# Industry Herding and Momentum Strategies

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### Abstract

This paper evaluates the impact of industry herding on return momentum. While the findings support that winner industries outperform loser industries in subsequent months, we find that the profitability of industry momentum strategies depends on the level of herding in an industry. Loser industries with high level of herding yield significantly lower subsequent returns than loser industries with low level of herding while no significant difference in subsequent returns is observed for winner industries across low and high herding levels. The asymmetry in the relationship between herding and momentum returns is in fact the driving factor behind profitable, zero-cost momentum strategies and suggests that the level of herding in an industry must be considered in the implementation of industry momentum strategies.



**JEL Classification Code:** G14, G15

**Keywords:** Momentum, Industry herding, Chinese stock markets

## 1. Introduction

Momentum effect in stock returns has been the topic of numerous studies in the asset pricing literature. Starting with the pioneering works of Jegadeesh and Titman (1993) and Asness (1994), the literature has presented compelling evidence on the relationship between a stock's return and its recent historical performance, suggesting profitable trading strategies based on long positions in winner and short positions in loser stocks over the previous 1-12 months. Later, Carhart (1997) formalizes the momentum effect in returns by documenting a significant momentum factor in the cross-section of stock returns even in the presence of the well-known size and value factors.

The literature has offered several behavioral explanations for the momentum effect.[1] Earlier papers including Daniel et al. (1998) and Hong and Stein (1999) have suggested behavioral drivers including overconfidence or underreaction to information in order to explain the momentum effect. On the other hand, Hong et al. (2000) suggest a gradual information diffusion model that helps explain return momentum and reversals while Hvidkjaer (2006) argues that the behavior of small traders can partially explain the momentum effect. Similarly, Sadka (2006) finds that the ratio of informed traders to noise traders can help explain a significant portion of momentum returns. On the other hand, in an early paper, Nofsinger and Sias (1999) suggest that mispricing due to herding can also lead to price momentum and excess volatility. Indeed a large literature documents evidence of herd behavior among market participants particularly in emerging stock markets due to a number of institutional and market issues including market transparency, liquidity, among others.[2] Interestingly, however, the relationship between herd behavior and the momentum effect in emerging stock markets has not

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[1] A number of papers including Jegadeesh and Titman (2001), Liu et al. (2008) and Avramov and Chordia (2006), among others, have suggested risk-based explanations without a definitive clarification.

[2] Studies on herding in emerging markets include Demirer and Kutan (2006) and Tan et al. (2008) on Chinese stocks, Chiang and Zheng (2010) on global stock markets, Balcilar et al. (2013) on Gulf Arab stock markets, and Demirer et al. (2010) on the Taiwanese stock market, among others.

yet been fully explored despite the consistent evidence of herd behavior in emerging stock markets.

Bikhchandani and Sharma (2001) define herd behavior as an obvious intent by investors to copy the behavior of other investors and suggest that it would be more likely to occur at the level of investments in a group of similar assets (e.g. stocks of firms in an industry or in a particular market segment) where investors face similar decision problems and can observe the trades of others. To that end, it can be argued that correlated actions of investors in a market where investors follow the trades of others can further contribute to possible return momentum in that market. In fact, focusing on herding among institutional investors in the U.S., studies including Nofsinger and Sias (1999) and Sias (2004) document that subsequent asset returns follow the direction of the herd resulting in return momentum while others including Dasgupta et al. (2011), Singh (2013) and Brown et al. (2014) document return reversals in the long run as a result of institutional herding.

Moskowitz and Grinblatt (1999) suggest that investors can capture much of the momentum effect through industry portfolios rather than individual stock portfolios and that momentum profits for individual stocks become significantly weak after adjusting for industry effects. On the other hand, Lang and Lundholm (1996) argue that investors may receive signals about a given firm based on information available about other firms in the same industry while Choi and Sias (2009) argue that analysts are usually assigned on an industry basis and that investors usually receive signals regarding fundamental classifications such as industries rather than statistical classifications like size and value. The natural question then is whether the level of herding in an industry is a determinant of momentum returns so that industries that exhibit high level of herding produces enhanced momentum returns compared to industries with low level of herding.

The main goal of this paper is to evaluate the impact of industry herding on return momentum by examining data from the Chinese stock market in which industry herding has been documented in numerous studies (e.g. Lee et al.; 2013, Yao et al., 2014). While return momentum is verified at the industry level with winner industries outperforming loser industries over intermediate investment horizons, we also find that the profitability of zero-cost momentum strategies indeed depends on the level of herding in an industry. Winner industries for high and low herding levels yield no significant difference in subsequent returns for the next 1, 2, and 3 months whereas loser industries with high level of herding yield significantly lower returns than loser industries with low level of herding. This observed asymmetry in the relationship between herding and momentum suggests that the profitability of industry momentum strategies indeed depends on the level of herding in an industry. While the strategy of taking a long position in winner industries with high level of herding and short position in loser industries with low level of herding yields insignificant subsequent returns, we find that long high herding-winner industries and short high herding-loser industries yields highly significant and positive returns for the subsequent 1, 2, and 3 months. The subsequent returns from the herding-based industry momentum strategy are also found to be significantly higher than those from a plain-vanilla industry momentum strategy, suggesting that the level of industry herding can be utilized to create excess economic value. Similar findings are observed across alternative herding measures and for different subsamples, suggesting the robustness of the findings. The findings have important implications for the implementation of zero-cost momentum strategies and clearly suggest that the level of herding in an industry must be considered when forming strategies based upon industry momentum.

An outline of the remainder of the paper is as follows. Section 2 provides the details of the methodology and data description. Section 3 presents empirical results. Finally, Section 4 concludes the paper.

## 2. Data and Methodology

### 2.1 Data

The dataset consists of all A-shares listed on the Shanghai and Shenzhen stock exchanges for the period January 1996 through December 2013 obtained from the China Stock Market & Accounting Research (CSMAR) database. Following the industry classification based on the China Securities Regulatory Commission's 2012 issue, we assign each stock to one of 78 industries based on the first two digits of its disclosed industry codes. We exclude industries with fewer than 5 stocks traded on any trading day during the sample period and end up with 50 industries and 2,430 stocks among them 942 stocks being traded on Shanghai and 1,488 traded on Shenzhen exchanges. Table 1 provides the list of industries included in the analysis.

**2.2 Methodology**

The literature offers two groups of herding measures used in tests to detect herding. The first group originates from early studies of Christie and Huang (1995) and Chang et al. (2000) and focuses on the relationship between stock market movements and the cross-sectional behavior of individual stock returns. The return-based herding tests in this group have been applied in numerous studies to a number of emerging and advanced markets.[3] The second group of herding measures originates from Lakonishok, Shleifer and Vishny (1992) and Sias (2004) and focuses on the simultaneous or subsequent changes in investors' holdings of assets under consideration.[4] While the second group is intuitive, the first group of tests does not require investors' specific holding information which may be incomplete or unavailable in many cases and, if available, at low frequency at best. However, since herding is a short-lived phenomenon (e.g. Avery and Zemsky, 1998), it can be argued that models that utilize high frequency data (daily or intra-daily) provide a more meaningful framework.

In this study, we follow the first group of herding measures as they are return-based

[3] Recent applications of these models include Economou et al. (2011) on southern European stock markets, Lee et al. (2013) and Yao et al. (2014) on Chinese stocks, Balcilar et al. (2013) on Gulf Arab stock markets, Philippas et al. (2013) on REITs, and Demirer et al. (2014) on ADRs.

[4] Choi and Sias (2009) provide a review of published works in this strand of the literature.

measures and thus provide an intuitive framework to evaluate the effect of herding on return momentum. Furthermore, the presence of industry herding in the Chinese stock market has been well documented by Lee et al. (2013) and Yao et al. (2014) who also use these return-based herding measures; thus relating these herding measures to return momentum allows for a meaningful comparison. As stated earlier, herding tests in the first group focus on the relationship between market movements and the cross-sectional behavior of returns in a portfolio. Christie and Huang (1995) utilize the cross-sectional standard deviation (CSSD) of firm returns in industry *k* expressed as

$$CSSD_{k,t} = \sqrt{\frac{\sum_{i=1}^{N_k} (R_{i,t} - R_{m.t})^2}{N_k - 1}} \tag{1}$$

where $N_k$ is the number of firms in industry *k*; $R_{i,t}$ is the return on firm *i* on day *t* and $R_{m,t}$ is the market return.[5] Christie and Huang (1995) argue that herding would be more prevalent during periods of market stress and examine the behavior of CSSD during periods of extreme market gains and losses defined by the upper/lower tails of the return distribution. In an improvement to this methodology, Chang et al. (2000) instead propose a non-linear model that focuses on the cross-sectional absolute deviation (CSAD) of firm returns in industry *k* expressed as[6]

$$CSAD_{k,t} = \frac{1}{N_k} \sum_{i=1}^{N_k} | R_{i,t} - R_{m.t} | \tag{2}$$

and estimate a general quadratic relationship between CSAD and market return

$$CSAD_{k,t} = \alpha_0^k + \alpha_1^k \left| R_{m,t} \right| + \alpha_2^k R_{m,t}^2 + \varepsilon_t \tag{3}$$

in which a significant and negative estimate for $\alpha_2^k$ is considered as support for the presence of herding in industry *k*. The basic rationale in this model is that cross-sectional dispersion in firm betas within the industry would normally lead to a positive relationship between market return

[5] To be consistent with the herding literature, the industry (market) return is calculated as the cross-sectional average return of all stocks in the industry (market), respectively (e.g. Lee et al., 2013; Yao et al., 2014).
[6] Demirer et al. (2010) provides a comparison of the alternative models to detect herd behavior.

and the cross-sectional dispersion of firm returns as each firm has a different degree of sensitivity to the market factor. However, in a market where herding is present, greater directional similarity in firm returns due to herding leads to a non-linear and negative relationship between return dispersion and market return so that firm returns become less dispersed for large movements in the market. Therefore, we focus on the herding coefficient ($\alpha_2^k$) in Equation (3) as a proxy for the level of herding in industry *k* so that increasingly negative values for the herding coefficient indicates higher degree of herding as firm returns in that industry would display greater degree of directional similarity for large market movements.

**2.3 Construction of portfolios**

In order to establish the preliminary evidence for industry momentum in the Chinese stock market, we first assign each stock in our final sample into one of 50 industries listed in Table 1. Next, at the end of each month (*t)*, we sort industries into two groups, i.e. winner and loser industries, based on their past-6 month returns (*M6*) excluding the most recent month, i.e. *M6* is calculated as the average monthly return over the period *t-1* through *t-6*. Following a number of studies including Asness (1994), Boudoukh et al. (1994), and Grinblatt and Moskowitz (2004), we skip the most recent month in order to mitigate problems associated with microstructure issues. However, calculating the momentum return (*M6*) without skipping the most recent month, i.e. *t* through *t-5*, yields similar results and are available upon request. Industries are then defined as winner (loser) industries if their momentum returns are above (below) the median momentum return across all industries.

Independently, we use daily data over the most recent 6-month period, i.e. *t* through *t-5*, and estimate Equation (3) for each industry.[7] This procedure yields the herding coefficient $\alpha_2^k$ for industry *k* each month. Industries are then sorted into top (30%), intermediate (40%) and

[7] The time frame to estimate the herding level includes the most recent 6-month period in order to take into account the dynamic nature of this phenomenon in our portfolio strategy.

bottom (30%) groups based on the estimated herding coefficients indicating the degree of herding in each industry. As stated earlier, the degree of industry herding is proxied by the herding coefficient ($\alpha_2^k$) so that greater (in absolute value) and negative values indicate higher level of herding. Finally, we sort industries based on their level of herding and momentum returns each month and rebalance these portfolios using the same procedure monthly. For example, if the herding/momentum portfolios are formed at the end of July, the momentum return (*M6*) is calculated over the period January through June and the herding level is estimated over the period February through July. Subsequent returns are then calculated at the end of August, September and October.

As noted earlier, following a number of papers in the momentum literature (e.g. Jegadeesh, 1990; Boudoukh et al., 1994; Asness, 1994; Grinblatt and Moskowitz, 2004), the momentum return (*M6*) is calculated by skipping the most recent month's return. However, a number of papers in the industry momentum literature includes the most recent month, i.e. *t* to *t-5*, in their calculation of momentum returns (e.g. Moskowitz and Grinblatt, 1999; Jegadeesh and Titman, 1993; Liu et al. 2011). On the other hand, Du and Denning (2005) use both methods to calculate momentum returns and notes that skipping a month between the ranking and the investment periods can increase momentum profits for individual stocks, but not substantially for industry portfolios. Nevertheless, we observe similar results when we form the portfolios using the most recent period (*t* through *t-5*) commonly for both momentum returns and the level of herding. These additional tests are not reported in the paper but are available upon request.

In a related study, Yan et al. (2012) use the z-score for an industry which corresponds to the normalized value of return dispersion measures in Equations (1) and (2) and use the normalized return dispersion values to determine the level of herding in an industry. Using data on U.S. stocks, they find that low herding enhances stock price momentum such that winner industries with high z-scores, i.e. low level of herding, generate higher subsequent returns while loser industries with high z-scores generate lower subsequent returns. On the other hand, we follow a different approach to determine the level of herding in an industry that is consistent with the testing methodologies to detect herding. According to the models by Christie and Huang (1995) and Chang et al. (2000), inference on herding is based on the relationship between return dispersion and market return and not the return dispersion value per se. So, a low level of return dispersion in an industry does not necessarily indicate herding whereas a negative and significant relationship between return dispersion and market return, implied by the sign of the herding coefficient, $\alpha_2^k$, suggests herding. To that end, the use of $\alpha_2^k$ as a proxy for the level of herding is consistent with the rationale behind the herding tests of Christie and Huang (1995) and Chang et al. (2000).

## 3. Empirical results

### 3.1 Descriptive statistics

Table 1 presents several descriptive statistics for the industries used in the study. *Market share* refers to the time-series average of industry market capitalization as a percentage of the whole market and *# of firms* is the time-series average of the number of firms in each industry. *Return* and *M6* are the mean monthly industry and momentum returns, respectively. *Herding level* indicates the time-series averages of the herding coefficients from each herding measure based on Equation (3) while subsequent returns are the time-series averages of the average monthly returns for the subsequent 1, 2, and 3-months.

We observe that banking is the largest industry in terms of market capitalization which accounts for about 16% of total market value whereas computer and telecommunications equipment industry has the largest number of firms among all industries with 145 listed firms. Examining mean industry returns, automobile and media stand out as the best performers with the highest monthly average returns while negative returns are observed for agriculture, forestry, livestock, and timber processing. On the other hand, largest (in absolute value) negative herding coefficients are observed particularly for agriculture, air transportation, telecom & broadcasting services and banking, suggesting that herding is more prevalent in these industries. The greater degree of herding in these industries suggests that diversification benefits through stocks in these industries will be limited at best. Finally, we observe positive subsequent returns in all industries with the largest subsequent returns in livestock, pharmacy, computer & telecom equipment and architectural decoration.

### 3.2 The level of herding and momentum returns

Table 2 presents the preliminary evidence for industry momentum. As explained earlier, at the end of each month between January 1996 and December 2013, industries are sorted into portfolios based on their momentum returns using the past 6-month returns. Industries are defined as winner (loser) industries if their momentum returns (monthly) are above (below) the median momentum returns. Following Jegadeesh and Titman (1993), we then calculate the average monthly returns for winner and loser industries over the subsequent 1, 2, and 3 months. We also calculate and report the return spread between winner and loser industry portfolios (*WML*). The findings clearly support the presence of industry momentum indicated by a highly significant and positive spread between average monthly returns to winner and loser industry portfolios. We observe significant and positive monthly spread for all three holding periods in subsequent months, which are 0.260%, 0.261% and 0.309% for the subsequent 1, 2, and 3-months, respectively. In Panels B, C and D, we also provide the subsequent returns for winner and loser industries and corresponding spreads during up, down markets and crisis periods, respectively. We generally observe the same pattern in which winner industries tend to outperform loser industries in subsequent returns.

Having established preliminary evidence on industry momentum, we proceed with our analysis of the effect of industry herding on momentum returns. Table 3 presents our findings for the portfolios sorted on momentum and the level of herding. Panel A in Table 3 presents the findings for the CSSD measure of Christie and Huang (1995) to estimate herding. We observe that the momentum effect holds at the industry level with winner industries significantly outperforming loser industries in general. Comparing the subsequent returns for winner industries, we observe no significant difference for high and low herding levels implied by an insignificant spread between high herding winners and low herding winners for each subsequent period. On the other hand, we observe that loser industries with low level of herding significantly outperform loser industries with high level of herding by 0.439%, 0.406%, and 0.280% in the subsequent 1, 2, and 3-months, respectively. This finding suggests that industry herding has an asymmetric effect on return momentum, particularly affecting returns in loser industries whereas no significant herding effect takes place in winner industries.

Similar results are found in Panel B when the estimations are done using the Chang et al. (2000) herding measure. While no significant difference in subsequent returns are observed for winner industries across low and high herding levels, we observe that loser industries with high level of herding generate significantly lower returns compared to loser industries with low degree of herding during the subsequent 1, 2, and 3 months. The finding that the momentum effect in loser industries is more significant when the herding level is high is consistent with Brown et al. (2014) that fund managers have a greater tendency to herd on negative stock information due to reputational concerns and greater litigation risk for holding losing stocks. It is also consistent with several studies in the herding literature documenting directional asymmetry in herding (e.g. Lee et al., 2013; Yao et al., 2014)

### 3.3 The profitability of zero-cost momentum strategies

The above asymmetric effect of industry herding on return momentum implies economic value of investment strategies based on this asymmetry. For this purpose, following Moskowitz and Grinblatt (1999), we create alternative zero-cost portfolios by taking a long position in winner and a short position in loser industries and evaluate their subsequent returns. Table 4 reports the return spread between winner and loser industry portfolios for low and high herding levels. Panels A and B report the spread in average monthly returns for the two alternative herding measures, CSSD and CSAD, respectively. The findings for both herding measures are consistent. We observe that the zero-cost momentum strategy yields insignificant subsequent returns when the short position is on low herding industries. Regardless of the herding level of the winner industry portfolio in the long position, shorting low herding loser industries yields insignificant subsequent returns. This finding suggests that a zero-cost momentum strategy does not work whenever the short position is in a loser industry with low degree of herding.

On the other hand, the zero-cost momentum strategy yields highly significant and positive subsequent returns from a long position in winner industries (regardless of the level of herding) and a short position in high herding losers, consistently for both herding measures in Panels A and B and for all subsequent 1, 2, and 3 months. For example, in Panel B of Table 4, we see that taking a long position in high herding winners and short position in high herding losers yields an average monthly return of 0.458%, 0.463%, and 0.357% over the next 1, 2, and 3 months whereas taking a long position in low herding winners and a short position in high herding losers yields an average monthly return of 0.316%, 0.415%, and 0.400%, over the next three subsequent months, all significant at 1% significance level. These findings suggest that the profitability of zero-cost industry momentum strategies indeed depends on the level of industry herding.

In order to examine the superior performance of the herding-based industry momentum strategy over the plain-vanilla momentum strategy reported in Panel A of Table 2, we report in Table 5, the excess returns from the herding-based industry momentum strategy over the plain-vanilla industry momentum strategy. The findings in Table 5 further support our finding that an enhanced, herding-based momentum strategy significantly outperforms the plain-vanilla strategy over each subsequent month following the formation of the momentum portfolio.

Regardless of the herding measure used, we observe that taking a short position in loser industries with high level of herding yields significant and positive excess returns over the plain-vanilla strategy. Overall, these findings clearly suggest that fund managers must take into account the level of herding in winner and loser industry portfolios and that the asymmetric relationship between herding and momentum can be explored for enhanced momentum strategies that can outperform plain-vanilla momentum strategies.

In order to check the robustness of our findings, several additional tests are performed. First, the data is split into pre- and post-2000 periods only to find similar results as in the case of the whole sample. Next, Shanghai and Shenzhen exchanges are examined separately. While similar findings to those reported so far are observed for Shenzhen, we find that the level of herding also impacts winner industries in Shanghai when CSSD is utilized as the herding measure. However, we find that the herding effect on winner industries disappears when CSAD is used as the herding measure, suggesting that the effect of industry herding is not robust in the case of winner industries. For brevity, the findings for the above robustness tests are not reported, but are available upon request. Finally, as we report in the next two subsections, we also extend the tests to up and down markets as well as periods of market crisis. These additional tests suggest that the findings are generally robust to different time periods and market specifications.

### 3.4 The effect of directional asymmetry in herding on momentum

Several studies in the literature report asymmetry in herding behavior and examine the presence of herding during periods of market gains or losses separately (e.g. Yao et al., 2014). In order to explore how directional asymmetry in herding affects our above findings, we run similar empirical analysis separately over up and down market periods, which are defined as months when the market return is non-negative (up) or negative (down). Table 6 reports the impact of herding on return momentum during down and up markets in Panels A (B) and C (D), respectively. Similarly,

Table 7 reports the return spread between winner and loser industry portfolios for low and high herding levels. Note that the herding/momentum portfolios are formed following the same procedure described in Section 2.3 and portfolio statistics are then calculated for up and down markets, respectively.[8] The results generally support our initial finding that a momentum strategy where a short position is taken in high herding losers generates significantly higher subsequent returns, regardless of the direction of market movement. For example, examining the findings for down markets reported in Panel A of Table 7, we observe that the strategy of longing in low herding winners and shorting in high herding losers yields average monthly returns of 0.169%, 0.221% and 0.216% for the subsequent 1, 2, and 3 months, respectively. On the other hand, during up markets reported in Panel C, the same strategy yields subsequent returns of 0.780%, 0.621%, and 0.606%, suggesting that the effect of herding on loser industries is more pronounced during up markets. Nevertheless, the return spreads reported in Table 7 provide further support for our initial finding that short positions on high herding loser industries provide the greatest momentum profits regardless of the direction of market movement.

### 3.5 Market crisis periods

The literature suggests in general that herding among market participants would be more prevalent during periods of market stress characterized by extreme market movements (e.g. Christie and Huang, 1995). Therefore, in order to explore whether market crisis periods have any impact on the relationship between herding and return momentum, we replicate our analysis by focusing on the Asian crisis (1997.1-1998.12), the dot-com crash (2000.1-2001.12), and the recent global financial crisis (2007.1-2008.12) periods.[9] Table 8 presents the results. Interestingly, we observe positive momentum returns for both the winner and loser industry portfolios in China despite the market crisis experienced during those periods, suggesting some degree of

[8] For brevity, the t-statistics are not reported in Tables 6 and 7; however, we still indicate the statistical significance of the estimates.
[9] The dates for the crisis periods are based on Chiang and Zheng (2010).

segmentation of the Chinese stock market from global financial markets during these periods. On the other hand, examining subsequent returns, we observe no significant difference between winner industries across low and high herding levels, consistent with the findings reported in Table 3 over the whole sample period. However, unlike the previous findings over the whole sample period, we do not find any significant difference in subsequent returns between high and low herding loser industries. Furthermore, we observe that subsequent returns for winner and loser industries reported in Table 8 are generally insignificant suggesting that a plain-vanilla industry momentum strategy does not work during crisis periods.

On the other hand, examining the profitability of zero-cost momentum strategies reported in Table 9, we see that a herding-based industry momentum strategy could generate zero-cost momentum profits even during market crisis periods. We observe that the herding-based industry momentum strategy works only when the short position is held in high herding loser industries while shorting low herding loser industries yields insignificant subsequent returns. Examining the findings for alternative herding measures in Table 9 (reported in Panels A and B), we observe consistent results that the zero-cost momentum strategy yields the largest subsequent returns when industries with high level of herding are utilized in both the long and short positions. For example, taking a long position in high herding winner and short position in high herding loser industries yields an average monthly return of 0.771%, 0.768%, and 0.436% in Panel A and 0.835%, 0.646%, 0.372% in Panel B, over the subsequent 1, 2, and 3 months, respectively, all highly significant at one percent level. On the other hand, all other portfolios involving low herding industries yield either lower or insignificant subsequent returns.

Further examining the excess returns from the herding-based momentum strategy over the plain-vanilla momentum strategy reported in Table 10, we observe that the herding-based momentum strategy offers the largest excess returns when high herding losers are held in short position. Overall, the results confirm our previous finding that the level of herding in an industry is indeed the driving factor behind profitable zero-cost industry momentum strategies even during periods of market crisis.

## 4. Conclusions

The main goal of this paper is to evaluate the impact of industry herding on industry momentum. Although the literature establishes a link between herding and return momentum, no conclusive evidence is provided with studies including Nofsinger and Sias (1999) and Sias (2004) documenting that subsequent asset returns follow the direction of the herd resulting in return momentum while others including Dasgupta et al. (2011), Singh (2013) and Brown et al. (2014) document return reversals in the long run as a result of herding. In this study, we examine the momentum-herding relationship in a formal and explicit way by utilizing a herding coefficient derived from two popularly used herding models proposed by Christie and Huang (1995) and Chang et al. (2000). In recent studies, Lee et al. (2013) and Yao et al. (2014) have documented industry herding in the Chinese stock market using these herding measures; thus relating these herding measures to return momentum in the same stock market allows for a meaningful comparison.

While industry momentum effect exists in the Chinese stock market with winner industries significantly outperforming loser industries, an asymmetric relationship between herding and return momentum is observed. Sorting winner industries into high and low herding groups, we observe no significant difference in subsequent returns. However, loser industries with low level of herding yield significantly higher returns than loser industries with high level of herding in subsequent months. This asymmetric effect of herding on momentum returns is in fact consistent with Brown et al. (2014) that fund managers have a greater tendency to herd on negative stock information and thus exacerbating losses in loser industries.

Furthermore, the profitability of zero-cost momentum portfolios, i.e. longing in winner and shorting in loser industries, indeed depends on the level of herding in an industry. We observe that the zero-cost momentum strategy yields insignificant subsequent returns when the short position is on low herding industries. That is, regardless of the herding level of the winner portfolio in the long position, shorting the low herding loser portfolio yields insignificant subsequent returns. On the other hand, taking long position in high herding winner and short position in high herding loser industries generates positive subsequent returns for the next 1, 2, and 3 months, all highly significant at 1% level. We observe identical findings across the alternative herding measures of Christie and Huang (1995) and Chang et al. (2000) and for different subsamples, including market crisis periods. The findings have important implications for the implementation of zero-cost momentum strategies and clearly suggest that the level of herding in an industry must be considered in strategies concerning industry momentum.

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**Table 1.** Summary statistics.

| Industries | # of Firms | Market Share (%) | Return (%) | M6 (%) | Herding level CSSD | CSAD | Subsequent returns (%) 1-mo. | 2-mo. | 3-mo. |
|---|---|---|---|---|---|---|---|---|---|
| Agriculture | 10 | 0.50 | -0.05 | 1.22 | -3.04 | -2.13 | 1.20 | 1.22 | 1.08 |
| Forestry | 7 | 0.16 | -0.09 | 0.54 | 0.01 | 0.02 | 1.02 | 1.29 | 0.84 |
| Livestock | 6 | 0.16 | -0.23 | 2.50 | -0.59 | -0.45 | 2.32 | 2.19 | 2.19 |
| Coal mining | 22 | 3.11 | 0.16 | 1.64 | 1.18 | 3.12 | 1.51 | 1.57 | 1.48 |
| Non-ferrous metal mining | 17 | 1.06 | 0.18 | 2.00 | -1.01 | -0.82 | 1.72 | 1.72 | 1.74 |
| Agricultural and sideline food | 30 | 1.10 | 0.25 | 1.56 | -1.27 | -2.13 | 1.44 | 1.41 | 1.43 |
| Food | 18 | 0.69 | 0.04 | 1.59 | -2.02 | -1.12 | 1.54 | 1.50 | 1.58 |
| Alcohol, tea and beverage | 26 | 3.10 | 0.27 | 2.01 | 2.56 | 1.16 | 1.97 | 1.96 | 1.95 |
| Textile | 38 | 0.90 | 0.03 | 1.50 | -1.40 | -1.57 | 1.55 | 1.54 | 1.45 |
| Apparel | 24 | 0.52 | 0.05 | 1.71 | -1.88 | -2.08 | 1.49 | 1.04 | 1.01 |
| Timber and grass processing | 6 | 0.11 | -0.22 | 0.16 | -0.12 | -0.08 | 0.58 | 0.90 | 1.27 |
| Paper | 22 | 0.65 | 0.34 | 0.97 | -1.34 | -0.61 | 1.10 | 1.15 | 1.10 |
| Art, sport and entertainment | 7 | 0.13 | -0.07 | 0.23 | 0.90 | 1.34 | 0.75 | 1.13 | 0.86 |
| Oil, coal and fuel processing | 15 | 1.86 | 0.02 | 1.39 | 5.49 | 19.16 | 1.00 | 1.07 | 1.14 |
| Chemical manufacturing | 131 | 4.57 | 0.11 | 1.70 | 4.94 | 2.23 | 1.87 | 1.90 | 1.89 |
| Pharmacy | 107 | 4.27 | 0.16 | 2.05 | 1.98 | 0.64 | 2.08 | 2.13 | 2.12 |
| Chemical fiber products | 21 | 1.19 | 0.01 | 1.39 | 4.40 | 5.75 | 1.50 | 1.45 | 1.33 |
| Rubber and plastic products | 45 | 0.96 | 0.18 | 1.63 | -0.18 | -0.19 | 1.44 | 1.41 | 1.37 |
| Non-metallic products | 60 | 2.10 | 0.21 | 1.69 | 10.84 | 6.95 | 1.74 | 1.77 | 1.76 |
| Ferrous metal rolling and refinery | 31 | 4.60 | -0.05 | 1.31 | -0.95 | -0.45 | 1.19 | 1.24 | 1.18 |
| Non-ferrous metal processing | 44 | 2.39 | 0.30 | 1.78 | 1.99 | 1.96 | 1.56 | 1.73 | 1.69 |
| Metal products | 35 | 0.77 | 0.08 | 1.08 | 7.22 | 31.44 | 1.10 | 1.15 | 1.17 |
| General equipment production | 74 | 1.97 | 0.15 | 1.53 | 0.34 | 0.29 | 1.70 | 1.68 | 1.64 |
| Specialized equipment production | 96 | 2.24 | 0.20 | 1.65 | -0.42 | -0.16 | 1.78 | 1.88 | 1.89 |
| Automobile | 63 | 3.29 | 1.33 | 1.80 | 1.58 | 1.77 | 1.90 | 1.99 | 1.99 |
| Rail, ship, airplane & airspace | 26 | 1.46 | 0.14 | 1.69 | -0.42 | -0.47 | 1.78 | 1.89 | 1.86 |
| Electronic machinery & equipment | 106 | 3.57 | 0.13 | 1.80 | 7.17 | 5.74 | 1.88 | 1.96 | 1.93 |
| Computer & telecom equipment | 145 | 6.07 | 0.16 | 1.87 | 0.71 | 0.45 | 2.03 | 2.13 | 2.08 |
| Instrument and apparatus | 20 | 0.16 | 0.09 | 1.74 | -1.41 | -1.77 | 1.62 | 1.70 | 1.21 |
| Other industrial manufacturing | 11 | 0.26 | 0.15 | 1.49 | 0.37 | 0.23 | 1.03 | 0.95 | 0.90 |
| Electricity and heating | 45 | 5.36 | 0.55 | 1.68 | 1.71 | 1.42 | 1.83 | 1.87 | 1.84 |
| Water | 10 | 0.73 | 0.15 | 1.71 | -0.66 | -0.56 | 1.29 | 1.30 | 1.38 |
| Civil engineering | 41 | 1.65 | 0.00 | 1.20 | 0.13 | 0.08 | 1.22 | 1.28 | 1.23 |
| Architectural decoration | 10 | 0.22 | -0.19 | 2.86 | -0.30 | -0.25 | 2.76 | 2.45 | 2.39 |
| Wholesale | 52 | 2.91 | 0.10 | 1.69 | -0.85 | -0.46 | 1.82 | 1.86 | 1.85 |
| Retailing | 49 | 3.65 | 0.15 | 1.58 | 11.41 | 6.87 | 1.69 | 1.70 | 1.68 |
| Road transportation | 26 | 2.23 | 0.05 | 1.09 | 0.04 | 0.01 | 1.29 | 1.28 | 1.29 |
| Water transportation | 26 | 2.11 | 0.11 | 1.50 | -0.52 | -0.41 | 1.62 | 1.65 | 1.64 |
| Air transportation | 8 | 1.70 | 0.24 | 1.22 | -4.53 | -1.88 | 1.16 | 1.17 | 1.18 |
| Telecom & broadcasting service | 8 | 1.56 | 0.07 | 1.58 | -5.57 | -2.86 | 1.63 | 1.60 | 1.65 |
| Ecommerce | 9 | 0.30 | 0.39 | 1.57 | 1.72 | 3.42 | 1.95 | 2.17 | 2.06 |
| Software & information technology | 70 | 1.37 | 0.47 | 1.89 | 2.13 | 1.43 | 2.07 | 2.02 | 2.04 |
| Banking | 11 | 15.76 | 0.27 | 1.11 | -3.07 | -2.04 | 1.30 | 1.59 | 1.61 |
| Financing | 16 | 1.94 | 0.42 | 2.65 | -1.93 | -2.27 | 0.91 | 1.03 | 0.99 |
| Real estate | 62 | 8.52 | 0.18 | 1.96 | 5.73 | 2.78 | 1.91 | 1.91 | 1.88 |
| Logistics | 17 | 0.84 | 0.19 | 1.76 | -1.23 | -1.27 | 1.72 | 1.59 | 1.56 |
| Specialized technology service | 7 | 0.12 | 0.69 | 0.86 | -1.08 | -1.73 | 0.76 | 1.44 | 1.79 |
| Public facility management | 14 | 0.88 | 0.23 | 1.40 | -1.22 | -0.96 | 1.46 | 1.42 | 1.38 |
| Media | 11 | 0.49 | 1.40 | 1.98 | 0.97 | 1.46 | 2.06 | 1.75 | 1.56 |
| Unclassified | 16 | 1.71 | 0.19 | 1.62 | 0.20 | 0.10 | 1.72 | 1.78 | 1.78 |

**Note:** Each month from January 1996 to December, 2013, all A shares listed in Shanghai and Shenzhen exchanges are assigned to an industry based on the first two-digits of industry codes following the China Securities Regulatory Commission's industry classification. We exclude industries with fewer than 5 stocks traded on any trading day during the sample period and end up with 50 industries. **Market share** and **# of firms** refer to the time-series average of industry market cap as a percentage of the whole market and time-series average of the number of firms in each industry, respectively. **Return** and **M6** are the time series average monthly industry and momentum returns, respectively. **Herding level** indicates the time-series averages of the herding coefficients from each herding measure based on Equation (3) while **subsequent returns** are the time-series averages for the average monthly returns held for the subsequent 1, 2, and 3-months.

**Table 2**. Momentum effect in industry portfolios.

| | **Spread in Subsequent Returns** | | |
|---|---|---|---|
| | 1-month | 2-months | 3-months |
| | | **Panel A:** Whole sample | |
| Winners | 1.978%** | 1.995%** | 1.996%** |
| | (2.35) | (2.37) | (2.31) |
| Losers | 1.719%*** | 1.733%*** | 1.688%*** |
| | (2.69) | (2.75) | (2.77) |
| ***Spread** (WML)* | 0.260*** | 0.261*** | 0.309*** |
| | (3.97) | (3.99) | (4.72) |
| | | **Panel B:** UP markets | |
| Winners | 8.537%*** | 5.788%*** | 4.649%*** |
| | (9.21) | (6.52) | (5.41) |
| Losers | 8.026%*** | 5.477%*** | 4.370%*** |
| | (9.56) | (6.37) | (5.17) |
| ***Spread** (WML)* | 0.510%* | 0.311% | 0.279%* |
| | (1.82) | (1.54) | (1.66) |
| | | **Panel C:** DOWN markets | |
| Winners | -5.783%*** | -2.545%*** | -1.213%* |
| | (-9.45) | (-4.43) | (-1.93) |
| Losers | -5.861%*** | -2.830%*** | -1.548%** |
| | (-9.80) | (-4.95) | (-2.47) |
| ***Spread** (WML)* | 0.078 | 0.285%** | 0.335%** |
| | (0.39) | (2.05) | (2.52) |
| | | **Panel D:** Crisis periods | |
| Winners | 2.084% | 1.355% | 1.155% |
| | (1.47) | (0.97) | (0.87) |
| Losers | 1.709% | 1.275% | 0.864% |
| | (1.04) | (0.89) | (0.64) |
| ***Spread** (WML)* | 0.375%** | 0.080% | 0.291%** |
| | (1.47) | (0.34) | (1.30) |

**Note:** Each month between January 1996 and December 2013, industries are grouped into portfolios based on their momentum returns using the past 6-month returns over the period (*t-1)* to (*t-6*) by skipping the most recent month's return. Industries are defined as winner (loser) industries if their momentum returns (monthly) are above (below) the median momentum returns. Portfolios are rebalanced monthly. 1-month, 2-months, and 3-months returns are the spread between the average monthly returns to winner and loser industries over the subsequent 1, 2, and 3 months. Market crisis periods (in Panel D) include the Asian crisis (1997.1-1998.12), the dot-com crash (2000.1-2001.12), and the recent global financial crisis (2007.1-2008.12). The Newey and West (1987) t-statistics are reported in parentheses and *, ** and *** indicate significance at 10%, 5% and 1%, respectively.

**Table 3**. The impact of herding on return momentum.

| Portfolio | Herding | Momentum | #of obs. | Herding coefficient | Momentum return | Subsequent returns 1-month | 2-months | 3-months |
|---|---|---|---|---|---|---|---|---|
| **Panel A:** Herding measured by CSSD | | | | | | | | |
| 1 | High | Winner | 1502 | -4.520*** | 2.711%*** | 1.915%** | 1.923%** | 1.864%** |
| | | | | (-37.93) | (19.37) | (2.44) | (2.57) | (2.59) |
| 2 | Low | Winner | 1617 | 30.266*** | 2.812%*** | 1.954%** | 1.899%** | 1.942%** |
| | | | | (33.44) | (22.09) | (2.36) | (2.39) | (2.54) |
| **Spread (**High herding winners-Low herding winners) | | | | | | -0.039% | 0.024% | -0.078% |
| | | | | | | (-0.27) | (0.18) | (-0.63) |
| 3 | High | Loser | 1388 | -5.213*** | 0.369%*** | 1.473%* | 1.462%** | 1.495%** |
| | | | | (-4.87) | (2.98) | (1.94) | (2.02) | (2.14) |
| 4 | Low | Loser | 1443 | 24.315*** | 0.431%*** | 1.912%** | 1.868%** | 1.775%** |
| | | | | (30.49) | (3.45) | (2.31) | (2.34) | (2.32) |
| **Spread (**High herding losers-Low herding losers) | | | | | | -0.439%** | -0.406%** | -0.280%* |
| | | | | | | (-2.27) | (-2.28) | (-1.88) |
| **Panel B:** Herding measured by CSAD | | | | | | | | |
| 1 | High | Winner | 1508 | -2.413*** | 2.808%*** | 1.890%** | 1.868%** | 1.809%** |
| | | | | (-37.64) | (20.23) | (2.42) | (2.51) | (2.51) |
| 2 | Low | Winner | 1601 | 11.398*** | 2.843%*** | 1.748%** | 1.821%** | 1.852%** |
| | | | | (42.47) | (21.46) | (2.09) | (2.27) | (2.42) |
| **Spread (**High herding winners-Low herding winners) | | | | | | 0.142% | 0.047% | -0.043% |
| | | | | | | (0.89) | (0.34) | (-0.36) |
| 3 | High | Loser | 1382 | -3.209*** | 0.321%** | 1.432%* | 1.406%* | 1.452%** |
| | | | | (-3.42) | (2.56) | (1.91) | (1.95) | (2.07) |
| 4 | Low | Loser | 1459 | 10.406*** | 0.428%*** | 1.867%** | 1.830%** | 1.728%** |
| | | | | (37.55) | (3.49) | (2.23) | (2.29) | (2.26) |
| **Spread (**High herding losers-Low herding losers) | | | | | | -0.435%** | -0.424%** | -0.275% |
| | | | | | | (-2.09) | (-2.16) | (-1.63) |

**Note:** Each month between January 1996 and December 2013, industries are grouped into 6 portfolios based on industry momentum and the level of herding using the past 6-month returns, respectively. Industries are defined as winner (loser) industries if their momentum returns (monthly) are above (below) the median momentum returns. Independently, industries are also sorted into top (30%), intermediate (40%) and bottom (30%) groups based on the estimated herding coefficients from Equation (3) over the most recent 6-month period. Portfolios are rebalanced monthly. 1-month, 2-months, and 3-months returns are the average monthly returns over each subsequent period. Panels A and B report the findings for the two alternative herding measures, CSSD and CSAD, respectively. The Newey and West (1987) t-statistics are reported in parentheses, and *, ** and *** indicate significance at 10%, 5% and 1%, respectively.

**Table 4**. Return spread between winner and loser portfolios

| Portfolios | Subsequent returns | | |
|---|---|---|---|
| | 1-month | 2-months | 3-months |
| **Panel A:** Herding measured by CSSD | | | |
| **Spread (**High herding winners-Low herding losers) | 0.003% | 0.055% | 0.089% |
| | (0.01) | (0.33) | (0.62) |
| **Spread (**Low herding winners-Low herding losers) | 0.042 | 0.031 | 0.167** |
| | (0.53) | (0.40 | (2.27) |
| **Spread (**High herding winners-High herding losers) | 0.442%** | 0.461%*** | 0.370%** |
| | (2.21) | (2.72) | (2.57) |
| **Spread (**Low herding winners-High herding losers) | 0.481%*** | 0.437%*** | 0.447%*** |
| | (6.29) | (5.98) | (6.34) |
| **Panel B:** Herding measured by CSAD | | | |
| **Spread (**High herding winners-Low herding losers) | 0.023% | 0.039% | 0.081% |
| | (0.11) | (0.22) | (0.53) |
| **Spread (**Low herding winners-Low herding losers) | -0.119 | 0.009 | 0.124* |
| | (-1.49) | (0.12) | (1.68) |
| **Spread (**High herding winners-High herding losers) | 0.458%** | 0.463%** | 0.357%** |
| | (2.30) | (2.57) | (2.22) |
| **Spread (**Low herding winners-High herding losers) | 0.316%*** | 0.415%*** | 0.400%*** |
| | (4.13) | (5.60) | (5.61) |

**Note:** Each month between January 1996 and December 2013, industries are grouped into 6 portfolios based on industry momentum and the level of herding using the past 6-month returns, respectively. Industries are defined as winner (loser) industries if their momentum returns (monthly) are above (below) the median momentum returns. Independently, industries are also sorted into top (30%), intermediate (40%) and bottom (30%) groups based on the estimated herding coefficients from Equation (3) over the most recent 6-month period. Portfolios are rebalanced monthly. 1-month, 2-months, and 3-months returns are the spread between the average monthly returns to winner and loser industries over the subsequent 1, 2, and 3 months. Panels A and B report the findings for the two alternative herding measures, CSSD and CSAD, respectively. The Newey and West (1987) t-statistics are reported in parentheses, and *, ** and *** indicate significance at 10%, 5% and 1%, respectively.

**Table 5**. Excess returns from the herding-based momentum strategy over the plain-vanilla momentum strategy.

| Herding-based momentum portfolios | **Excess returns over the plain-vanilla industry momentum strategy** | | |
|---|---|---|---|
| | 1-month | 2-months | 3-months |
| **Panel A:** Herding measured by CSSD | | | |
| High herding winners-Low herding losers | -0.257%*** | -0.206%*** | -0.220%*** |
| | (-12.19) | (-16.83) | (-20.40) |
| Low herding winners-Low herding losers | -0.218%*** | -0.230%*** | -0.142%*** |
| | (-31.02) | (-33.18) | (-21.09) |
| High herding winners-High herding losers | 0.182%*** | 0.201%*** | 0.061%*** |
| | (12.65) | (16.15) | (5.64) |
| Low herding winners-High herding losers | 0.221%*** | 0.176%*** | 0.138%*** |
| | (32.11) | (26.25) | (20.98) |
| **Panel B:** Herding measured by CSAD | | | |
| High herding winners-Low herding losers | -0.237%*** | -0.222%*** | -0.228%*** |
| | (-15.82) | (17.19) | (-20.06) |
| Low herding winners-Low herding losers | -0.379%*** | -0.252%*** | -0.185%*** |
| | (-53.68) | (-37.04) | (-27.43) |
| High herding winners-High herding losers | 0.198%*** | 0.202%*** | 0.048%*** |
| | (13.82) | (15.42) | (4.04) |
| Low herding winners-High herding losers | 0.056%*** | 0.154%*** | 0.091%*** |
| | (8.13) | (22.79) | (13.75) |

**Note:** This table reports the excess subsequent returns offered by each herding-based industry momentum strategy (Table 4) over the plain-vanilla industry momentum strategy (Table 2). Panels A and B report the findings for the two alternative herding measures, CSSD and CSAD, respectively. The Newey and West (1987) t-statistics are reported in parentheses, and *, ** and *** indicate significance at 10%, 5% and 1%, respectively.

**Table 6**. The impact of herding on return momentum during up and down markets.

| | Herding | Mom. | #of obs. | Herding coefficient | Momentum return | Subsequent returns | | |
|---|---|---|---|---|---|---|---|---|
| | | | | | | 1-month | 2-months | 3-months |
| **Panel A:** Herding measured by coefficient on CSSD: **DOWN markets** (98 months) | | | | | | | | |
| 1 | High | High | 694 | -4.738*** | 2.128%** | -5.897%*** | -2.569%*** | -1.238%** |
| 2 | Low | High | 751 | 29.884*** | 2.249%** | -5.735%*** | -2.634%*** | -1.297%** |
| **Spread** (High herding winners-Low herding winners) | | | | | | -0.162%* | 0.065% | 0.059% |
| 3 | High | Low | 646 | -4.251*** | -0.112% | -5.904%*** | -2.855%*** | -1.513%** |
| 4 | Low | Low | 665 | 24.769*** | -0.005% | -5.753%*** | -2.769%*** | -1.465%** |
| **Spread** (High herding losers-Low herding losers) | | | | | | -0.151%* | -0.086% | -0.048% |
| **Panel B:** Herding measured by coefficient on CSAD: **DOWN markets** | | | | | | | | |
| 1 | High | High | 702 | -2.394*** | 2.350%** | -5.904%*** | -2.633%*** | -1.294%** |
| 2 | Low | High | 740 | 11.346*** | 2.197%** | -5.873%*** | -2.645%*** | -1.338%** |
| **Spread:** High herding winners-low herding winners | | | | | | -0.031% | 0.012% | 0.044% |
| 3 | High | Low | 638 | -2.309*** | -0.295%* | -5.822%*** | -2.838*** | -1.50%** |
| 4 | Low | Low | 676 | 10.74*** | 0.056% | -5.750%*** | -2.769%*** | -1.536%** |
| **Spread** (High herding losers-Low herding losers) | | | | | | -0.072% | 0.069% | 0.036% |
| **Panel C:** Herding measured by coefficient on CSSD: **UP markets** (116 months) | | | | | | | | |
| 1 | High | High | 808 | -4.333*** | 3.244%** | 8.563%*** | 5.759%*** | 4.514%*** |
| 2 | Low | High | 870 | 30.531*** | 3.269%** | 8.447%*** | 5.730%*** | 4.662%*** |
| **Spread:** High herding winners-low herding winners | | | | | | 0.116% | 0.029% | -0.148% |
| 3 | High | Low | 745 | -26.74 | 0.777%** | 7.667%*** | 5.109%*** | 4.056%*** |
| 4 | Low | Low | 777 | 23.870*** | 0.804%** | 8.454%*** | 5.789%*** | 4.536%*** |
| **Spread** (High herding losers-Low herding losers) | | | | | | -0.787%** | -0.680%** | -0.480%*** |
| **Panel D:** Herding measured by coefficient on CSAD: **UP markets** (116 months) | | | | | | | | |
| 1 | High | High | 809 | -2.424*** | 3.235%** | 8.517%*** | 5.709%*** | 4.462%*** |
| 2 | Low | High | 864 | 11.421*** | 3.361%** | 8.264%*** | 5.648%*** | 4.598%*** |
| **Spread:** High herding winners-low herding winners | | | | | | 0.253% | 0.061% | -0.136% |
| 3 | High | Low | 744 | -18.339 | 0.847%** | 7.568%*** | 5.025%*** | 4.002%*** |
| 4 | Low | Low | 783 | 10.092*** | 0.757%** | 8.401%*** | 5.776%*** | 4.518%*** |
| **Spread** (High herding losers-Low herding losers) | | | | | | -0.833%** | -0.751%** | -0.516%** |

**Note:** Each month between January 1996 and December 2013, industries are grouped into 6 portfolios based on industry momentum and the level of herding using the past 6-month returns, respectively. Industries are defined as winner (loser) industries if their momentum returns (monthly) are above (below) the median momentum returns. Independently, industries are also sorted into top (30%), intermediate (40%) and bottom (30%) groups based on the estimated herding coefficients from Equation (3) over the most recent 6-month period. Portfolios are rebalanced monthly. 1-month, 2-months, and 3-months returns are the average monthly returns held over each subsequent period. Panels A (B) and C (D) report the findings for down and up markets, respectively. Down (up) market is defined by a negative (non-negative) market return for a given month, respectively. For brevity, the Newey and West (1987) t-statistics are not reported and are available upon request. *, ** and *** indicate significance at 10%, 5% and 1%, respectively.

**Table 7**. Return spread between winner and loser portfolios during up and down markets.

| Portfolios | Subsequent returns 1-month | 2-months | 3-months |
|---|---|---|---|
| **Panel A:** Herding measured by CSSD (**DOWN markets)** | | | |
| **Spread (**High herding winners-Low herding losers) | -0.144% | 0.200%** | 0.227%** |
| **Spread (**Low herding winners-Low herding losers) | 0.018% | 0.135% | 0.168%* |
| **Spread (**High herding winners-High herding losers) | 0.007% | 0.286%*** | 0.275%*** |
| **Spread (**Low herding winners-High herding losers) | 0.169%* | 0.221%** | 0.216%*** |
| **Panel B:** Herding measured by CSAD (**DOWN markets)** | | | |
| **Spread (**High herding winners-Low herding losers) | -0.154%* | 0.136%* | 0.241%*** |
| **Spread (**Low herding winners-Low herding losers) | -0.123% | 0.124% | 0.198%** |
| **Spread (**High herding winners-High herding losers) | -0.082% | 0.205%** | 0.206%** |
| **Spread (**Low herding winners-High herding losers) | -0.051% | 0.193%** | 0.162%** |
| **Panel C:** Herding measured by CSSD (**UP markets)** | | | |
| **Spread (**High herding winners-Low herding losers) | 0.109% | -0.030% | -0.022% |
| **Spread (**Low herding winners-Low herding losers) | -0.007% | -0.059% | 0.126% |
| **Spread (**High herding winners-High herding losers) | 0.896%*** | 0.650%*** | 0.548%*** |
| **Spread (**Low herding winners-High herding losers) | 0.780%*** | 0.621%*** | 0.606%*** |
| **Panel D:** Herding measured by CSAD (**UP markets)** | | | |
| **Spread (**High herding winners-Low herding losers) | 0.116% | -0.067% | -0.056% |
| **Spread (**Low herding winners-Low herding losers) | -0.137% | -0.128% | 0.080% |
| **Spread (**High herding winners-High herding losers) | 0.949%*** | 0.684%*** | 0.460%*** |
| **Spread (**Low herding winners-High herding losers) | 0.696%*** | 0.623%*** | 0.596%*** |

**Note:** This table reports the subsequent returns for alternative herding-based momentum strategies. Each month between January 1996 and December 2013, industries are grouped into 6 portfolios based on industry momentum and the level of herding using the past 6-month returns, respectively. Industries are defined as winner (loser) industries if their momentum returns (monthly) are above (below) the median momentum returns. Independently, industries are also sorted into top (30%), intermediate (40%) and bottom (30%) groups based on the estimated herding coefficients from Equation (3) over the most recent 6-month period. Portfolios are rebalanced monthly. 1-month, 2-months, and 3-months returns are the average monthly returns over each subsequent period. Panels A (B) and C (D) report the findings for down and up markets, respectively. Down (up) market is defined by a negative (non-negative) market return for a given month, respectively. For brevity, the Newey and West (1987) t-statistics are not reported and are available upon request. *, ** and *** indicate significance at 10%, 5% and 1%, respectively.

**Table 8**. Herding and return momentum during market crisis periods.

| Portfolio | Herding | Momentum | #of obs | Herding coefficient | Momentum return | Subsequent returns 1-month | 2-months | 3-months |
|---|---|---|---|---|---|---|---|---|
| **Panel A:** Herding measured by CSSD | | | | | | | | |
| 1 | High | Winner | 493 | -4.489*** | 4.480%*** | 2.211% | 1.922% | 1.537% |
| | | | | (-18.71) | (16.37) | (1.42) | (1.34) | (1.16) |
| 2 | Low | Winner | 531 | 41.539*** | 4.557%*** | 2.274% | 1.859% | 1.715% |
| | | | | (22.38) | (17.63) | (1.34) | (1.20) | (1.19) |
| **Spread (**High herding winners-Low herding winners) | | | | | | -0.063% | 0.064% | -0.177% |
| | | | | | | (-0.25) | (0.28) | (-0.86) |
| 3 | High | Loser | 437 | -3.637*** | 2.088%*** | 1.440% | 1.154% | 1.101% |
| | | | | (-16.56) | (7.73) | (0.90) | (0.79) | (0.81) |
| 4 | Low | Loser | 465 | 35.292*** | 2.030%*** | 1.818% | 1.571% | 1.335% |
| | | | | (19.98) | (8.18) | (1.09) | (1.03) | (0.94) |
| **Spread (**High herding losers-Low herding losers) | | | | | | -0.385% | -0.461%* | -0.279% |
| | | | | | | (-1.16) | (-1.67) | (-1.28) |
| **Panel B:** Herding measured by CSAD | | | | | | | | |
| 1 | High | Winner | 482 | -2.612*** | 4.691%*** | 2.227% | 1.829% | 1.483% |
| | | | | (-19.18) | (17.03) | (1.46) | (1.29) | (1.12) |
| 2 | Low | Winner | 521 | 14.382*** | 4.715%*** | 2.004% | 1.668% | 1.591% |
| | | | | (27.21) | (17.01) | (1.14) | (1.07) | (1.11) |
| **Spread (**High herding winners-Low herding winners) | | | | | | 0.223% | 0.160% | -0.108% |
| 3 | High | Loser | 448 | -2.004*** | 1.993%*** | 1.440% | 1.154% | 1.101% |
| | | | | (-14.90) | (7.43) | (0.90) | (0.79) | (0.81) |
| 4 | Low | Loser | 475 | 13.272*** | 1.927%*** | 1.818% | 1.571% | 1.335% |
| | | | | (24.37) | (7.83) | (1.09) | (1.03) | (0.94) |
| **Spread (**High herding losers-Low herding losers) | | | | | | -0.292% | -0.337% | -0.203% |
| | | | | | | (-0.87) | (-1.23) | (-0.91) |

**Note:** The sample period is restricted to the Asian crisis (1997.1-1998.12), the dot-com crash (2000.1-2001.12), and the recent global financial crisis (2007.1-2008.12). Each month, industries are grouped into 6 portfolios based on industry momentum and the level of herding using the past 6-month returns, respectively. Industries are defined as winner (loser) industries if their momentum returns (monthly) are above (below) the median momentum returns. Independently, industries are also sorted into top (30%), intermediate (40%) and bottom (30%) groups based on the estimated herding coefficients from Equation (3) over the most recent 6-month period. Portfolios are rebalanced monthly. 1-month, 2-months, and 3-months returns are the average monthly returns held over each subsequent period. Panels A and B report the findings for the two alternative herding measures, CSSD and CSAD, respectively. The Newey and West (1987) t-statistics are reported in parentheses and *, ** and *** indicate significance at 10%, 5% and 1%, respectively.

**Table 9**. Return spread between winner and loser portfolios: Market crisis periods

| Portfolios | Subsequent returns | | |
|---|---|---|---|
| | 1-month | 2-months | 3-months |
| **Panel A:** Herding measured by CSSD | | | |
| **Spread (**High herding winners-Low herding losers) | 0.406% | 0.330% | 0.184% |
| | (1.22) | (1.16) | (0.75) |
| **Spread (**Low herding winners-Low herding losers) | 0.456 | 0.288 | 0.380 |
| | (1.33) | (0.92) | (1.30) |
| **Spread (**High herding winners-High herding losers) | 0.771%*** | 0.768%*** | 0.436%*** |
| | (7.43) | (8.07) | (4.94) |
| **Spread (**Low herding winners-High herding losers) | 0.834** | 0.705 | 0.614** |
| | (2.48) | (1.11) | (2.15) |
| **Panel B:** Herding measured by CSAD | | | |
| **Spread (**High herding winners-Low herding losers) | 0.589%* | 0.371% | 0.229% |
| | (1.72) | (1.19) | (0.86) |
| **Spread (**Low herding winners-Low herding losers) | 0.388 | 0.252 | 0.389 |
| | (1.11) | (0.80) | (1.34) |
| **Spread (**High herding winners-High herding losers) | 0.835%*** | 0.646%*** | 0.372%*** |
| | (8.18) | (6.84) | (4.20) |
| **Spread (**Low herding winners-High herding losers) | 0.612* | 0.485 | 0.480* |
| | (1.79) | (1.57) | (1.68) |

**Note:** The sample period is restricted to the Asian crisis (1997.1-1998.12), the dot-com crash (2000.1-2001.12), and the recent global financial crisis (2007.1-2008.12). Each month, industries are grouped into 6 portfolios based on industry momentum and the level of herding using the past 6-month returns, respectively. Industries are defined as winner (loser) industries if their momentum returns (monthly) are above (below) the median momentum returns. Industries are also sorted into top (30%), intermediate (40%) and bottom (30%) groups based on the estimated herding coefficients from Equation (3) over the most recent 6-month period. Portfolios are rebalanced monthly. 1-month, 2-months, and 3-months returns are the spread between the average monthly returns to winner and loser industries over the subsequent 1, 2, and 3 months. Panels A and B report the findings for the two alternative herding measures, CSSD and CSAD, respectively. The Newey and West (1987) t-statistics are reported in parentheses and *, ** and *** indicate significance at 10%, 5% and 1%, respectively.

**Table 10**. Excess returns from the herding-based momentum strategy over the plain-vanilla momentum strategy during market crisis periods.

| Herding-based momentum portfolios | **Excess returns over the plain-vanilla industry momentum strategy** | | |
|---|---|---|---|
| | 1-month | 2-months | 3-months |
| **Panel A:** Herding measured by CSSD | | | |
| High herding winners-Low herding losers | 0.031%<br>(0.63) | 0.250%***<br>(5.75) | -0.107%***<br>(-3.59) |
| Low herding winners-Low herding losers | 0.081%<br>(1.61) | 0.208%***<br>(4.51) | 0.089%**<br>(2.05) |
| High herding winners-High herding losers | 0.396***<br>(12.20) | 0.688%***<br>(23.00) | 0.145%***<br>(5.11) |
| Low herding winners-High herding losers | 0.459%***<br>(9.23) | 0.625%***<br>(7.83) | 0.323%***<br>(7.55) |
| **Panel B:** Herding measured by CSAD | | | |
| High herding winners-Low herding losers | 0.214%***<br>(4.25) | 0.291%***<br>(6.32) | -0.062%<br>(-1.51) |
| Low herding winners-Low herding losers | 0.013%<br>(0.25) | 0.172%***<br>(3.71) | 0.098%**<br>(2.27) |
| High herding winners-High herding losers | 0.460%<br>(14.21) | 0.566%***<br>(18.94) | 0.081%***<br>(2.86) |
| Low herding winners-High herding losers | 0.237%***<br>(4.71) | 0.405%***<br>(8.85) | 0.189%***<br>(4.42) |

**Note:** This table reports the excess subsequent returns offered by each herding-based momentum strategy (Table 9) over the plain-vanilla industry momentum strategy (Table 2) during market crisis periods. Market crisis periods include the Asian crisis (1997.1-1998.12), the dot-com crash (2000.1-2001.12), and the recent global financial crisis (2007.1-2008.12). Panels A and B report the findings for the two alternative herding measures, CSSD and CSAD, respectively. The Newey and West (1987) t-statistics are reported in parentheses and *, ** and *** indicate significance at 10%, 5% and 1%, respectively.