Journal of Economic Behavior & Organization 76 (2010) 283–295

Contents lists available at ScienceDirect

Journal of Economic Behavior & Organization

journal homepage: www.elsevier.com/locate/jebo

Do investors herd in emerging stock markets?: Evidence from the Taiwanese market

Riza Demirer[a], Ali M. Kutan[a,b,c,*], Chun-Da Chen[d]

[a] Southern Illinois University Edwardsville, United States
[b] The William Davidson Institute, University of Michigan Business School, United States
[c] The Emerging Markets Group, Cass Business School, London, United Kingdom
[d] Tennessee State University, United States

ARTICLE INFO

Article history:
Received 8 April 2009
Received in revised form 22 June 2010
Accepted 30 June 2010
Available online 8 July 2010

JEL classification:
G14
G15

Keywords:
Herd behavior
Equity return dispersion
Taiwan Stock Exchange
Non-linear and state space models

ABSTRACT

This paper has three main contributions to the literature on investor herds. First, it extends investor herding studies to an emerging yet relatively sophisticated Taiwanese stock market at the sector level by using firm level data. Second, it employs different methodologies designed to test the existence of investor herds to better understand the sources of herd behavior. Third, it discusses the implications of different herding measures for investors exposed to systematic and unsystematic risks. We find that the linear model based on the cross-sectional standard deviation (CSSD) testing methodology yields no significant evidence of herding. 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 periods of market losses. Our results suggest limited diversification opportunities for investors in this market, especially during periods of market losses when diversification is most needed. Further research is necessary to see whether similar findings hold for other emerging markets.

Published by Elsevier B.V.

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, 2001). In this paper, we extend herding tests to the Taiwanese stock market using firm level data within industry portfolios. To do so, we employ different testing methodologies proposed in the literature in order to provide further insight on the driving forces behind herd behavior. Finally, we explore the implications of the findings for diversified and undiversified investors.

We select the Taiwanese stock market for several reasons. First, the market is dominated by domestic individual investors, rather than institutional and foreign investors. Most individual investors tend to have less professional knowledge and cannot access information accurately and easily. However, there has been an increasing interest in the Taiwanese stock market by foreign investors over the past 6 years following the lifting of the trading restrictions on qualified foreign institutional investors in 2000. As a result, the value percentage traded by foreign institutional investors has exceeded that traded by domestic institutional investors since 2005 (Chen et al., 2008). In a market dominated by domestic individual investors with

* Corresponding author at: Southern Illinois University Edwardsville, United States. Tel.: +1 618 650 3473.
E-mail address: akutan@siue.edu (A.M. Kutan).

0167-2681/$ – see front matter Published by Elsevier B.V.
doi:10.1016/j.jebo.2010.06.013

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 domestic and foreign institutional investors.

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.[1] If the results indicate evidence of herding, this suggests that herding may take place in a relatively developed yet still emerging stock market like Taiwan.

Third, we further focus on industry-wide evidence from Taiwan. In this regard, our study is a significant addition to the recent literature that tests herding behavior in an industry context (Choi and Sias, 2009). Providing evidence from an industry/sector perspective is interesting for several reasons: (i) the typical assignment of financial analysts takes place at the industry level and institutions also signal information through their industry classifications, (ii) many business managers make recommendations at the sector level, and (iii) investors may receive signals about a given firm based on information available about other firms in the same industry (Choi and Sias, 2009). Bikhchandani and Sharma (2001) also suggest that 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.

Fourth, there is limited and conflicting evidence on herd behavior in the Taiwanese stock market. To our best knowledge, there are only four 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. Lin and Swanson (2003) also study herd behavior in the Taiwanese stock market during the period 1996–2003 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. Lin et al. (2007) examine daily trading data by foreign and domestic institutional investors for the fifty stocks that are most actively traded by institutional investors in Taiwan and find the herding tendencies of stocks to be more prominent for small cap stocks with high share turnover and high return volatility, thus suggesting market conditions and firm characteristics to be significant factors driving herd behavior. Using buying and selling volume data, Chen et al. (2008) find that qualified foreign institutional investors herd in the Taiwanese stock market. They show that industry effects, besides firm characteristics such as high past returns and large market capitalization, explain the herding behavior of foreign institutional investors.

Fifth, we employ two major testing methodologies. Previous studies based on return data hypothesize that herd behavior may be captured by examining 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 results consistent with herd behavior provides information about the ways in which investors herd. Furthermore, the findings from the different testing methodologies have different portfolio diversification implications for currently diversified and undiversified investors as these methodologies are related to different types of risks in a portfolio, i.e. the firm-specific risk and the market risk. Therefore, employing different testing methodologies on the same data set provides valuable insight about the performance of diversification strategies for different types of investors in this market.

Given the limited work and conflicting evidence on herd behavior on Taiwan and the interesting institutional characteristic of this market (i.e. a large number of domestic individual investors with a small but growing number of foreign investors), we extend the earlier studies in three significant aspects by (i) providing industry/sector-specific evidence, (ii) employing different testing methodologies, and (iii) providing evidence using recent daily data from January 1995 to December 2006.

Looking forward, we find no significant evidence for herd behavior based on the linear model. 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 herd behavior may be captured by examining either cross-sectional return dispersions in a non-linear fashion or through beta dispersions. This indicates that investors will have limited diversification opportunities in this market regardless of whether they currently hold diversified portfolios or undiversified positions. Portfolio diversification implications of our findings are consistent with the finding of Lin et al. (2007) that foreign investors and domestic mutual funds outperform the market in relatively stable periods, i.e. periods during which diversification is not as big of a concern as during periods of high volatility. In Section 2, we briefly summarize previous theoretical and empirical work on investor herds. Section 3 provides the details of different testing methodologies employed and compares the different theoretical implications of the methodologies for the sources of herd behavior. Section 4 presents data description and empirical results, as well as a comparison of the findings from the return dispersion based models and state space models. It also discusses the economic implications of the findings for investors. Finally, Section 5 concludes the paper and proposes further research.

[1] See Beck et al. (2000).

2. Previous theoretical and empirical studies on investor herds

2.1. Theoretical work

Prior theoretical studies differ in their explanation of what might trigger herd behavior. Lux (1995) focuses on psychology-related herding. In his model, non-sophisticated traders do not have access to information about market fundamentals and, therefore, they act based on what they observe in the market. Assuming that the market mostly consists of optimistic traders, because traders are non-sophisticated and may follow other traders' behavior, pessimistic traders change their attitudes and become optimistic as well. In the Lux (1995) model, herding then takes place as contagion of sentiment.[2] Devenow and Welch (1996) also use the arguments of investor psychology where investors feel a sense of security in following the crowd.

A second set of theories focus on information-driven herding. According to the information-related herding theory, the actions of more informed traders may reveal useful information which may not be accessible to individual investors (Shleifer and Summers, 1990; Froot et al., 1992; Chari and Kehoe, 2004; Calvo and Mendoza, 2000; Avery and Zemsky, 1998). On the other hand, informational cascades theory, developed by Banerjee (1992), Bikhchandani et al. (1992) and Shiller (2002), suggests that the behavior of other individuals signals information to observing investors who may ignore their own information and follow the decisions of others by engaging in herding.[3]

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 (Palley, 1995; Scharfstein and Stein, 1990; Rajan, 1994; Maug and Naik, 1996; Admati and Pfleiderer, 1988; Graham, 1999; Swank and Visser, 2008). Finally, some studies focus on event-related herding (see, for example, Choe et al., 1999 and Kim and Wei, 2002).

2.2. Empirical studies

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 et al. (2000) on international equities, Gleason et al. (2003) on commodity futures traded on European exchanges, Gleason et al. (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 (2006) employs 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 et al. (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. Next we explain the details of the methodologies employed in this study.

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 et al. (2000), Gleason et al. (2003), Lin and Swanson (2003), Gleason et al. (2004), and Demirer and Kutan (2006). Cross-sectional standard deviations (CSSD), used as a measure

[2] For related studies, see Lux (1998); Goldbaum (2008) and Omurtag and Sirovich (2006).

[3] Recent studies include Cipriani and Guarino (2008) and Spiwoks et al. (2008). The latter study provides experimental evidence on informational cascades.

of return dispersion, is formulated as follows:

$$\mathrm{CSSD}_t = \sqrt{\frac{\sum_{i=1}^{N}(r_{i,t} - r_{p,t})^2}{N-1}} \tag{1}$$

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:

$$\mathrm{CSSD}_t = \alpha + \beta_D D_t^L + \beta_U D_t^U + \varepsilon_t \tag{2}$$

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 Eq. (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

$$\mathrm{CSAD}_t = \frac{1}{N}\sum_{i=1}^{N}|r_{i,t} - r_{m,t}| \tag{3}$$

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:

$$\mathrm{CSAD}_t = \alpha + \gamma_1\,|r_{mt}| + \gamma_2 r_{mt}^2 + \varepsilon_t \tag{4}$$

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,

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

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 Eq. (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 Eq. (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 Eq. (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

$$Std_c(\beta_{imt}^b) = \sqrt{E_c((\beta_{imt} - h_{mt}(\beta_{imt} - 1) - 1)^2)} = \sqrt{E_c((\beta_{imt} - 1)^2)}(1 - h_{mt}) = Std_c(\beta_{imt})(1 - h_{mt}) \tag{7}$$

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

$$\log\,[Std_c(\beta_{imt})] = \mu_m + \upsilon_{mt}$$

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

$$\log[Std_c(\beta_{imt}^b)] = \mu_m + H_{mt} + \upsilon_{mt} \tag{8}$$

$$H_{mt} = \phi_m H_{mt-1} + \eta_{mt} \tag{9}$$

where $H_{mt} = \log(1 - h_{mt})$ and $\eta_{mt} \sim iid(0, \sigma_{m\eta}^2)$. Eqs. (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}. When $\sigma_{m\eta}^2 = 0$, 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 $\sigma_{m\eta}^2$ 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 Eq. (8) market volatility, $\log \sigma_{mt}$, and return, r_{mt}, as independent variables. This leads to *state space model 2* formulated as

$$\log\,[Std_c(\beta_{imt}^b)] = \mu_m + H_{mt} + c_{m1} \log \sigma_{mt} + c_{m2} r_{mt} + \upsilon_{mt} \tag{10}$$

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

3.3. An evaluation and comparison of the herding tests

It is important to note that the results of herding tests can be driven by the price co-movement between the returns on individual assets and the market, rather than herd behavior.[4] This is particularly the case in the linear CSSD model. In the linear model, observing a drop in all asset prices along with the market portfolio on a given day would lead the dispersion measure to take on a lower value for that day providing support for the existence of herds. However, this might simply be due to investors' common reaction to unanticipated news on that day and the test would fail to see that. As the linear CSSD model fails to capture the price co-movement, it may lead to incorrect results. The non-linear CSAD methodology provides a better alternative by allowing a non-linear relationship between return dispersions and the market return. The non-linear model allows return dispersions to co-move with the market return, but tests the existence of herds by examining the additional non-linear term in the model. As a result, the non-linear CSAD model provides a more flexible and correct way of testing herd formation than the linear CSSD model. In terms of the driving forces of herding, the CSSD model suggests that herding will take place during periods of extreme large negative or positive returns whereas the CSAD model does not limit this to extreme market returns, but allows us to examine the behavior of dispersions during up and down market periods separately.

On the other hand, the state space models assume beta herding in that the herding measure is based on the relative dispersion of factor sensitivities for all assets in the market and allow for market-wide herding. Because the state space models focus on the cross-sectional variability of factor sensitivities rather than returns, their herding measure is free from the influence of idiosyncratic components (Hwang and Salmon, 2004). In addition, the state space models control for movements in fundamentals and allow for herding during not only periods of extreme market movements, but also during normal market conditions, hence providing a more detailed analysis of the dynamic evaluation of herding over time. The state space model 2 is more robust than the state space model 1 as the former controls for movements in market volatility and market returns.

All four herding models employed in this study are based on the CAPM specification and assume that the existence of investor herds leads to a bias in the risk-return relationship consistent with CAPM, at least in the short run, causing deviations from CAPM equilibrium.

[4] We thank an anonymous referee for pointing out this shortcoming of the CSSD test.

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 and 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 and 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 and 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						

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, 2001). 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 et al., 2004; Chang et al., 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 and Cable, Chemicals, Glass and Ceramics, Pulp and Paper, Steel, Rubber, Automobile, Electronics, Construction, Transportation, Tourism, Banking and Securities, and Retailing. We then calculate portfolio returns based on an equally weighted portfolio of all firms in each sector classification.

Table 1 presents data on shareholding percentage of market participants by sector. We observe that 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 share of foreign investors over the past 6 years due to the relaxation of trading restrictions on these investors, 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 this case, one might expect the formation of investor herds in this market dominated by the less informed domestic individual investors.

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

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 and Cable	14	3154	0.021	2.670
Chemicals	35	3154	0.035	2.476
Glass and Ceramics	7	3154	0.003	3.019
Pulp and 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 and 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 and Securities			1.644	0.639
Retailing			1.845	0.778
Others			2.073	0.590

sector. Consistent with the findings from Panel A, we observe the highest cross-sectional volatility in Electronics followed by Construction.[5]

4.2. Results of return dispersion models

Table 3 presents estimation results for the CSSD-based model in Eq. (2). Given the significant variation in dispersions and strong correlation, all estimations are done using the Newey-West heteroskedasticity and autocorrelation consistent standard errors.[6] 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 Eq. (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)

[5] 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.

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

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 and 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)

*** Statistical significance at 1%.
** Statistical significance at 5%.
* Statistical significance at 10%.

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.

Focusing on Table 4, we first note that the non-linear term (γ_2) is statistically significant almost in all cases, suggesting that inferences from the non-linear model reported in Table 3 are more relevant. Furthermore, as explained earlier, the linear model fails to capture the co-movement between individual asset returns and the aggregate market return which might lead to incorrect test results. We therefore 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 herd behavior is more likely to be observed during periods of market losses.[7]

[7] 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 market gains and losses.

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 and 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 and 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 and 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 and 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)

*** Statistical significance at 1%.
** Statistical significance at 5%.
* Statistical significance at 10%.

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 control 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, $Std_c(\beta_{imt}^b)$, could be explained by herding rather than changes in fundamentals. 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, $Std_c(\beta_{imt}^b)$, 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 and Cable, Glass, Electronics, and Banking and Securities sectors in Table 6, our findings suggest that the volatility of factor sensitivities, $Std_c(\beta_{imt}^b)$, 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). One possible explanation for the different findings for these sectors might be that investors in these sectors may exhibit herding behavior regardless of the level of market conditions, as signals

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 and 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)

*Statistical significance at 10%.
*** Statistical significance at 1%.
** Statistical significance at 5%.

from a significant body of foreign investors in these sectors may be stronger or more visible to domestic individual investors.

4.4. Economic implications of the findings from different tests

The return dispersion-based methodologies proposed by Christie and Huang (1995) and Chang et al. (2000) consider firm-level volatility within industry portfolios during extreme market periods, and during up and down markets separately. Let r_{ijt} be the return on day t for firm j in industry i and suppose that the firm level return is generated by a model of the form

$$r_{ijt} = \beta_j r_{it} + \varepsilon_{ijt} \quad (11)$$

where r_{it} is the return on the industry portfolio for day t and ε_{ijt} is the firm specific error term with $E(\varepsilon_{ijt}) = 0$ and $\mathrm{Var}(E(\varepsilon_{ijt})) = \sigma_j^2$. The return dispersion measure for a given day in fact estimates the variance of the idiosyncratic error term at the firm level. Therefore, the linear and non-linear models based on return dispersions explore the behavior of idiosyncratic risk during different market conditions. Since these methodologies examine firm level volatility, these tests have significant implications for investors who are currently undiversified. Finding evidence of herding using these methodologies suggests that currently undiversified investors would need to include a larger number of assets in their portfolios in order to achieve a certain desirable level of diversification. In other words, comparing a market where this methodology rejects the existence of investor herds, investors in the Taiwanese market would need to invest in more stocks in order to reduce the same amount of firm specific risk. However, for those investors who are not concerned about diversification, such as style investors or funds that concentrate on certain sectors, this would be good news as they would be able to achieve the same sector specific performance they desire by investing in fewer stocks in each industry.

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 and 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)

** Statistical significance at 5%.
*** Statistical significance at 1%.
* Statistical significance at 10%.

On the other hand, the results from state space models apply to a completely different set of investors as these models explore the behavior of factor sensitivities within industry portfolios. The results from these methodologies would therefore be of interest to investors who currently own diversified portfolios such as index funds. Finding support for herding in these models would then suggest that portfolio managers in Taiwan would find it more challenging to design portfolios that limit their clients' exposure to systematic market risks. If systematic risks tend to show similar behavior, then index fund managers in this market will need larger portfolios and a combination of short and long positions in order to achieve the same level of exposure to market risk.

As we find evidence of herding under both the non-linear and state-space models, it implies that herding in Taiwanese stock market can be due to market crashes (i.e. financial crisis or devaluation) or during normal market periods. The evidence from the state space 2 model provides further support by suggesting that herding can take place in Taiwan independently from market conditions (i.e. market return volatility and the level of market returns). This suggests that policymakers need to design appropriate policies to deal with the negative effects of herd behavior (i.e. mispricing) on asset prices in financial markets not only during periods of market stress but also during normal market conditions. A recent example is the joint work by U.S. Securities and Exchange Commission (SEC) and U.K. Financial Services Authority to temporarily ban short sales of financial stocks in September 2008 following the market turmoil. Today, as a result of the historic events of the late 2008 period, the SEC has made permanent changes on short selling transactions and hedge fund activity in order to better control the unintended negative effects of bad news. Therefore, our results provide valuable insight for regulators in Taiwan.

5. Conclusions and suggestions for further research

There are scant studies on herding behavior in Taiwan, and while they produce conflicting inferences, they 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 different herding measures under different approaches to better understand the sources of herd behavior and discuss their implications for investors exposed to systematic and unsystematic risks.

The linear model proposed by Christie and Huang (1995) provides no evidence of investor herds, except for the Electronics sector. However, as explained earlier, this methodology might lead to incorrect inferences as it fails to take into account the co-movement between individual asset returns and the aggregate market return. Furthermore, we find that the assumption of linearity between return dispersions and the market return in this methodology is rejected, and for this reason, we rely more on the findings from the non-linear model proposed by Chang et al. (2000). The results from the non-linear model indicate significant non-linear effects and provide support for herding in all sectors analyzed. 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 for the formation of investor herds in Taiwan across all sectors. For further research, it would be interesting to examine herd behavior across industries along the lines of Choi and Sias (2009).

Our results, which are based on dispersions of returns and factor sensitivities, should be interpreted cautiously, however, as there are other tests of investor herds. It would be interesting to compare our findings with those from different methodologies including tests that employ trading data.

Acknowledgements

We like to thank J. Barkley Rosser, Jr. (the Editor) and two anonymous referees for their useful comments and suggestions. The usual disclaimer applies.

References

Admati, A., Pfleiderer, P., 1988. A theory of intraday patterns: volume and price variability. Review of Financial Studies 1, 3–40.
Avery, C., Zemsky, P., 1998. Multidimensional uncertainty and herd behavior in financial markets. American Economic Review 88, 724–748.
Banerjee, A., 1992. A simple model of herd behavior. Quarterly Journal of Economics 107, 797–818.
Beck, T., Demirgüç-Kunt, A., Levine, R., 2000. A new database on financial development and structure. World Bank Economic Review 14, 597–605.
Bikhchandani, S., Hirshleifer, D., Welch, I., 1992. A theory of fads, fashion, custom and cultural change as informational cascades. Journal of Political Economy 100, 992–1026.
Bikhchandani, S, Sharma, S., 2001. Herd behavior in financial markets: a review. IMF Staff Papers 47, 279–310.
Calvo, G., Mendoza, E., 2000. Rational herd behavior and globalization of securities markets. Journal of International Economics 51, 79–113.
Chang, E.C., Cheng, J.W., Khorana, A., 2000. An examination of herd behavior in equity markets: an international perspective. Journal of Banking and Finance 24 (10), 1651–1699.
Chari, V.V., Kehoe, P., 2004. Financial crises as herds: overturning the critiques. Journal of Economic Theory 119, 129–150.
Chen, Y., Wang, C., Lin, F., 2008. Do qualified foreign institutional investors herd in Taiwan's securities market? Emerging Markets Finance and Trade 44, 62–74.
Christie, W.G., Huang, R.D., 1995. Following the pied piper: do individual returns herd around the market? Financial Analyst Journal (July–August), 31–37.
Choe, H., Kho, B., Stulz, R., 1999. Do foreign investors destabilize stock markets? The Korean experience in 1997. Journal of Financial Economics 54, 227–326.
Choi, N., Sias, R.W., 2009. Institutional industry herding. Journal of Financial Economics 94, 469–491.
Cipriani, M., Guarino, A., 2008. Transaction costs and informational cascades in financial markets. Journal of Economic Behavior and Organization 68, 581–592.
Demirer, R., Kutan, A.M., 2006. Does herding behavior exist in Chinese stock market? Journal of International Financial Markets, Institutions and Money 16, 123–142.
Devenow, A., Welch, I., 1996. Rational herding in financial economics. European Economic Review 40, 603–615.
Froot, K., Scharfstein, D., Stein, J., 1992. Herd on the street: informational inefficiencies in a market with short-term speculation. Journal of Finance 47, 1461–1484.
Gleason, K.C., Lee, C.I., Mathur, I., 2003. Herding behavior in European futures markets. Finance Letters 1, 5–8.
Gleason, K.C., Mathur, I., Peterson, M.A., 2004. Analysis of intraday herding behavior among the sector ETFs. Journal of Empirical Finance 11, 681–694.
Goldbaum, D., 2008. Coordinated investing with feedback and learning. Journal of Economic Behavior and Organization 65, 202–223.
Graham, J.R., 1999. Herding among investment newsletters: theory and evidence. Journal of Finance 54 (1), 237–268.
Hwang, S., Salmon, M., 2004. Market stress and herding. Journal of Empirical Finance 11, 585–616.
Kahneman, D., Tversky, A., 1979. Prospect theory: an analysis of decision under risk. Econometrica 47, 263–291.
Kim, W., Wei, S., 2002. Foreign portfolio investors before and during a crisis. Journal of International Economics 56 (1), 77–96.
Lakonishok, J., Shleifer, A., Vishny, R.V., 1992. The impact of institutional trading on stock prices. Journal of Financial Economics 32, 23–43.
Lin, A.Y., Swanson, P.E., 2003. The behavior and performance of foreign investors in emerging equity markets: evidence from Taiwan. International Review of Finance, 4189–4210.
Lin, A.Y., Huang, L., Chen, M., 2007. Price comovement and institutional performance following large market movements. Emerging Markets Finance and Trade 43 (5), 37–61.
Lux, T., 1995. Herd behavior, bubbles and crashes. Economic Journal 105, 881–896.
Lux, T., 1998. The socio-economic dynamics of speculative markets: interacting agents, chaos, and the fat tails of return distributions. Journal of Economic Behavior and Organization 33, 143–165.
Maug, E, Naik, N., 1996. Herding and Delegated Portfolio Management. London Business School, Mimeo.
Omurtag, A., Sirovich, L., 2006. Modeling a large population of traders: mimesis and stability. Journal of Economic Behavior and Organization 61, 562–576.
Palley, T.I., 1995. Safety in numbers: a model of managerial herd behavior. Journal of Economic Behavior and Organization 28, 443–450.
Rajan, R.G., 1994. Why credit policies fluctuate: a theory and some evidence. Quarterly Journal of Economics 436, 399–442.
Scharfstein, D., Stein, J., 1990. Herd behavior and investment. American Economic Review 80, 465–479.
Shiller, R.J., 2002. From efficient market theory to behavioral finance. Cowles Foundation Discussion Papers 1385, Cowles Foundation, Yale University.

Shleifer, A., Summers, L.H., 1990. The noise trader approach to finance. Journal of Economic Perspectives 4 (2), 19–33.
Spiwoks, M., Bizer, K., Hein, O., 2008. Informational cascades: a mirage? Journal of Economic Behavior and Organization 67, 193–199.
Swank, O., Visser, B., 2008. The consequences of endogenizing information for the performance of a sequential decision procedure. Journal of Economic Behavior and Organization 65, 667–681.
Tan, L., Chiang, T.C., Mason, J.R., Nelling, E., 2008. Herding behavior in Chinese stock markets: an examination of A and B shares. Pacific-Basin Finance Journal 16, 61–77.
Tversky, A., Kahneman, D., 1991. Loss aversion in riskless choice: a reference dependent model. Quarterly Journal of Economics 106, 1039–1061.
Uchida, H., Nakagawa, R., 2007. Herd behavior in the Japanese loan market: evidence from bank panel data. Journal of Financial Intermediation 16, 555–583.
Weiner, R.J., 2006. Do birds of a feather flock together? Speculator herding in the world oil market. Discussion Paper No: 06-31, Resources for the Futures.