.655)	(21.435)
Chemicals	-0.657***	0.954***	0.025***	0.081***
	(-20.784)	(143.880)	(3.276)	(17.644)
Glass and Ceramics	-0.577***	0.919***	0.082***	0.142***
	(-14.992)	(100.782)	(11.846)	(21.611)
Pulp and Paper	-0.809***	0.892***	0.070***	0.165***
	(-22.822)	(78.357)	(7.603)	(23.430)
Steel	-0.707***	0.949***	0.047***	0.103***
	(-21.097)	(149.692)	(6.952)	(20.184)
Rubber	-0.828***	0.905***	0.100***	0.165***
	(-18.120)	(77.216)	(11.559)	(20.181)
Automobile	-0.457***	0.920***	0.022***	0.082***
	(-21.511)	(106.424)	(4.300)	(29.282)
Electronics	-1.282***	0.997***	0.038***	0.054***
	(-21.152)	(624.326)	(18.075)	(23.420)
Construction	-0.622***	0.942***	0.014	0.070***
	(-29.220)	(131.795)	(1.536)	(17.702)
Transportation	-0.690***	0.942***	0.080***	0.105***
	(-21.305)	(156.531)	(12.039)	(16.675)
Tourism	-0.555***	0.932***	0.033**	0.113***
	(-11.245)	(76.183)	(2.383)	(14.307)
Banking & Securities	-0.757***	0.956***	0.039***	0.085***
	(-22.293)	(171.375)	(11.205)	(28.180)
Retailing	-0.606***	0.933***	0.039***	0.101***
	(-21.166)	(121.470)	(4.920)	(17.390)
Others	-1.374***	0.916***	0.085***	0.091***
	(-10.797)	(460.285)	(21.045)	(19.421)

(***, **, and * denote statistical significance at 1%, 5%, and 10%, respectively)

Table 6. State Space Model 2 (t-ratios in parentheses)

$\log[Std_c(\beta^b_{imt})] = \mu_m + H_{mt} + c_{m1}\log\sigma_{mt} + c_{m2}r_{mt} + \upsilon_{mt}$ and $H_{mt} = \phi_m H_{mt-1} + \eta_{mt}$

Industry	μ	ϕ_m	$\sigma_{m\upsilon}$	$\sigma_{m\eta}$	$\log\sigma_m$	r_m
Cement	0.451***	0.941***	0.085***	0.098***	0.659***	-0.005
	(13.803)	(131.070)	(18.904)	(19.428)	(34.854)	(-0.040)
Food	0.589***	0.931***	0.019***	0.091***	0.682***	0.005
	(24.607)	(138.585)	(3.376)	(34.885)	(51.060)	(0.066)
Plastics	-0.848***	0.944***	0.048***	0.091***	-0.151***	0.046
	(-32.457)	(137.411)	(9.191)	(18.795)	(-10.268)	(0.510)
Textile	0.897***	0.957***	0.040***	0.068***	0.876***	0.027
	(32.465)	(172.134)	(15.143)	(26.050)	(56.141)	(0.374)
Electrical App.	-0.806***	0.913***	0.053***	0.113***	-0.058***	-0.069
	(-39.118)	(113.037)	(9.079)	(22.353)	(-4.683)	(-0.520)
Wire and Cable	1.437***	0.917***	0.015***	0.063***	1.658***	0.037
	(22.304)	(677.640)	(4.315)	(33.953)	(45.111)	(0.820)
Chemicals	-1.628***	0.950***	0.024***	0.082***	-0.545***	0.026
	(-56.555)	(157.520)	(5.994)	(32.524)	(-34.230)	(0.336)
Glass and Ceramics	1.330***	0.917***	0.082***	0.142***	1.092***	-0.068
	(36.300)	(99.504)	(10.205)	(21.199)	(52.221)	(-0.415)
Pulp and Paper	-2.479***	0.892***	0.070***	0.164***	-0.970***	-0.092
	(-70.245)	(78.008)	(7.548)	(23.473)	(-47.373)	(-0.503)
Steel	-1.470***	0.945***	0.047***	0.104***	-0.429***	0.029
	(-42.510)	(150.194)	(10.907)	(28.278)	(-22.200)	(0.266)
Rubber	-0.471***	0.907***	0.100***	0.165***	0.211***	0.006
	(-10.372)	(79.038)	(10.540)	(18.077)	(7.917)	(0.026)
Automobile	-0.541***	0.919***	0.021***	0.082***	-0.047***	0.017
	(-25.690)	(107.362)	(4.277)	(29.303)	(-4.000)	(0.205)
Electronics	0.481	0.997***	0.038***	0.053***	1.022*	0.007
	(0.527)	(604.024)	(13.811)	(17.754)	(1.933)	(0.118)
Construction	0.998***	0.937***	0.015***	0.069***	0.947***	-0.03
	(50.873)	(150.635)	(2.584)	(35.092)	(82.499)	(-0.587)
Transportation	-0.179***	0.941***	0.080***	0.105***	0.293***	-0.028
	(-5.391)	(142.554)	(17.725)	(21.771)	(15.301)	(-0.222)
Tourism	-6.787***	0.926***	0.032***	0.111***	-3.535***	-0.228*
	(-226.046)	(100.682)	(4.499)	(23.539)	(-208.998)	(-1.823)
Banking & Securities	-0.293***	0.957***	0.040***	0.085***	0.264***	-0.058
	(-8.487)	(169.286)	(11.260)	(28.132)	(13.559)	(-0.687)
Retailing	-2.139***	0.926***	0.038***	0.102***	-0.833***	0.009
	(-90.847)	(128.728)	(8.629)	(31.852)	(-65.823)	(0.074)
Others	-0.547***	0.954***	0.084***	0.095***	0.013	0.137
	(-14.520)	(159.310)	(20.375)	(20.390)	(0.631)	(0.870)

(***, **, and * denote statistical significance at 1%, 5%, and 10%, respectively)