Industry herding and the profitability of momentum strategies during market crises

Rıza Demirer[†], Huacheng Zhang*

Abstract

The degree of industry herding is significantly related to the subsequent performance of winner and loser industries. While the herding effect on losers can be explained by investors' tendency to herd on negative information, the herding effect on winners reflects institutional demand for overpriced securities. An alternative momentum strategy based on the degree of herding within an industry significantly outperforms the conventional industry momentum strategy over the subsequent 1, 3, 6 and 12 months. The findings suggest that behavioral patterns could be utilized to generate enhanced momentum profits, even during market stress periods when the conventional momentum strategy performs poorly.

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[†] **Corresponding author:** Riza Demirer. Department of Economics and Finance, Southern Illinois University Edwardsville, Edwardsville, IL 62026-1102. E-mail: rdemire@siue.edu; Tel: 618-650-2939; Fax: 1-618-650-3047.

[*] Institute of Financial Studies, Southwestern University of Finance and Economics, Chengdu 610074, China

1. Introduction

A number of studies in the literature suggest a possible link between investor herding and return momentum (or reversal).[1] However, despite the extensive literature on the presence of herd behavior in financial markets, whether the herding phenomenon impacts return momentum is still understudied, particularly in the context of the profitability of momentum strategies. In this paper, we explore whether the level of herding in a market could be exploited to improve the effectiveness of momentum strategies even during periods when the conventional momentum strategy is not profitable. Motivated by the findings that herd formation would be more likely to occur at the industry level rather than stock level (e.g. Lang and Lundholm, 1996; Bikhchandani and Sharma, 2001; and Choi and Sias, 2009), this study examines the relationship between the level of herding in an industry and return momentum.[2] We also test whether this relationship is economically significant for investors by examining whether a herding-based industry momentum strategy delivers enhanced profits compared to the conventional momentum strategy of buying past winner and selling past loser industries. Finally, inspired by the recent research suggesting that the conventional momentum strategy performs poorly during periods of market stress (Daniel and Moskowitz, 2013; Kadan and Liu, 2014; Barroso and Santa-Clara, 2015), we examine whether the herding-based momentum strategy yields desirable outcomes even during alternative market stress periods characterized by high market volatility, market losses or high momentum volatility.

Following the herding test developed by Chang et al. (2000) and assigning each qualified CRSP stock to one of 49 Fama and French industries, we estimate the herding level

[1] See, for example, Nofsinger, Sias (1999), Sias (2004) Dasgupta et al. (2011), Brown et al. (2014), Singh (2013) and Celiker et al. (2015).

[2] Moskowitz and Grinblatt (1999), Swinkles (2002), Pan et al. (2004), Du and Denning (2005), Nijman et al. (2005) and Celiker et al., (2015) show that industry momentum is a significant determinant of profitability in momentum strategies.

for each industry each month between 1964 and 2013. We then form portfolios of winner and loser industries characterized by high and low degree of herding based on the estimated herding coefficients and evaluate the performance of the industry portfolios in subsequent months to examine the relationship between industry herding and return momentum. The empirical results suggest that the degree of herding within an industry has a significant effect on return momentum. The herding effect is particularly significant for past loser industries regardless of the formation period used to identify loser industries. For example, loser industries with high level of herding significantly outperform loser industries with low herding by 0.15% over the subsequent month and 1.04% over the next twelve months. The spread in subsequent returns between high and low herding loser industries becomes significantly high during market crisis periods, jumping to 0.91% in the subsequent month, amounting to 4.58% over the subsequent twelve month period, all significant at one percent level.

Examining the profits from zero-cost momentum portfolios, we find that exploiting the effect of herding on industry momentum strategies can yield economically significant outcomes as well. An alternative momentum strategy that takes into account the degree of herding in an industry significantly outperforms the conventional industry momentum strategy over all subsequent periods and this superior performance is robust to alternative formation periods and adjustment to Fama-French risk factors. These findings extend the evidence by Nofsinger and Sias (1999) and Sias (2004) who examine herding among institutional investors in the U.S. and find that asset returns follow the direction of the herd, resulting in return momentum. Our findings also support the recent evidence by Celiker et al. (2015) that industry momentum is related to herding by mutual funds and extend it by devising a herding-based momentum strategy that yields significant profits compared to the conventional momentum strategy.

By examining the effect of herding on industry momentum during crisis periods, this study also provides insight to the recent evidence on the presence of momentum crashes (Daniel and Moskowitz, 2013) and that the momentum strategy performs poorly following periods of market declines (Cooper et al., 2004; Kadan and Liu, 2014; Barroso and Santa-Clara, 2015) and following periods of increased market volatility (Wang and Xu, 2015). Focusing on periods of market crisis and alternative market stress periods during which the conventional momentum strategy is found to perform poorly, we find that the herding-based momentum strategy delivers significant and positive returns, implying that momentum can still work during periods of market stress. Examining the crash periods that correspond to the tech bubble of 2000-2002 and the credit crunch of 2007-2009, the herding-based momentum strategy is found to yield excess returns over the conventional momentum strategy that can be as high as 0.48%, 0.78%, 1.65%, and 3.53% over the subsequent 1, 3, 6 and 12 months, respectively. The superior performance of the herding-based momentum strategy is robust to alternative formation and holding periods as well as adjustment to risk factors. Finally, we observe that the herding-based momentum strategy yields positive and significant profits during periods of market stress, regardless of whether market stress is defined in terms of market returns, market volatility or the volatility of momentum.

The relevance of industry herding in the profitability of momentum strategies irrespective of how market stress is defined suggests that the herding effect is not subsumed by the conditional variables that can be used to describe crisis periods. Furthermore, the superior performance of the herding-based momentum strategy even during alternative panic states (Daniel and Moskowitz, 2013) suggests that investor herding could be exploited even during periods when the conventional momentum strategy fails. To that end, the findings provide an interesting opening to how behavioral patterns, particularly during distressed market periods, can potentially be exploited in profitable investment strategies even when conventional strategies do not work. An outline of the remainder of the paper is as follows. Section 2 provides data description and the procedure to construct industry portfolios based on past performance and the level of herding. Section 3 presents empirical results and Section 4 concludes the paper.

2. Data and Methodology

2.1 Data

The data consists of individual stock returns for all ordinary shares obtained from the Center for Research and Security Prices (CRSP) from January 1964 through December 2013. Following the industry definitions by Fama and French obtained from Kenneth French's website and the industry codes (SIC, Standard Industrial Codes) obtained from CRSP, we assign each stock to one of 49 Fama and French industries in each month.[3] Following the convention in the literature, we exclude the smallest 20% stocks to mitigate the effect of small, inactive stocks and further require at least 5 individual stocks in each industry each month and at least 20 industries in each month. We end up with 5,895 unique stocks, 49 industries and 28,937 industry-month observations summarized in Table 1. Daily returns are used in the estimation of herding coefficients as will be described in the next section. All subsequent calculations for momentum portfolios are performed using monthly returns.

2.2 Methodology

2.2.1 Detecting Herd Behavior

There is a large literature on herding behavior in financial markets offering several alternative methodologies to test the presence of herding. Earlier studies including Lakonishok et al. (1992) and Sias (2004) focus on asset holdings and conduct herding tests based on the changes in asset positions across investors. The methodology by Lakonishok et

[3] Fama-French industry definitions are available on Kenneth French's website: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

al. (1992) utilizes a measure of the simultaneous investor demand for underlying assets whereas Sias (2004) focuses on the cross-sectional autocorrelation of institutional demand.[4] These herding measures have been utilized in several applications to advanced markets for which investors' holding information is readily available, typically on a quarterly basis. We skip this procedure due to lack of database availability.

The herding tests by Christie and Huang (1995) and Chang et al. (2000), on the other hand, utilize return data that is easily accessible and available at a higher frequency. Specifically, these studies examine the relationship between market movements and the cross-sectional behavior of asset returns and make inferences on the possible presence of herding behavior in the market accordingly. Christie and Huang (1995) examine the cross-sectional standard deviation of stock returns during periods of large price movements in herding tests. Noting that cross-sectional return dispersion could be also driven by the covariance between the returns on individual assets and the market, rather than herding, Chang et al. (2000) later propose an improved model that incorporates a non-linear term that controls for market movements. Specifically, Chang et al. (2000) propose the cross-sectional absolute deviation (CSAD) of security returns expressed as

$$CSAD_t = \frac{1}{n}\sum_{i=1}^{n} | R_{i,t} - R_{m,t} | \tag{1}$$

where n is the number of firms in the portfolio, $R_{i,t}$ is the return on firm i at time t and $R_{m,t}$ is the cross-sectional average of n stock returns in the portfolio at time t. Noting that investor herding would lead firm returns to display greater directional similarity, particularly during periods of large price movements, Chang et al. (2000) propose the following quadratic model to conduct herding tests

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

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

where a significant and negative estimate for $_2$ is used as support for the presence of herding. This testing methodology has since been utilized extensively in numerous studies including Chiang and Zheng (2010) on global stock markets, Lee et al. (2013) on Chinese industries, and Demirer et al. (2014) on the market for American Depository Receipts, among others.

As the herding test in Equation (2) is based on the coefficient of the non-linear term, we focus on the herding coefficient ($_2$) as a proxy for the level of herding in an industry so that increasingly negative values for the herding coefficient indicate higher degree of herding in the industry. This indicates that firms in the industry display greater directional similarity in their returns during periods of large price movements in the industry, even after controlling for the common market factor. As described in the next section, this herding coefficient forms the basis for identifying industries with high and low degree of herding.

It must be noted that compared with the asset holding based herding measures, the return dispersion based tests may suffer from higher biases because this approach interprets deviations from theoretical asset pricing models in the context of herding. To that end, the herding coefficient described earlier may be driven by possible model specification bias rather than herding. Nevertheless, following Chiang and Zheng (2010), we use a modified version of the return dispersion specification in Chang et al. (2000) which does not require the estimation of beta and thus avoids the possible specification error associated with the CAPM. Furthermore, our empirical tests yield consistent findings for both Christie and Huang (1995) and Chang et al. (2000) return dispersion measures as well as for alternative market stress conditions considered in robustness tests, providing support for the robustness of the inferences from the herding tests utilized in this study. In sum, both holding and return dispersion based herding measures are similar in spirit as they both make inferences on herding by comparing what can be expected in a market where herding is present with rational or theoretical expectations and develop testing methodologies accordingly.

2.2.2 Construction of Industry Portfolios

As explained earlier, we first assign each stock into one of 49 Fama-French industries listed in Table 1. In order to examine the evidence for the long-, intermediate- and short-term effects, we consider several (F, H) momentum strategies based on alternative formation (F) and holding (H) periods. At the end of each month, we sort industries into two portfolios, i.e. winner and loser industries, based on their average monthly returns over the previous F months (3, 6, and 12 months).[5] Industries are defined as winner (loser) industries if their formation period returns are above (below) the median formation period return across the industries. The self-financing portfolio that is long (short) in winner (loser) industries is then held over the subsequent H months (1, 3, 6, and 12 months) and cumulative subsequent returns are recorded accordingly.

A number of papers in the literature skip the most recent month's return in the calculation of momentum returns in order to mitigate the problems associated with microstructure issues (e.g. Jegadeesh, 1990; Boudoukh et al., 1994; Asness, 1994; Grinblatt and Moskowitz, 2004). On the other hand, other studies include the most recent month in their calculation of momentum returns (e.g. Moskowitz and Grinblatt, 1999; Jegadeesh and Titman, 1993; Liu et al. 2011). Du and Denning (2005) use both methods to calculate momentum returns and find that skipping a month between the formation and holding periods can increase momentum profits for individual stocks, but not substantially for industry portfolios. In this study, we follow the industry momentum literature and present our analysis without placing a gap between formation and holding periods. However, it must be noted that both methods yield similar results as Du and Denning (2005) document and the additional results are available upon request.

[5] We avoid the 1-month formation period in order to allow sufficient number of observations for the subsequent estimation of the herding coefficients.

Having identified winner/loser industries each month, independently, we estimate Equation (2) for each industry using daily data over each alternative formation period (F) explained earlier. This procedure yields the herding coefficient $_2$ for each industry each month. Industries are then sorted into top (30%) and bottom (30%) groups based on the estimated herding coefficients indicating the degree of herding in each industry. Considering that lower negative values for the herding coefficient indicate higher level of herding, we finally classify industries in the top (bottom) 30% as low (high) herding industries. This double-sorting procedure yields industry portfolios each month sorted on their formation returns and the level of herding, i.e. winner/loser industries with high/low degree of herding.

A similar procedure is recently applied in Demirer et al. (2015) who focus on short-term momentum and reversal effects and find evidence of a significant herding effect on the short-run performance of momentum strategies in the Chinese stock market. However, the findings in that study may suffer from small sample bias due to the limited number of industries in the Chinese market and the short sample period available for that market.[6] Furthermore, Demirer et al. (2015) examine short-term momentum payoffs in their analysis and their findings may be limited to the particular formation and holding periods used in the analysis. In contrast, we examine a wide range of momentum strategies based on alternative formation and holding periods and thus provide a more comprehensive insight to the relationship between herding and momentum in stock markets. We also provide additional robustness checks by examining the performance of alternative strategies after adjusting for market and firm-level risk factors as well as during alternative market stress periods suggested in the literature. In a similar application to the U.S. market, Yan et al. (2012) use the normalized value of the return dispersion measure in Equation (1) in order to determine the level of herding in an industry.

[6] The findings by Demirer et al. (2015) may also be biased by small stocks included in the sample. In contrast, we mitigate possible size and liquidity effects by excluding the smallest 20% of stocks based on market capitalization.

In contrast, we determine the level of herding in a manner that is more consistent with respect to the testing methodologies proposed by Christie and Huang (1995) and Chang et al. (2000) as herding is implied by the pattern of return dispersion during large price movements and not the actual value of return dispersion.[7]

3. Empirical Results

3.1 Descriptive Statistics

Table 1 presents several descriptive statistics for the 49 industries used in the study. Oil (petroleum and natural gas) industry dominates the market value, accounting for 10.51% of the total stock market capitalization. Trading (financials), on the other hand, has the largest number of firms among the 49 industries with 892 firms. The time-series averages of monthly industry returns range between a low of 0.72% for agriculture and a high of 1.78% for the defense industry. Computer software industry is also among the top performing industries with an average monthly return of 1.71%.

Examining the time-series averages of monthly cross-sectional absolute deviation values described in Equation (1), we observe that technology driven computer software and hardware and electronic equipment industries experience the highest dispersion in firm returns with average CSAD values of 2.30%, 2.07%, and 2.05%, respectively. It is possible that the technological shifts in these industries drive much of the cross-sectional variability across firm level returns. Interestingly, gold stocks exhibit high degree of cross-sectional dispersion in firm-level returns as well with an average CSAD value of 2.35%. Not surprisingly, the heavily regulated utilities industry is characterized by the lowest level of return dispersion (1.10%), implying relatively stronger directional similarity in firm returns within this industry.

[7] Chang et al. (2000) also note that CSAD is not a measure of herding, instead the relationship between CSAD and market return is used to make inferences on the presence of herding.

3.2 The Profitability of the Conventional Industry Momentum Strategy

Table 2 presents the subsequent returns of winner and loser industries and the profits from buying past winner and selling past loser industries, termed the conventional industry momentum strategy hereafter. As explained earlier, we consider alternative portfolio formation periods (*F*) ranging between 3 and 12 months. At the end of each month between January 1964 and December 2013, industries are sorted into portfolios based on their formation period returns over the past *F*-month period (i.e. months *t* through *t-F+1*). Industries are then defined as winner (loser) industries if their formation period returns (monthly) are above (below) the median formation period return. Similarly, we consider alternative holding periods (*H*) and calculate the cumulative returns for winner and loser industries over the subsequent *H*-months, (i.e. months *t+1* through *t+H*). The Newey and West (1987) standard errors with three lags are reported in parentheses. The calculation of returns and associated standard errors for the zero-investment momentum strategy follows Grundy and Martin (2011).

The results based on the whole sample period are reported in Panel A and support the presence of industry momentum indicated by a positive and statistically significant return spread between winner and loser industry portfolios. For example, winner industries over the past six months deliver a cumulative return of 1.56%, 4.49%, 8.75%, and 16.9% over the next 1, 3, 6, and 12 months, respectively, and significantly outperform past loser industries by 0.63%, 1.50%, 2.50% and 3.81%. We observe that the superior performance of past winner industries over past loser industries is robust to the formation period.

Panel B presents the findings for market crisis periods. Following Brunnermeier et al. (2004) and Fahlenbrach et al. (2012), we focus on two major crisis periods experienced in the U.S., i.e. the tech bubble (March 2000– December 2002) and the credit crunch (June 2007– December 2009) that correspond to a subsample of 65 months. In an early study, Cooper et al.

(2004) differentiate up and down market states and find that down market states are associated with lower momentum profits. Similarly, Kadan and Liu (2014) document that investment strategies based on market anomalies, including momentum, lose their appeal when high moments and rare events are taken into consideration. More recently, Wang and Xu (2015) establish a link between market volatility and the performance of momentum strategies and find that the momentum strategy performs poorly following periods of increased market volatility. Consistent with these studies, the results reported in Panel B suggest that the conventional industry momentum strategy is largely unprofitable during market crisis periods, implied by insignificant or negative return spreads in subsequent months between winner and loser industries.

3.3 The Effect of Herding on Industry Momentum

Having established preliminary evidence on industry momentum, we next examine the effect of industry herding on momentum. Similar to the procedure followed to identify winner and loser industries, we use daily return data over alternative formation periods (*F*) and estimate the herding coefficient ($_2$) for each industry using Equation (2). At the end of each month *t*, industries are sorted into top (30%), intermediate (40%) and bottom (30%) groups based on the herding coefficients in Equation (2) estimated over the previous *F*-month period. We then divide winner and loser industries into high and low herding groups, respectively, and record each sub-portfolio's performance by calculating its equally-weighted industry portfolio return over the subsequent *H*-month period. We repeat this procedure throughout the whole sample period. Table 3 presents the statistics for winner and loser industry portfolios with high and low degree of herding, the corresponding cumulative returns over the subsequent 1, 3, 6 and 12 months, and the difference in cumulative returns between high and low herding industry portfolios.

The empirical results in Table 3 suggest that, in general, winner industries with high degree of herding experience greater formation period returns compared to winner industries with low degree of herding, while high herding losers have greater losses during the formation period compared to low herding loser industries. For example, considering the three-month formation period, the formation period return for high herding loser industries is -2.04% compared to -1.87% for low herding loser industries. Similarly, the formation period return for high herding winner industries is 9.86% compared to 8.74% for low herding winners. This finding suggests that higher level of herding is associated with greater formation period gains (losses) for winner (loser) industries, possibly exacerbating gains and losses in winner and loser industries, respectively.

Interestingly, we observe in Table 3 that high herding loser industries consistently outperform low herding loser industries in all subsequent periods regardless of the length of the formation period used to form the portfolios. For example, examining loser industries over the past six-month period, we see that the spread in cumulative returns between high and low herding loser industries is 0.15%, 0.38%, 0.77% and 1.04% over subsequent 1, 3, 6 and 12 months, respectively. Considering the earlier finding that high herding loser industries have lower past returns compared to low herding losers, the subsequent superior performance of high herding loser industries suggests that herding drives prices in these industries away from fundamental values during periods of negative information, thus leading to larger subsequent gains during the holding period, further implying that herding contributes to price volatility, particularly during periods of negative information. The herding effect on loser industries is in fact consistent with the finding by 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. To that end, our herding-based analysis quantifies the economic impact of this tendency to herd on negative information by relating it to the subsequent performance of high and low herding industries.[8]

On the other hand, we observe that the effect of herding on winner industries is confined to short holding periods only. We find that high herding winner industries underperform low herding winners for holding periods up to 3 months. For example, for all formation periods considered, we see that winner industries with high degree of herding yield significantly lower returns than low herding winners during the next 1 to 3 month periods. However, this pattern reverses for longer holding periods with high herding winner industries outperforming low herding winners for longer holding periods. In a recent study, Edelen et al. (2016) find that institutions have a strong tendency to buy stocks classified as overvalued and that these stocks experience negative abnormal returns subsequently. To that end, it can be argued that the short-run underperformance of high herding winner industries is related to the institutional demand for winner industries that is captured by the level of herding. Overall, the findings indicate a significant herding effect on the subsequent performance of winner and loser industries, with a more prevalent and consistent effect observed in the case of losers.

The herding effect on subsequent returns presented in Table 3 may not be pervasive if the high and low herding groups are persistently clustered with particular industries. In other words, if high or low herding industry portfolios are consistently populated by certain industries, then the patterns observed in Table 3 would in fact be a manifestation of the industry effect and not due to the level of herding. To address this concern, we report in Panel A of Table 4 the percentage of periods for each industry during which the industry is classified as high or low herding over the whole sample period. The findings in Panel A Table 4 yield no evident pattern in the type of industries that would consistently be characterized by high or low herding, implying that the cluster concern is not severe in our analysis. We

[8] Similar, although somewhat weaker, results are observed when herding is measured using the cross-sectional standard deviation of returns along the lines of Christie and Huang (1995). These results are available upon request. We attribute the superior performance of the Chang et al. (2000) herding measure to the non-linear specification that corrects the bias in the Christie and Huang (1995) methodology. A comparison of these herding models is provided in Demirer et al. (2010).

observe a somewhat different pattern for market crisis periods (Panel B) when several industries including Entertainment, Rubber & Plastic Products and Real Estate fall into the high herding category around 60% of the time. Nevertheless, the findings in Table 4 suggest significant variation in the rank order of the herding level estimates over time and that the herding effect is not confined to particular industries. This implies that the observed return spread between industry portfolios across the high and low herding levels is indeed driven by the degree of herding in those industries and not a manifestation of particular industries falling consistently into a particular herding category.

3.4 The Profitability of Herding-Based Industry Momentum Strategies

Given the evidence of a significant herding effect on the subsequent performance of past winner and loser industries, we next direct our attention to examine the economic significance of this effect on the profitability of zero-cost industry momentum strategies and how it relates to the conventional industry momentum strategy. 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 performance in subsequent months. We consider alternative short-long portfolios based on the level of herding in industries. Panel A in Table 5 reports the mean cumulative returns for alternative holding periods along with the Newey and West (1987) standard errors (in parentheses). Consistent with the findings for the conventional industry momentum strategy reported in Table 2 (Panel A), we observe that all herding-based industry momentum portfolios yield positive and highly significant subsequent returns over the short and long holding periods.

Comparing alternative herding-based short-long portfolios, however, we observe higher subsequent returns when the short position is taken in loser industries with low degree of herding. Regardless of the level of herding for the winner industries in the long position, taking a short position in low herding loser industries consistently yields the highest subsequent returns in each case. This finding suggests that the level of herding could in fact be used to enhance the performance of industry momentum strategies. For example, in the case of the three-month formation period (*F*=3), the strategy of buying low herding winners and selling low herding losers yields 0.79%, 1.84%, 2.52% and 4.09% over the subsequent 1-, 3-, 6- and 12-month periods while the corresponding conventional momentum strategy (reported in Table 2, Panel A) yields 0.67%, 1.48%, 2.21% and 3.75% over the same holding periods. At the same time, the strategy of buying high herding winners and selling high herding losers yields much lower subsequent returns of 0.56%, 1.23%, 1.87% and 3.59%, suggesting that the level of herding in winner and loser industry portfolios could potentially be utilized to enhance the performance of momentum strategies.

In order to examine whether the herding-based industry momentum strategy indeed improves the conventional industry momentum strategy, we report in Panel B in Table 5 the mean excess returns for alternative herding-based momentum strategies over the corresponding conventional strategy presented in Table 2 (Panel A). Consistent with the findings in Panel A in Table 5, the herding-based momentum strategy that involves selling low herding loser industries significantly outperforms the conventional industry momentum strategy, implied by positive and highly significant excess returns observed across all subsequent periods. For example, considering the three-month formation period (*F*=3), the herding-based momentum strategy with a long position in high herding winner industries and short position in low herding loser industries yields 0.73% excess cumulative return over the next 12 months over the conventional momentum strategy of taking a long position in winner and a short position in loser industries. On the other hand, the herding-based momentum strategies that involve selling high herding loser industries significantly underperform the corresponding conventional strategy presented in Table 2 (Panel A).

It may be argued that the superior returns delivered by the herding-based momentum strategy are largely driven by higher systematic risk associated with the herding-based portfolios. For this reason, following Jegadeesh and Titman (2001), we report in Table 6 the Fama and French (1993) alphas for the herding-based and conventional momentum strategies as well as the difference in risk-adjusted returns from these strategies.[9] Following the findings in Table 5, we only report in Table 6 the risk-adjusted returns for the best performing herding-based strategies that involve selling low herding loser industries. The corresponding Newey-West standard errors are reported in parentheses.

The comparison of risk-adjusted returns in Table 6 suggests that the superior performance of the herding-based momentum strategy is robust to risk adjustment implied by highly significant and positive spreads in estimated Fama-French alphas, suggesting that the higher returns delivered by the herding-based momentum strategy is not a manifestation of greater risk undertaken by this strategy. Regardless of the formation period used to form the momentum portfolios, the herding-based momentum strategy yields significantly higher risk-adjusted returns compared to the conventional momentum strategy. For example, considering the twelve-month formation period, the strategy of buying low herding winners and selling low herding losers delivers highly significant Fama-French alphas of 0.74%, 0.57%, 0.42%, and 0.23% per month over the subsequent 1, 3, 6 and 12 months, respectively. These risk-adjusted returns are significantly higher than those from the corresponding conventional momentum strategy by 10, 8, 6 and 4 basis points per month or equivalently 1.20%, 0.96%, 0.72% and 0.48% per year. Overall, the findings clearly suggest that the level of herding in an industry could indeed be exploited in order to generate improved momentum profits relative to the conventional momentum strategy. As will be reported later, we observe that the excess returns from the herding-based momentum strategy over the conventional alternative become significantly high during market crisis periods, suggesting that the herding effect on return

[9] We observe qualitatively similar results for CAPM-alphas. These results are not reported for brevity and are available upon request.

momentum is particularly significant during periods of market stress.

3.5 Market Crisis Periods

A number of studies in the literature suggest that herding behavior would be more prevalent during periods of increased market uncertainty or periods of large market movements (e.g. Christie and Huang, 1995; Bikhchandani and Sharma, 2001). On the other hand, Demirer et al. (2010) suggest that herding would have greater impact on stock returns during periods of market losses. It can therefore be argued that the herding effect on return momentum or reversals would be more pronounced during market crisis periods and that such an effect could be exploited to make the momentum strategy work even during market crisis periods. Note that the findings reported in Panel B of Table 2 suggest that the conventional industry momentum strategy performs poorly during market crisis periods, consistent with the evidence in Daniel et al. (2012), Kadan and Liu (2014), Barroso and Santa-Clara (2015) and Wang and Xu (2015). For this purpose, we replicate the analysis by focusing on the market crisis periods that correspond to the tech bubble (March 2000–December 2002) and the credit crunch (June 2007–December 2009).

Table 7 presents the empirical findings for market crisis periods. We observe that past loser industries with high degree of herding significantly outperform past losers with low degree of herding, suggesting that the effect of herding on loser industries is also present during periods of market crisis. Considering the six-month formation period, high herding loser industries significantly outperform low herding losers by 0.91%, 2.16%, 3.03% and 4.58% over the subsequent 1, 3, 6, and 12 months, respectively. It is worth mentioning that the spread in subsequent returns for high and low herding loser industries are significantly higher during market crisis periods compared to the corresponding spread values of 0.15%, 0.38%, 0.77%, and 1.04% observed for the whole sample (reported in Table 3). It can therefore be argued that herding plays a particularly significant role in the subsequent performance of past loser industries during market crisis periods, leading to a significant positive spread in subsequent returns between high and low herding loser industries. On the other hand, we observe mixed effects on winner industries although past winners with high degree of herding generally outperform past winners with low degree of herding. Overall, the analysis for market crisis periods suggests that industry herding plays a significant role in the subsequent performance of winner and loser industries during market crisis periods, particularly in the case of past loser industries, consistent with the suggestion by Brown et al. (2014) that fund managers have a greater tendency to herd on negative stock information.

Having established the presence of the herding effect during market crisis periods, we report in Table 8 (Panel A) the profits from alternative herding-based industry momentum strategies during crisis periods. Unlike the conventional momentum strategy that is unprofitable during market crisis periods (Table 2 Panel B), the herding-based momentum strategy that involves selling low herding loser industries generates significantly positive subsequent returns, regardless of the formation period used to form the zero-cost momentum portfolios. Considering the six-month formation period ($F=6$) for example, taking a long position in high herding winners and short position in low herding losers yields significant subsequent returns up to 6 months with 0.57%, 1.54%, 2.23% over the next 1, 3, and 6 months, respectively. The superior performance of the herding-based momentum strategy is further supported by significant and positive excess returns over the conventional momentum strategy reported in Panel B of Table 8. For example, considering again the six-month formation period, the strategy of buying high herding winners and selling low herding losers yields excess returns (over the conventional momentum strategy) of 0.28%, 1.06%, 2.37% and 2.66% over the subsequent 1, 3, 6 and 12 months, respectively, all significant at one percent level.

Further examining the risk-adjusted returns reported in Table 9, we see that the herding-based industry momentum strategy yields significant and positive Fama-French alphas while the conventional momentum strategy delivers negative and statistically insignificant risk-adjusted returns in most cases. On the other hand, the herding-based momentum strategies that involve selling low herding losers deliver positive and significant risk-adjusted returns regardless of the formation period considered. It must be noted, however, that although the difference in the estimated alphas between the herding-based and conventional strategies is positive and statistically significant in most cases, we observe several insignificant or negative alpha spread values particularly in the case of the three-month formation period. This is mainly driven by the high values of alpha estimates, although statistically insignificant, from the conventional momentum strategy and should not weaken our conclusions regarding the profitability of the herding-based momentum strategy. Overall, the findings clearly suggest that the herding-based industry momentum strategy could indeed be used to generate significant profits even during market crisis periods when the conventional momentum strategy does not work. Once again, these findings are robust to alternative formation periods used to construct the self-financing momentum portfolios as well as to adjustment to risk factors.

3.6 Robustness checks with alternative market stress periods

The findings for market crisis periods presented in Section 3.5 provide an interesting opening in the light of the recent evidence suggesting that the conventional momentum strategy may fail during periods of high market volatility (Wang and Xu, 2015), high momentum volatility (Barrosso and Santa-Clara, 2015), or during periods of large market losses (Cooper, et al, 2004). In a related study, Daniel and Moskowitz (2013) document the presence of momentum crashes and argue that strong and persistent strings of negative momentum returns occur during panic states following high market volatility or market losses.

It is thus interesting to check the robustness of the superior performance of the herding-based momentum strategy, particularly during alternative market crisis periods suggested in these studies. This also allows us to examine whether the herding-based strategy could be implemented using predefined criteria to identify market stress periods since the crisis period analysis presented in Section 3.5 assumes that the investor knows that the market is in crisis state, which is often hard to determine ex-ante.

In alternative definitions of market stress periods suggested in the literature, Daniel and Moskowitz (2013) and Cooper et al. (2004) define DOWN markets as periods when the lagged three-year market return is negative. Focusing on market volatility, Wang and Xu (2015) identify HIGH volatility periods as months when the lagged 12-month market volatility is larger than the lagged 36-month market volatility. Barroso and Santa-Clara (2015), on the other hand, focus on the volatility of momentum, defined as the realized variance of daily momentum returns in a given month, and identify HIGH momentum volatility periods when the momentum volatility for the month is higher than the volatility of the CRSP value-weighted daily index returns in the previous six months.

Table 10 presents the raw returns (Panel A) and the risk-adjusted returns (Panel B) from the *best performing* herding-based industry momentum strategies documented in Table 8 during the above mentioned alternative market stress periods.[10] Consistent with the findings reported in Tables 5 and 8, we observe that the herding-based industry momentum strategy yields positive and significant profits in all alternative market stress periods, regardless of whether the market state is defined in terms of market returns, volatility or the volatility of momentum. Once again, the positive returns are robust to adjustment to the Fama-French risk factors (Panel B). This finding implies that the momentum crashes during panic states documented by Daniel and Moskowitz (2013) could be avoided by considering the herding

[10] For brevity, the table reports the findings for the herding-based strategy for the 12-month formation period only and the findings for the 3- and 6-month formation periods are available upon request.

effect in the formation of the momentum strategy. Furthermore, the relevance of the herding level in our tests regardless of the conditioning variable used to define market stress periods suggests that the herding effect is not subsumed by the conditional variables suggested in the literature. Nevertheless, the significant returns reported in Table 10 suggest that considering the level of herding in an industry can indeed be utilized to improve the profitability of industry momentum strategies, even during panic states when momentum crashes are documented to occur.

It can be argued that the superior performance of the herding-based momentum strategy over the conventional alternative, particularly during market crisis periods, is partially due to the poor performance of the conventional momentum strategy during such periods as shown in Daniel and Moskowitz (2013). However, the evidence in Tables 8 and 9 combined with the robustness checks presented in Table 10 imply that the presence of industry herding, particularly prevalent during market crisis periods, is the main factor driving the superior performance of the herding-based strategy. The stronger herding effect on the profitability of momentum strategies particularly during periods of market stress, is consistent with the theories on herding behavior that investors would have a greater tendency to herd during such periods (e.g. Bikhchandani and Sharma, 2001), thus leading to a greater effect on the subsequent performance of past winner and loser industries.

The findings for market crisis periods are also consistent with the information externality exploitation argument (e.g. Bikhchandani et al., 1992; Froot et al. 1992) that successor investors may ignore their own private information when the inferred information from predecessor investors is believed to be superior. The finding of a consistent herding effect particularly in the case of loser industries and more prevalently during market crisis periods suggests that investors would have a greater tendency to use such inferred information during periods when they face greater uncertainty and during periods of negative market information. This is also in line with the theoretical argument that herding behavior could be rational as investors are able to enjoy the information externality from other investors' trading behavior. Nevertheless, the findings reported in this study extend the theories of herding behavior in a new direction and show that such behavior could indeed be exploited in order to generate enhanced profits.

4. Conclusions

We document a significant relationship between the level of herding within an industry and the subsequent performance of past winner and loser industries, especially in the case of loser industries and during market crisis periods. Regardless of the formation period used to measure past performance and the level of herding, we find that loser industries with high degree of herding significantly outperform loser industries with low degree of herding, implied by positive and highly significant spread values estimated over each subsequent holding period. We argue that the herding effect on loser industries is likely due to the tendency of fund managers to herd on negative stock information as noted by Brown et al. (2014).

In the case of winner industries, however, we find that high herding winner industries underperform low herding winners for short holding periods up to 3 months. The herding effect on winner industries can be explained by institutions' tendency to buy stocks classified as overvalued, as noted by Edelen et al. (2016), which leads to negative abnormal returns subsequently. To that end, it can be argued that the short-run underperformance of high herding winner industries is related to the institutional demand for winner industries that is captured by the level of herding.

Examining the economic value of the herding effect on industry momentum, we find that a herding-based industry momentum strategy significantly outperforms the conventional industry momentum strategy, implied by positive and highly significant excess returns observed for all subsequent periods. The superior performance of the herding-based momentum strategy over the conventional momentum strategy is robust to alternative formation and holding periods and also to adjustment to Fama-French risk factors, implied by significantly higher risk-adjusted returns observed for the herding-based momentum strategy in each case.

Finally, we show that the herding-based industry momentum strategy generates significant (raw and risk-adjusted) returns even during market crisis periods when the conventional momentum strategy is documented to perform poorly. We conclude that investors must avoid industries that experience high degree of herding during periods of market crisis and momentum strategies involving industries that experience low degree of herding could still be utilized to generate significant profits even during market crisis periods. The finding of a consistent herding effect particularly in the case of loser industries and more prevalently during market crisis periods is consistent with the information externality exploitation argument that investors may choose to ignore their own private information when the inferred information from predecessor investors is believed to be superior, more so during periods when market uncertainty is high. Consequently, the superior performance of the herding-based momentum strategy even during alternative panic states suggests that rational herding (or anti-herding) could indeed be exploited to generate enhanced profits even during periods when momentum crashes occur.

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Table 1. Summary Statistics

This table reports the summary statistics for the 49 Fama-French industries between January 1964 and December 2013. The data is collected from CRSP and the smallest 20% stocks are excluded to control the effect of small, inactive stocks. Each month, stocks are assigned to one of 49 Fama-French industries based on the industry codes listed on Kenneth French's website. Market share and No. 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 is the time series average of monthly industry returns and CSAD is the time-series mean of the cross-sectional average deviation defined in Equation (1).

Industry	No. of Firms	Market Share	Return (%)	CSAD(%)
Agriculture	19	0.08	0.72	1.76
Food Products	85	2.23	1.27	1.40
Candy & Soda	18	1.37	1.43	1.31
Beer & Liquor	22	0.58	1.12	1.36
Tobacco Products	11	1.07	1.56	1.26
Recreation	51	0.47	0.96	1.81
Entertainment	64	0.69	1.36	1.86
Printing and Publishing	53	0.98	1.27	1.43
Consumer Goods	108	4.85	1.14	1.49
Apparel	71	0.47	1.05	1.65
Healthcare	91	0.62	1.54	1.98
Medical Equipment	116	1.25	1.46	1.81
Pharmaceutical Products	172	5.39	1.61	1.87
Chemicals	95	3.10	1.30	1.45
Rubber and Plastic Products	42	0.16	1.29	1.64
Textiles	46	0.25	1.04	1.62
Construction Materials	141	1.68	1.30	1.47
Construction	58	0.33	1.27	1.81
Steel	83	1.58	1.20	1.65
Fabricated Products	19	0.10	1.31	1.66
Machinery	168	2.22	1.36	1.61
Electrical Equipment	115	1.32	1.38	1.88
Automobiles	78	3.23	1.12	1.54
Aircraft	27	0.92	1.54	1.49
Ship & Rail Equip.	10	0.16	1.25	1.51
Defense	9	0.21	1.78	1.61
Gold	62	0.55	1.44	2.35
Mines	45	0.87	1.13	1.84
Coal	11	0.21	1.34	1.67
Oil	247	10.51	1.43	1.77
Utilities	171	5.92	1.03	1.10
Communication	129	5.91	1.43	1.66
Personal Services	51	0.28	1.16	1.83
Business Services	267	1.76	1.40	1.87
Computer hardware	127	4.70	1.37	2.07
Computer software	254	2.81	1.71	2.30
Electronic Equipment	240	3.28	1.53	2.05
Measuring & Control Equip.	93	0.73	1.58	1.82
Paper	52	1.27	1.20	1.36
Boxes	30	0.86	1.32	1.39
Transportation	128	1.99	1.17	1.66
Wholesale	188	1.16	1.29	1.68
Retail	251	4.86	1.26	1.66
Meals	99	0.96	1.19	1.72
Banking	366	4.58	1.14	1.41
Insurance	138	2.95	1.23	1.38
Real Estate	66	0.24	1.01	1.68
Trading	892	7.54	1.05	1.23
Unclassified	216	1.43	1.19	1.79

Table 2. Profitability of Industry Momentum Strategy.

This table reports the out-of-sample returns (in percentage) for various (F,H) industry momentum strategies. F and H refer to the length of the formation and holding periods, respectively. At the end of each month, momentum portfolios are formed using F-month lagged returns and are held for H-months. There is no gap between the formation and holding periods. Spread is the return of the long-short portfolio, i.e. the difference between the average return of winner and loser industry portfolios. Panel A reports the results over the whole sample period of 1964.1-2.13.12 and Panel B provides the results for the tech bubble (2000.3–2002.12) and credit crunch periods (2007.6–2009.12) including 65 months. Newey and West (1987) standard errors (in percentage) with three lags are reported in parentheses.

Formation period		Holding Period (*H months*)							
(*F months*)		1		3		6		12	
Panel A. 49 FF industries, Jan. 1964 –Dec. 2013									
3	Winners	1.579	(0.28)	4.480	(0.78)	8.604	(1.33)	16.930	(1.92)
	Losers	0.908	(0.30)	2.997	(0.80)	6.393	(1.35)	13.184	(1.97)
	Spread (WML)	0.670	(0.02)	1.483	(0.05)	2.211	(0.09)	3.745	(0.13)
6	Winners	1.560	(0.28)	4.489	(0.79)	8.749	(1.35)	16.965	(1.93)
	Losers	0.927	(0.29)	2.990	(0.79)	6.249	(1.34)	13.152	(1.98)
	Spread (WML)	0.634	(0.02)	1.499	(0.05)	2.500	(0.09)	3.813	(0.13)
12	Winners	1.556	(0.29)	4.476	(0.79)	8.602	(1.33)	16.243	(1.93)
	Losers	0.933	(0.29)	3.005	(0.79)	6.403	(1.36)	13.897	(1.98)
	Spread (WML)	0.622	(0.02)	1.472	(0.05)	2.199	(0.09)	2.346	(0.13)
Panel B: Crisis periods, Mar. 2000 –Dec. 2002 and June 2007 – Dec. 2009									
3	Winners	0.224	(1.10)	0.646	(3.23)	2.163	(5.62)	8.573	(7.97)
	Losers	-0.126	(1.33)	-0.203	(3.50)	1.218	(6.02)	8.349	(8.69)
	Spread (WML)	0.350	(0.21)	0.843	(0.59)	0.945	(1.02)	0.224	(1.46)
6	Winners	0.193	(1.15)	0.457	(3.25)	1.628	(5.64)	7.594	(7.61)
	Losers	-0.097	(1.29)	-0.022	(3.51)	1.766	(6.01)	9.363	(9.11)
	Spread (WML)	0.290	(0.21)	0.478	(0.59)	-0.138	(1.02)	-1.769	(1.47)
12	Winners	0.087	(1.15)	-0.051	(3.21)	0.691	(5.44)	6.185	(7.46)
	Losers	0.016	(1.28)	0.510	(3.53)	2.752	(6.21)	10.846	(9.20)
	Spread (WML)	0.072	(0.21)	-0.561	(0.59)	-2.061	(1.02)	-4.661	(1.47)

Table 3. The Impact of Herding on Industry Momentum Portfolios.

This table reports the subsequent returns (in percentage) for winner and loser industry portfolios with high and low degree of herding. At the end of each month, industries are grouped into 6 portfolios based on industry momentum and the level of herding using data over the formation period (*F*). Industries are defined as winner (loser) industries if their momentum returns (monthly) are above (below) the median momentum returns. Independently, industries are sorted into top (30%), intermediate (40%) and bottom (30%) groups based on the herding coefficients in Equation (2) estimated over the same formation period (*F*). Herding Coefficient and Formation Return refer to the average herding coefficient and the average return in the formation period for each industry portfolio, respectively. Cumulative returns (in percent) and the difference in returns between high and low herding industry portfolios over the subsequent 1, 3, 6, and 12 months are reported for each case. The sample period is between January 1964 and December 2013. Newey and West (1987) standard errors (in percentage) with three lags are reported in parentheses.

Formation (*F months*)	Herding Level		Herding Coeff.	Form. Return	Holding Period (*H months*)							
					1		3		6		12	
3	High		-25.008	9.863	1.560	(0.29)	4.396	(0.81)	8.758	(1.36)	17.292	(2.01)
	Low	Winner	28.372	8.743	1.615	(0.29)	4.627	(0.81)	8.659	(1.39)	16.908	(1.96)
	Spread				-0.055	(0.02)	-0.231	(0.05)	0.099	(0.09)	0.384	(0.13)
	High		-24.458	-2.037	1.000	(0.31)	3.163	(0.82)	6.872	(1.36)	13.700	(2.03)
	Low	Loser	26.405	-1.871	0.827	(0.31)	2.792	(0.81)	6.141	(1.38)	12.822	(1.96)
	Spread				0.173	(0.02)	0.371	(0.05)	0.731	(0.09)	0.878	(0.13)
6	High		-12.706	16.345	1.514	(0.29)	4.493	(0.80)	8.967	(1.39)	17.009	(2.02)
	Low	Winner	18.607	15.162	1.562	(0.29)	4.460	(0.82)	8.769	(1.41)	17.240	(1.98)
	Spread				-0.048	(0.02)	0.034	(0.05)	0.198	(0.09)	-0.232	(0.13)
	High		-17.726	-1.009	1.044	(0.29)	3.244	(0.82)	6.732	(1.38)	13.726	(2.08)
	Low	Loser	18.919	-0.885	0.889	(0.30)	2.861	(0.81)	5.958	(1.36)	12.689	(1.97)
	Spread				0.154	(0.02)	0.383	(0.05)	0.774	(0.09)	1.036	(0.13)
12	High		-6.314	27.992	1.549	(0.30)	4.531	(0.83)	8.647	(1.41)	16.410	(1.99)
	Low	Winner	12.793	26.708	1.583	(0.30)	4.512	(0.82)	8.762	(1.39)	16.492	(1.99)
	Spread				-0.035	(0.02)	0.019	(0.05)	-0.115	(0.09)	-0.083	(0.13)
	High		-6.406	2.361	1.027	(0.30)	3.152	(0.84)	6.567	(1.44)	14.154	(2.13)
	Low	Loser	13.159	2.923	0.831	(0.29)	2.773	(0.80)	6.168	(1.37)	13.726	(1.96)
	Spread				0.196	(0.02)	0.379	(0.05)	0.399	(0.09)	0.428	(0.13)

Table 4. Herding levels across industries.

This table reports the percentage of months during which an industry enters into a high or low herding industry portfolio based on the herding coefficient in Equation (2) estimated over the 12-month formation period. High (Low) herding indicates that the industry is allocated into the bottom (top) 30% group based on its estimated herding coefficient. Panel A reports the results over the whole sample period of 1964.1-2.13.12 and Panel B provides the results for the tech bubble (2000.3–2002.12) and credit crunch periods (2007.6–2009.12) including 65 months.

	Panel A: Whole Period		Panel B: Crisis Periods	
Industry	High Herding	Low Herding	High Herding	Low Herding
Agriculture	33.67	44.42	24.07	38.89
Food Products	14.08	30.42	30.77	10.77
Candy & Soda	39.37	25.58	36.92	24.62
Beer & Liquor	41.91	24.27	58.46	27.69
Tobacco Products	33.01	30.58	46.15	27.69
Recreation	34.86	38.30	15.38	50.77
Entertainment	39.16	31.39	69.23	13.85
Printing and Publishing	25.89	30.10	23.08	46.15
Consumer Goods	20.39	22.01	27.69	3.08
Apparel	37.54	31.07	43.08	20.00
Healthcare	35.90	30.77	18.46	20.00
Medical Equipment	41.36	28.07	29.23	21.54
Pharmaceutical Products	38.35	27.35	46.15	24.62
Chemicals	25.89	16.50	27.69	0.00
Rubber and Plastic Products	43.02	23.09	63.08	9.23
Textiles	25.74	37.87	46.15	10.77
Construction Materials	10.68	30.10	7.69	24.62
Construction	31.72	38.51	20.00	36.92
Steel	25.40	27.67	4.62	40.00
Fabricated Products	40.69	34.93	52.31	16.92
Machinery	16.67	22.65	27.69	4.62
Electrical Equipment	25.40	28.32	18.46	56.92
Automobiles	18.93	37.70	12.31	56.92
Aircraft	37.38	33.82	49.23	33.85
Ship & Rail Equip.	42.77	32.03	9.26	62.96
Defense	37.41	46.88	41.51	41.51
Gold	30.40	53.32	30.77	66.15
Mines	25.57	42.72	26.15	55.38
Coal	27.82	46.18	16.92	49.23
Oil	16.67	41.42	26.15	41.54
Utilities	7.12	50.65	6.15	53.85
Communication	27.67	27.83	3.08	41.54
Personal Services	37.31	25.37	13.85	27.69
Business Services	8.79	31.11	0.00	32.31
Computer hardware	36.41	35.76	26.15	29.23
Computer software	37.91	29.68	30.77	38.46
Electronic Equipment	33.33	25.40	10.77	36.92
Measuring & Control Equip.	40.94	33.66	43.08	27.69
Paper	33.06	15.12	40.00	21.54
Boxes	31.88	22.33	49.23	38.46
Transportation	24.92	23.62	30.77	23.08
Wholesale	23.62	19.42	9.23	20.00
Retail	14.72	13.11	12.31	35.38
Meals	31.22	21.95	15.38	21.54
Banking	21.84	19.90	20.00	24.62
Insurance	25.98	20.54	32.31	23.08
Real Estate	41.93	24.13	61.54	1.54
Trading	9.06	24.27	29.23	38.46
Unclassified	33.13	24.69	30.77	15.38

Table 5. Profitability of "Herding-Based" Industry Momentum Strategies

This table reports the profits from alternative herding-based industry momentum portfolios over subsequent 1, 3, 6 and 12 months. At the end of each month, industries are grouped into 6 portfolios based on industry momentum and the level of herding using data over the formation period (*F*). Industries are defined as winner (loser) industries if their momentum returns (monthly) are above (below) the median momentum returns. Independently, industries are sorted into top (30%), intermediate (40%) and bottom (30%) groups based on the herding coefficients in Equation (2) estimated over the same formation period (*F*). The sample period is between January 1964 and December 2013. Panel A reports the cumulative returns (in percentage) and Panel B reports the excess returns (in percentage) of each 'herding-based' industry momentum strategy against the conventional industry momentum strategy (reported in Table 2 Panel A). Newey and West (1987) standard errors (in percentage) with three lags are reported in parentheses.

Formation	Momentum portfolios		Holding Period (*H months*)							
(*F months*)	Long	Short	1		3		6		12	
Panel A: Cumulative Returns (in percentage)										
3	High herding Winners	High herding Losers	0.559	(0.05)	1.233	(0.14)	1.886	(0.24)	3.592	(0.35)
	Low herding Winners	Low herding Losers	0.787	(0.05)	1.835	(0.14)	2.518	(0.24)	4.086	(0.34)
	High herding Winners	Low herding Losers	0.732	(0.05)	1.605	(0.14)	2.617	(0.24)	4.470	(0.35)
	Low herding Winners	High herding Losers	0.614	(0.05)	1.464	(0.14)	1.787	(0.24)	3.208	(0.35)
6	High herding Winners	High herding Losers	0.470	(0.05)	1.249	(0.14)	2.235	(0.24)	3.283	(0.36)
	Low herding Winners	Low herding Losers	0.673	(0.05)	1.599	(0.14)	2.811	(0.24)	4.551	(0.35)
	High herding Winners	Low herding Losers	0.624	(0.05)	1.632	(0.14)	3.009	(0.24)	4.319	(0.36)
	Low herding Winners	High herding Losers	0.518	(0.05)	1.215	(0.14)	2.038	(0.25)	3.515	(0.35)
12	High herding Winners	High herding Losers	0.522	(0.05)	1.379	(0.15)	2.080	(0.25)	2.256	(0.35)
	Low herding Winners	Low herding Losers	0.753	(0.05)	1.739	(0.14)	2.593	(0.24)	2.767	(0.35)
	High herding Winners	Low herding Losers	0.718	(0.05)	1.758	(0.14)	2.478	(0.24)	2.684	(0.35)
	Low herding Winners	High herding Losers	0.556	(0.05)	1.360	(0.15)	2.195	(0.25)	2.339	(0.36)
Panel B: Excess Returns (in percentage) against the Conventional Strategy										
3	High herding Winners	High herding Losers	-0.111	(0.01)	-0.250	(0.02)	-0.324	(0.03)	-0.153	(0.05)
	Low herding Winners	Low herding Losers	0.117	(0.01)	0.353	(0.02)	0.307	(0.03)	0.341	(0.05)
	High herding Winners	Low herding Losers	0.062	(0.01)	0.122	(0.02)	0.406	(0.03)	0.725	(0.05)
	Low herding Winners	High herding Losers	-0.056	(0.01)	-0.019	(0.02)	-0.423	(0.03)	-0.537	(0.05)
6	High herding Winners	High herding Losers	-0.163	(0.01)	-0.250	(0.02)	-0.265	(0.03)	-0.530	(0.05)
	Low herding Winners	Low herding Losers	0.039	(0.01)	0.099	(0.02)	0.311	(0.03)	0.738	(0.05)
	High herding Winners	Low herding Losers	-0.009	(0.01)	0.133	(0.02)	0.509	(0.03)	0.507	(0.05)
	Low herding Winners	High herding Losers	-0.115	(0.01)	-0.284	(0.02)	-0.463	(0.03)	-0.298	(0.05)
12	High herding Winners	High herding Losers	-0.101	(0.01)	-0.093	(0.02)	-0.120	(0.03)	-0.090	(0.05)
	Low herding Winners	Low herding Losers	0.131	(0.01)	0.267	(0.02)	0.394	(0.03)	0.421	(0.05)
	High herding Winners	Low herding Losers	0.096	(0.01)	0.286	(0.02)	0.279	(0.03)	0.339	(0.05)
	Low herding Winners	High herding Losers	-0.066	(0.01)	-0.112	(0.02)	-0.005	(0.03)	-0.007	(0.05)

Table 6. Risk-Adjusted Returns (alphas) of Herding-Based and Conventional Industry Momentum Strategies.

This table reports the Fama-French three-factor adjusted returns (in percentage) of the conventional and the *best performing* herding-based momentum strategies (Table 5) and the excess risk-adjusted returns of herding-based momentum strategies over the corresponding conventional momentum strategies. The sample period is between January 1964 and December 2013. At the end of each month, industries are grouped into 6 portfolios based on industry momentum and the level of herding using data over the formation period (*F*). Industries are defined as winner (loser) industries if their momentum returns (monthly) are above (below) the median momentum returns. Independently, industries are sorted into top (30%), intermediate (40%) and bottom (30%) groups based on the herding coefficients in Equation (2) estimated over the same formation period (*F*). The Newey and West (1987) standard errors (in percentage) with three lags are reported in parentheses.

Formation	Momentum portfolios		Holding Period (*H months*)							
(*F months*)	Long	Short	1		3		6		12	
3		Conventional momentum strategy	0.681	(0.10)	0.477	(0.08)	0.356	(0.06)	0.302	(0.05)
	Low herding Winners	Low herding Losers	0.802	(0.14)	0.601	(0.10)	0.415	(0.08)	0.337	(0.06)
		Spread in alpha	0.122	(0.01)	0.124	(0.01)	0.060	(0.01)	0.035	(0.00)
	High herding Winners	Low herding Losers	0.717	(0.13)	0.512	(0.10)	0.421	(0.08)	0.359	(0.06)
		Spread in alpha	0.036	(0.01)	0.035	(0.01)	0.065	(0.01)	0.057	(0.00)
6		Conventional momentum strategy	0.646	(0.10)	0.486	(0.09)	0.405	(0.07)	0.311	(0.05)
	Low herding Winners	Low herding Losers	0.695	(0.13)	0.524	(0.11)	0.463	(0.09)	0.382	(0.08)
		Spread in alpha	0.049	(0.01)	0.038	(0.01)	0.059	(0.01)	0.071	(0.00)
	High herding Winners	Low herding Losers	0.623	(0.13)	0.530	(0.11)	0.492	(0.10)	0.350	(0.07)
		Spread in alpha	-0.023	(0.01)	0.044	(0.01)	0.088	(0.01)	0.039	(0.00)
12		Conventional momentum strategy	0.634	(0.10)	0.483	(0.09)	0.361	(0.07)	0.188	(0.05)
	Low herding Winners	Low herding Losers	0.736	(0.13)	0.566	(0.12)	0.424	(0.10)	0.225	(0.09)
		Spread in alpha	0.102	(0.01)	0.083	(0.01)	0.063	(0.01)	0.036	(0.01)
	High herding Winners	Low herding Losers	0.708	(0.13)	0.572	(0.13)	0.401	(0.10)	0.206	(0.08)
		Spread in alpha	0.074	(0.01)	0.089	(0.01)	0.040	(0.01)	0.018	(0.01)

Table 7. The Impact of Herding on Industry Momentum Portfolios during Market Crisis Periods.

This table reports the subsequent returns (in percentage) for winner and loser industry portfolios with high and low degree of herding during two major crisis periods in the U.S., i.e. the tech bubble (2000.3–2002.12) and the credit crunch (2007.6–2009.12). At the end of each month, industries are grouped into 6 portfolios based on industry momentum and the level of herding using data over the formation period (*F*). Industries are defined as winner (loser) industries if their momentum returns (monthly) are above (below) the median momentum returns. Independently, industries are sorted into top (30%), intermediate (40%) and bottom (30%) groups based on the herding coefficients in Equation (2) estimated over the same formation period (*F*). Herding Coefficient and Formation Return refer to the average herding coefficient and the average return in the formation period for each industry portfolio, respectively. Cumulative returns (in percent) and the difference in returns between high and low herding industry portfolios over the subsequent 1, 3, 6, and 12 months are reported for each case. Newey and West (1987) standard errors (in percentage) with three lags are reported in parentheses.

Formation (*F months*)	Herding Level		Herding Coeff.	Form. Return	Holding Period (*H months*) 1		3		6		12	
3	High	Winner	-1.138	8.448	0.105	(1.17)	0.691	(3.35)	2.783	(5.71)	8.500	(8.24)
	Low		16.231	9.136	0.070	(1.11)	0.563	(3.27)	1.963	(5.61)	9.467	(7.85)
	Spread				0.035	(0.20)	0.128	(0.58)	0.820	(0.99)	-0.967	(1.41)
	High	Loser	-1.137	-6.752	0.368	(1.31)	0.547	(3.44)	2.662	(5.92)	9.789	(8.72)
	Low		17.123	-8.734	-0.681	(1.41)	-0.952	(3.59)	0.291	(6.05)	6.329	(8.68)
	Spread				1.049	(0.24)	1.499	(0.62)	2.371	(1.05)	3.460	(1.53)
6	High	Winner	-0.324	13.056	0.052	(1.26)	0.480	(3.35)	2.370	(5.92)	7.804	(7.80)
	Low		13.040	15.157	0.251	(1.13)	0.197	(3.28)	1.647	(5.75)	8.673	(7.61)
	Spread				-0.200	(0.22)	0.282	(0.58)	0.723	(1.02)	-0.869	(1.35)
	High	Loser	-0.139	-9.341	0.395	(1.22)	1.098	(3.56)	3.168	(6.19)	11.492	(9.49)
	Low		12.486	-11.929	-0.517	(1.33)	-1.058	(3.51)	0.140	(5.87)	6.911	(8.93)
	Spread				0.912	(0.22)	2.156	(0.62)	3.028	(1.06)	4.581	(1.62)
12	High	Winner	0.244	16.225	0.320	(1.20)	0.629	(3.32)	1.226	(5.86)	8.160	(7.48)
	Low		10.435	19.855	-0.073	(1.24)	-0.482	(3.34)	0.573	(5.54)	6.357	(7.69)
	Spread				0.393	(0.21)	1.111	(0.58)	0.653	(1.00)	1.802	(1.33)
	High	Loser	0.791	-13.438	0.273	(1.32)	1.352	(3.72)	4.538	(6.49)	14.891	(9.88)
	Low		8.601	-18.114	-0.450	(1.32)	-0.226	(3.53)	2.355	(6.38)	9.580	(9.30)
	Spread				0.723	(0.23)	1.578	(0.64)	2.182	(1.130	5.311	(1.68)

Table 8. Profitability of the "Herding-Based" Industry Momentum Strategy during Market Crisis Periods.

This table reports the cumulative subsequent returns (in percentage) from alternative herding-based industry momentum portfolios during market crisis periods defined in Table 7. At the end of each month, industries are grouped into 6 portfolios based on industry momentum and the level of herding using data over the formation period (*F*). Industries are defined as winner (loser) industries if their momentum returns (monthly) are above (below) the median momentum returns. Independently, industries are sorted into top (30%), intermediate (40%) and bottom (30%) groups based on the herding coefficients in Equation (2) estimated over the same formation period (*F*). . Panel A reports the cumulative returns (in percentage) and Panel B reports the excess returns (in percentage) of each 'herding-based' industry momentum strategy against the conventional industry momentum strategy (reported in Table 2 Panel B). Newey and West (1987) standard errors (in percentage) with three lags are reported in parentheses.

Formation	Momentum portfolios		Holding Period (*H months*)							
(*F months*)	Long	Short	1		3		6		12	
Panel A: Cumulative Returns (in percentage)										
3	High herding Winners	High herding Losers	-0.262	(0.22)	0.144	(0.57)	0.121	(1.02)	-1.288	(1.49)
	Low herding Winners	Low herding Losers	0.751	(0.22)	1.515	(0.60)	1.672	(1.02)	3.139	(1.45)
	High herding Winners	Low herding Losers	0.786	(0.23)	1.644	(0.61)	2.492	(1.03)	2.171	(1.48)
	Low herding Winners	High herding Losers	-0.298	(0.21)	0.016	(0.59)	-0.700	(1.10)	-0.321	(1.46)
6	High herding Winners	High herding Losers	-0.343	(0.22)	-0.618	(0.61)	-0.798	(1.06)	-3.688	(1.52)
	Low herding Winners	Low herding Losers	0.768	(0.27)	1.255	(0.60)	1.507	(1.11)	1.763	(1.46)
	High herding Winners	Low herding Losers	0.569	(0.23)	1.538	(0.60)	2.231	(1.03)	0.893	(1.47)
	Low herding Winners	High herding Losers	-0.144	(0.21)	-0.900	(0.60)	-1.521	(1.05)	-2.818	(1.51)
12	High herding Winners	High herding Losers	0.047	(0.22)	-0.722	(0.62)	-3.312	(1.08)	-6.731	(1.54)
	Low herding Winners	Low herding Losers	0.377	(0.26)	-0.256	(0.60)	-1.782	(1.05)	-3.223	(1.50)
	High herding Winners	Low herding Losers	0.770	(0.22)	0.856	(0.60)	-1.129	(1.07)	-1.420	(1.48)
	Low herding Winners	High herding Losers	-0.346	(0.23)	-1.833	(0.62)	-3.965	(1.05)	-8.533	(1.53)
Panel B: Excess Returns (in percentage) against the Conventional Strategy										
3	High herding Winners	High herding Losers	-0.613	(0.04)	-0.699	(0.10)	-0.824	(0.18)	-1.512	(0.26)
	Low herding Winners	Low herding Losers	0.401	(0.04)	0.672	(0.11)	0.727	(0.18)	2.915	(0.26)
	High herding Winners	Low herding Losers	0.436	(0.04)	0.800	(0.11)	1.547	(0.18)	1.947	(0.26)
	Low herding Winners	High herding Losers	-0.648	(0.04)	-0.827	(0.11)	-1.644	(0.19)	-0.545	(0.26)
6	High herding Winners	High herding Losers	-0.633	(0.04)	-1.096	(0.11)	-0.660	(0.18)	-1.919	(0.26)
	Low herding Winners	Low herding Losers	0.478	(0.04)	0.777	(0.10)	1.645	(0.19)	3.532	(0.26)
	High herding Winners	Low herding Losers	0.279	(0.04)	1.060	(0.11)	2.368	(0.18)	2.662	(0.26)
	Low herding Winners	High herding Losers	-0.434	(0.04)	-1.378	(0.11)	-1.383	(0.18)	-1.049	(0.26)
12	High herding Winners	High herding Losers	-0.024	(0.04)	-0.161	(0.15)	-1.251	(0.19)	-2.070	(0.26)
	Low herding Winners	Low herding Losers	0.305	(0.04)	0.306	(0.15)	0.279	(0.18)	1.438	(0.26)
	High herding Winners	Low herding Losers	0.699	(0.04)	1.417	(0.15)	0.932	(0.18)	3.240	(0.26)
	Low herding Winners	High herding Losers	-0.417	(0.04)	-1.272	(0.15)	-1.903	(0.18)	-3.872	(0.26)

Table 9. Risk-Adjusted Returns (alphas) of Herding-Based and Conventional Industry Momentum Strategies during Market Crisis Periods.

This table reports the Fama-French three-factor adjusted returns (in percentage) of the conventional and the *best performing* herding-based momentum strategies (Table 8) and the excess risk-adjusted returns during market crisis periods. At the end of each month, industries are grouped into 6 portfolios based on industry momentum and the level of herding using data over the formation period (*F*). Industries are defined as winner (loser) industries if their momentum returns (monthly) are above (below) the median momentum returns. Independently, industries are sorted into top (30%), intermediate (40%) and bottom (30%) groups based on the herding coefficients in Equation (2) estimated over the same formation period (*F*). The Newey and West (1987) standard errors (in percentage) with three lags are reported in parentheses.

Formation	Momentum Portfolio		Holding Period (*H months*)							
(*F months*)	Long	Short	1		3		6		12	
3		Conventional momentum strategy	0.183	(0.44)	0.234	(0.26)	0.130	(0.23)	0.010	(0.18)
	Low herding Winners	Low herding Losers	0.269	(0.04)	0.123	(0.02)	0.082	(0.02)	0.206	(0.01)
		Spread in alpha	0.086	(0.07)	-0.111	(0.04)	-0.048	(0.03)	0.196	(0.03)
	High herding Winners	Low herding Losers	0.462	(0.04)	0.306	(0.03)	0.289	(0.02)	0.143	(0.02)
		Spread in alpha	0.279	(0.07)	0.071	(0.04)	0.159	(0.04)	0.132	(0.03)
6		Conventional momentum strategy	0.117	(0.48)	0.213	(0.34)	-0.017	(0.23)	-0.158	(0.22)
	Low herding Winners	Low herding Losers	0.352	(0.04)	0.245	(0.03)	0.211	(0.02)	0.265	(0.01)
		Spread in alpha	0.235	(0.07)	0.032	(0.05)	0.229	(0.03)	0.423	(0.03)
	High herding Winners	Low herding Losers	0.309	(0.04)	0.381	(0.03)	0.399	(0.03)	0.223	(0.02)
		Spread in alpha	0.192	(0.07)	0.169	(0.05)	0.417	(0.04)	0.380	(0.03)
12		Conventional momentum strategy	-0.120	(0.46)	-0.177	(0.30)	-0.372	(0.23)	-0.412	(0.19)
	Low herding Winners	Low herding Losers	0.230	(0.04)	0.115	(0.03)	-0.005	(0.02)	0.074	(0.02)
		Spread in alpha	0.351	(0.07)	0.292	(0.05)	0.367	(0.04)	0.486	(0.03)
	High herding Winners	Low herding Losers	0.643	(0.04)	0.492	(0.04)	0.161	(0.03)	0.259	(0.02)
		Spread in alpha	0.763	(0.07)	0.669	(0.05)	0.532	(0.04)	0.672	(0.02)

Table 10. Profits from the “Herding-Based” Momentum Strategy during Alternative Market Stress Periods.

This table reports the cumulative subsequent returns (Panel A) and the risk-adjusted returns (Panel B) of the *best performing* ‘herding-based’ industry momentum strategies (Table 8) during alternative market stress periods suggested in the literature. DOWN market is when the lagged three-year market return is negative. HIGH volatility market is when the lagged 12-month market volatility is larger than the lagged 36-month market volatility. HIGH momentum volatility market is when the momentum volatility for the month is higher than the volatility of the CRSP value-weighted daily index returns in the previous six months. All returns are in percentage. The risk-adjusted returns in Panel B are based on the 3-factor Fama-French model. For brevity, the findings based on the 12-month formation period are presented. The Newey and West (1987) standard errors (in percentage) with three lags are reported in parentheses.

	Momentum portfolios		Holding Period (*H months*)							
	Long	Short	1		3		6		12	
Panel A: Cumulative returns										
DOWN Market	Low herding Winners	Low herding Losers	0.777	(0.20)	1.782	(0.44)	2.361	(0.73)	2.669	(1.31)
	High herding Winners	Low herding Losers	0.785	(0.18)	2.127	(0.38)	2.733	(0.53)	3.293	(1.09)
HIGH Market Volatility	Low herding Winners	Low herding Losers	0.694	(0.20)	1.331	(0.49)	2.048	(0.78)	3.107	(1.34)
	High herding Winners	Low herding Losers	0.758	(0.18)	1.272	(0.42)	1.581	(0.75)	2.433	(1.25)
HIGH Momentum Volatility	Low herding Winners	Low herding Losers	0.584	(0.25)	1.534	(0.53)	2.332	(0.79)	2.324	(1.37)
	High herding Winners	Low herding Losers	0.588	(0.19)	1.532	(0.41)	2.373	(0.65)	2.436	(1.14)
Panel B: Risk-adjusted returns (3-factor alpha)										
DOWN Market	Low herding Winners	Low herding Losers	0.711	(0.21)	1.653	(0.45)	2.223	(0.72)	2.418	(1.21)
	High herding Winners	Low herding Losers	0.736	(0.17)	2.044	(0.40)	2.624	(0.58)	2.930	(1.01)
HIGH Market Volatility	Low herding Winners	Low herding Losers	0.776	(0.21)	1.406	(0.49)	2.088	(0.70)	3.142	(1.21)
	High herding Winners	Low herding Losers	0.825	(0.19)	1.293	(0.43)	1.533	(0.68)	2.245	(1.11)
HIGH Momentum Volatility	Low herding Winners	Low herding Losers	0.799	(0.24)	1.707	(0.51)	2.489	(0.73)	2.492	(1.17)
	High herding Winners	Low herding Losers	0.592	(0.21)	1.551	(0.42)	2.387	(0.65)	2.506	(1.02)