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Abstract

The study analyzes daily cross-sectional market-wide herd behavior as a potential factor that may help in predicting next day's stock returns. Assuming that herding may lead to stock price overreaction and result in subsequent price reversals, I suggest that for a given stock, daily returns should be higher (lower) following trading days characterized by negative (positive) stock's returns and high levels of herd behavior. Analyzing daily price data for all the constituents of S&P 500 Index over the period from 1993 to 2019, and using two alternative market-wide herding measures, I document that following trading days characterized by high levels of herding, stock returns tend to exhibit significant reversals, while following trading days characterized by low levels of herding, stock returns tend to exhibit significant drifts. This effect is found to be more pronounced for smaller and more volatile stocks. Based on the study's findings, I formulate a trading strategy and demonstrate that it yields significantly positive returns.

Keywords: Behavioral Finance; herd behavior; herding; stock price drifts; stock price reversals; trading strategy

JEL Classifications: G11, G14, G19

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1. Introduction

Stock prices are affected by an enormous, and virtually indefinite, number of factors. Some of these factors may be clearly established, giving rise to a vast strand of literature dealing with the possibilities for price prediction, while others remain unobserved and may be revealed only in a broader perspective. In many instances, the stock price changes themselves are analyzed in attempt to predict future price patterns.

Recent financial literature documents and discusses a long standing list of systematic deviations of investors' decisions from full rationality that give rise to behavioral biases, suggesting that stock prices may also substantially deviate from the underlying fundamentals. This study focuses on one of the best-known and widely-discussed behavioral biases, namely, herding.

Herding (or herd behavior) is usually defined as the behavior of an investor imitating the observed actions of others or the movements of market instead of following her own beliefs and information. Some studies regard herding as a result of rational incentives (e.g., Shleifer and Summers, 1990; Chari and Kehoe, 2004; Calvo and Mendoza, 2000), while others believe that it arises from investors' cognitive bias (e.g., Devenow and Welch, 1996; Lux, 1995). Herding can be spurious, referring to a clustering of investment decisions owing to similar underlying information environment, or intentional, which is a situation where investors follow each other's trading decisions regardless of their own beliefs. Herd behavior has been both discussed and analyzed in theoretical settings (e.g., Avery and Zemsky, 1998; Lee, 1998; Cipriani and Guarino, 2008; Park and Sabourian, 2010) and documented empirically, in both laboratory experiments (e.g., Cipriani and Guarino, 2005, 2009; Drehman et al., 2005) and real financial markets (e.g., Chen et al., 2003; Tan et al., 2008; Zhou and Lai, 2009; Chiang and Zheng, 2010).

A group of studies show that herding may potentially contradict stock market efficiency, by pushing stock prices away from the equilibrium proposed by the traditional financial theory. It leads to the situation when the stock prices no longer reflect the true value of companies (e.g., Hwang and Salmon, 2004; Brown et al., 2014). Continuing this line of reasoning, a number of studies find that herding may lead to overreaction and result in subsequent stock price reversals (e.g., Dasgupta et al., 2011; Antonacci, 2015; Thaler, 2015; Hu et al., 2018). Moreover, on the market-wide level, both positive and negative daily market returns tend to be followed by price reversals (drifts), if the market-wide levels of herding are high (low) (Kudryavtsev, 2019).

The present study continues the latter strand of literature, but in a different perspective. Unlike Kudryavtsev (2019), who detects reversals in the general stock market index following days characterized by high market-wide herding measures, the goal of this study is to establish if similar thing also takes place on the individual stocks' level. I suggest that if, for some reasons, a given trading day was characterized by relatively high levels of herding (as proxied by market-wide herding measures), this may potentially mean that this day's individual stocks' returns were at least partially driven by herding and may contain an element of overreaction to underlying information, creating the opposite-direction pressure on the stocks' prices on the next trading day. In other words, I hypothesize that for a given stock, daily returns should be higher (lower) following trading days characterized by negative (positive) stock's returns *and* high levels of herd behavior.

I analyze the daily price data for all the stocks that were making up S&P 500 Index over the period from 1993 to 2019, and use two alternative market-wide herding measures suggested by the previous literature (e.g., Christie and Huang, 1995; Chang et al., 2000) and based on cross-sectional daily deviation of stock returns. Consistently with the study's hypothesis, I find that following trading days characterized by high levels of herding, stock returns tend to exhibit significant reversals, while following trading days characterized by low levels of herding, stock returns tend to exhibit significant drifts.

Furthermore, I split the total sample of stocks according to their market capitalization and historical volatility. In line with the previous literature, which documents that low capitalization and highly volatile stocks are especially likely to be disproportionately sensitive to broad waves of investor sentiment (Baker and Wurgler, 2006), I establish that the herding effect on the next day's stock returns is stronger pronounced for smaller and more volatile stocks.

Finally, I suggest and test an actual trading strategy taking advantage of the study's findings. I divide the sampling period in two sub-periods, when the first one is used for calculating the break point values of the herding measures, while the second one serves as a platform for testing the suggested trading strategy. The latter is based on the following approach: (i) at the end of each trading day characterized by high market-wide herding, suggesting the expectations for the next day's reversals, construct an equally-weighted zero-cost portfolio made of buying stocks whose prices have decreased during this given day and selling short stocks whose prices have increased during this day; (ii) at the end of each trading day characterized by low market-wide herding, suggesting the expectations for the next day's drifts, construct an equally-weighted zero-cost portfolio made of buying stocks whose prices have increased during this given day and selling short stocks whose prices have decreased during this day; (iii) at the end of the days characterized by medium levels of herding, when there are no clear expectations for the next day's reversals or drifts, leave the portfolio composition unchanged. The strategy is documented to yield significantly positive returns, both before and after the trading fees.

The rest of the paper is structured as follows. Section 2 reviews the previous literature dealing with herding and its implications for stock trading. Section 3 formulates the study's research hypothesis. Section 4 introduces the database and the research design. Section 5 presents the results of the empirical tests. Section 6 concludes and provides a brief discussion.

2. Literature review: Herding. Definition, causes and implications

Herding, or herd behavior, in financial markets refers to the behavior of an investor who observes and imitates the others' actions or the movements of market, rather than following her own information and beliefs. Herding is probably among the most mentioned terms in the financial lexicon, but seems to remain largely ununderstood. This kind of behavior is actually difficult to uncover, measure and quantify, which creates obstacles for extensive research. Nonetheless, there seem to be at least two points people tend to unanimously agree upon. First, as one of the major concepts of behavioral finance, herd behavior plays an important role in explaining market-wide anomalies. Most individual biases are not influential enough to move market prices and returns, and therefore, they produce effects of real anomalies only if there is a social contamination with a strong emotional content, leading to more widespread phenomena such as herd behavior. Second, it is generally accepted that herding may lead to a situation in which stock prices do not correctly reflect all relevant underlying information, leading the market in general towards informational inefficiency.

Previous literature analyzes herd behavior both theoretically and empirically. The theoretical research (e.g., Avery and Zemsky, 1998; Lee, 1998; Cipriani and Guarino, 2008; Park and Sabourian, 2010) primarily makes an effort to identify the mechanisms that can lead investors to herd. Studies in this strand of literature emphasize that in financial markets, stock price adjustment to the order flow makes herd behavior more difficult to arise than in other setups, discussed in the social learning literature, where there is no price mechanism. Still, rational investors may herd because of the different sources of uncertainty existing in the market, because investors' motives to trade may be informational or non-informational (e.g., liquidity or hedging), or because trading activity may be affected by reputation concerns.

Empirical studies of herding are based either on laboratory or market data. In all the models, the term "herding" refers to making decisions independently of the private information that an individual receives. The point that makes the empirical analysis problematic is the lack of data on the investors' private information. Consequently, it is difficult to establish if investors make similar decisions because they disregard their own private information and imitate, or, for instance, because they react to the same piece of public information. In order to overcome this problem, several authors (e.g., Cipriani and Guarino, 2005, 2009; Drehman et al., 2005) test herd behavior in simulated laboratory financial settings, and document types of behavior consistent with herd motives.

Another group of empirical studies analyze different aspects of herding in real market situations. Chen et al. (2003) document that foreign investors are more inclined to herd if they are less knowledgeable or informed about individual stocks than domestic investors. Therefore, they conclude that investors' tendency to herd increases when information is scarce or not easily available. Tan et al. (2008) find that in the Chinese stock market, herd behavior is more prevalent in high volatility, positive market returns and high trading volume. Zhou and Lai (2009) detect that herd behavior in Hong Kong tends to be stronger pronounced in small stocks, and that investors are more likely to herd when selling rather than buying stocks. Chiang and Zheng (2010) analyze daily stock return data for 18 countries and find herd behavior of stock markets in both developed (except in the U.S.) and developing countries.

Measuring herd behavior may be quite challenging, and thus, various empirical methodologies have been employed for implementing this task. One group of studies directly concentrates on investors' behavior and requires explicit and detailed information on their trading activities and the changes in their investment portfolios. The first and the best known herd measure related to this group is the one proposed by Lakonishok et al. (1992). The idea behind this measure is to examine the buying pressure on a given asset for a homogeneous subgroup (e.g., mutual funds, pension funds, individual investors). For the market as a whole, the number of buyers equals the number of sellers, since each purchase is balanced by a sale. However, for a given subgroup of investors and a given asset, there can be an excess of buyers or sellers, suggesting that the investors composing the subgroup exhibit herd behavior. Wermers (1995) comes with a portfolio-change measure, by which herd behavior is proxied by the extent to which portfolio weights assigned to the various stocks by different money managers move in the same direction.

Another group of studies treats herding r as individuals' collective buying and selling actions in an attempt to follow the performance of the market or any other economic factors or styles. Here, herd behavior is established by employing the information contained in the cross-sectional stock price movements. Christie and Huang (1995), for example, analyze cross-sectional standard deviations (CSSD) in the U.S. equity market. Their method is based on the intuition that if market participants ignore their own expectations about asset prices during periods of significant market movements and make their investment decisions based only on market consensus, then individual assets' returns should be relatively close to the overall market return. On the other hand, rational asset pricing model would predict that an increase in the absolute value of market return should increase the dispersion of individual stock returns. Therefore, during large market swings, a reduction of CSSD may serve an indication of the existence of herd behavior. Chang et al. (2000) suggest a variant of the methodology employed by Christie and Huang (1995). They calculate cross-sectional absolute deviation (CSAD) of stock returns, which is less subject to the influence of outliers than the respective stocks' CSSD. A rational asset pricing model would assume a linear and positive relation between CSAD and the absolute value of market return, so that the evidence that CSAD decreases with the absolute value of market return provides empirical support for herd behavior.

In many instances, herding is discussed in the context of the Efficient Market Hypothesis. Hwang and Salmon (2004) argue that the presence of herd behavior in a market contradicts market efficiency. They state that herd behavior leads to deviations of asset prices from the equilibrium suggested by traditional financial theory, finally resulting in prices that may no longer serve a reflection of the companies' true value.

Continuing this line of reasoning, several studies assert that herd behavior may lead to overreaction and result in stock price reversals. Dasgupta et al. (2011) demonstrate that in markets dominated by fund managers, assets persistently bought (sold) by the latter trade at prices that are too high (low) and therefore, after uncertainty is resolved, experience negative (positive) long-term returns. Brown et al. (2014) document that mutual fund herding during a certain quarter is associated with the same quarter “price-pressure” effect on the stock, when buy-herds push stock prices up, and sell-herds push prices down. Antonacci (2015) claims that investors may overreact due to herding, representativeness and overconfidence. Thaler (2015) concludes that herding may significantly drive stock prices, either upwards or downwards, away from their fundamental values, leading to overreaction and creating a ground for subsequent price reversals. Hu et al. (2018) find that most loser stocks with a high degree of mutual fund herding outperform loser stocks with a low degree of mutual fund herding, revealing that the profitability of contrarian investments strategies, based on buying loser stocks and selling winner ones, depends on the degree of mutual fund herding. Kudryavtsev (2019) uses two alternative market-wide herding measures based on cross-sectional daily deviation of stock returns and documents that the days of both positive and negative market returns tend to be followed by price reversals (drifts), if the market-wide levels of herding are high (low). Furthermore, he demonstrates that this herding effect on the next day's stock market returns is more pronounced following the days when the sign of the market return corresponds to the direction of the longer-term stock market tendency and the days characterized by relatively large stock market movements.

3. Research hypothesis

In this study, I focus on short-term effects of herding on stock returns. Following the above-mentioned literature, which documents that herding may lead to overreaction and result in subsequent stock price reversals (e.g., Dasgupta et al., 2011; Brown et al., 2014; Antonacci, 2015; Thaler, 2015; Hu et al., 2018), and that the days characterized by high levels of herding tend to be followed by reversals in market returns (Kudryavtsev, 2019), I hypothesize that if, for some reasons, a given trading day was characterized by relatively high market-wide herding measures (as will be explained in Section 4), this may potentially mean that this day's individual stocks' returns were at least partially driven by herding and may contain an element of overreaction to underlying information, creating the opposite-direction pressure on the stocks' prices on the next trading day.

Thus, the study's major research hypothesis may be formulated as follows:

Hypothesis: For a given stock, daily returns should be higher (lower) following trading days characterized by negative (positive) stock's returns *and* high levels of herd behavior.

It should be noted that unlike Kudryavtsev (2019), who detects reversals in the general stock market index following days characterized by high market-wide herding measures, the goal of this study is to establish if similar thing also takes place on the individual stocks' level, that is, if there are reversals in individual stocks' prices following days characterized by high market-wide herding measures.

4. Data description and research design

In order to test the study's hypothesis, I employ the daily price data for all the stocks that were making up the S&P 500 Index over the period from 1993 to 2019, retrieved from the Center for Research in Security Prices (CRSP). Seeking to define daily market-wide herding measures, I resort to the group of previous studies that views herd behavior as collective buying and selling actions of the individuals in an attempt to follow the performance of the market or any other economic factors or styles. Similarly to Kudryavtsev (2019), I define and employ two alternative herding measures:

1. Cross-Sectional Standard Deviation of stock returns (CSSD): Christie and Huang (1995) were the first to introduce this measure with the goal of testing for herd behavior in the U.S. equity market. CSSD is a measure of the average proximity of individual stock returns to the average market-wide returns for each given day *t*. Specifically:

$$CSSD_t = \sqrt{\frac{\sum_{i=1}^{N}(r_{it}-r_{mt})^2}{N-1}} \qquad (1)$$

where: r_{it} represents stock *i*'s return on day *t*; r_{mt} is the cross-sectional average day-*t* return of all the stocks making up the market portfolio (i.e., equally-weighted average day-*t* return of all S&P 500 constituents); and *N* represents the number of stocks in the aggregate portfolio (500 constituents of S&P 500, in this case).

The main idea behind this measure is based on the argument that the presence of herd behavior would lead stock returns to be relatively close to the average return. Therefore, low values of CSSD may be regarded as an indication of the market consensus, or in other words, as a sign of herding.

2. Cross-Sectional Absolute Deviation of stock returns (CSAD): This measure was suggested by Chang et al. (2000). For each given day *t*, CSAD is calculated as:

$$CSAD_t = \frac{\sum_{i=1}^{N}|r_{it}-r_{mt}|}{N} \qquad (2)$$

The interpretation and implications of this measure are quite similar to those of CSSD, yet, compared to the latter, CSAD is less subject to the influence of outliers, that is, of daily stock returns significantly deviating from the cross-sectional average. Similarly to CSSD, low values of CSAD may be seen as a display of herding.

Table 1 reports some basic descriptive statistics of the two herding measures. Over the sampling period, CSSD (CSAD) measures range from 0.8445 (0.6581) to 6.0894 (3.5287) with mean values of 2.2144 (1.6514) and standard deviations of 0.4875 (0.4294). As expected, since CSAD is less affected by outliers, its distribution is closer to the normal one. Quite obviously, the two measures are highly positively correlated (correlation coefficient = 0.7877), but still, as a kind of robustness check, the empirical tests in the rest of the paper are performed for both of them.

5. Results description

5.1. Herding effect on the next day's stock returns: Total sample

In order to analyze the effect of investor herding on the first-order autocorrelation of stock returns, I first of all divide the total sample of trading days by each of the herding measures in three roughly equal sub-periods, namely, days with low, medium and high cross-sectional deviation of stock returns, corresponding to the days with high, medium and low levels of herd behavior. Subsequently, for each of the stocks that were included in the sample (S&P 500 Index) during the sampling period, I run the following intuitive time-series regression, only for the period when the stock was a part of the sample:

$$r_{it} = \beta_1 r_{it-1} * HM\_LOW_{t-1} + \beta_2 r_{it-1} * HM\_MEDIUM_{t-1} + \\ +\beta_3 r_{it-1} * HM\_HIGH_{t-1} + \varepsilon_t \qquad (3)$$

where: HM_LOW_{t-1} is a dummy variable, taking the value 1 if on day *t-1* the market-wide herding measure (HM – either CSSD or CSAD) was low, and 0 otherwise; HM_MEDIUM_{t-1} is a dummy variable, taking the value 1 if on day *t-1* the market-wide herding measure was medium, and 0 otherwise; and HM_HIGH_{t-1} is a dummy variable, taking the value 1 if on day *t-1* the market-wide herding measure was high, and 0 otherwise.

Table 2 comprises mean regression coefficients for the stocks making up the sample, with both CSSD and CSAD being employed as alternative market-wide herding measures. The results corroborate the existence of the herding effect on the next day's stock returns, indicating that:

- Mean regression coefficients of $r_{it-1} * HM\_LOW_{t-1}$ equal -0.548 (-0.561) with CSSD (CSAD) used as a measure of market-wide herding, 58.24% (60.14%) of the coefficients being statistically significant. This finding implies that following trading days characterized by high levels of herding, stock returns tend to exhibit significant reversals.
- Mean regression coefficients of $r_{it-1} * HM\_MEDIUM_{t-1}$ are 0.042 (0.048), and the vast majority of the coefficients are non-significant, suggesting that stock returns do

not exhibit any significant patterns following days characterized by medium levels of herding.

- Mean regression coefficients of $r_{it-1} * HM\_HIGH_{t-1}$ equal 0.387 (0.394), 42.15% (43.23%) of the coefficients being statistically significant. This result indicates that following trading days characterized by low levels of herding, stock returns tend to exhibit significant drifts, though less pronounced than the reversals following high-herding days.
- In the bottom line, the mean difference between β_1 and β_3 coefficient estimates is -0.935 (-0.955), 74.68% (75.84%) of the differences being statistically significant. It means that in line with the study's hypothesis, the stock returns' tendency to exhibit one-day reversals significantly increases following high-herding trading days.

5.2. Herding effect on the next day's stock returns: Subsample analysis

Having documented the effect of market-wide herding on the first-order autocorrelations in stock returns, I furthermore test it for different groups of stocks. The motivation for this analysis arises from the findings by Baker and Wurgler (2006), who argue that low capitalization and highly volatile stocks are especially likely to be disproportionately sensitive to broad waves of investor sentiment.

First, I classify the total sample of stocks according to their market capitalization at the beginning of the sampling period or at the date when they entered S&P 500 Index, as recorded on a quarterly basis at http://ycharts.com/._I split the sample into three roughly equal parts by the firms' market capitalization: high, medium and low.

Table 3 presents the results of regression (3) separately for high and low market capitalization stocks. Consistently with Baker and Wurgler (2006), the herding effect on the next day's stock returns is stronger pronounced for low capitalization stocks. To summarize, for large stocks, the mean difference between β_1 and β_3 coefficient estimates with CSSD (CSAD) used as measures of market-wide herding equals -0.560 (-0.581), 51.38% (52.34%) of the differences being statistically significant, while for small stocks, the mean difference between β_1 and β_3 coefficient estimates is -1.201 (-1.224), 81.36% (81.98%) of the differences being statistically significant.

Furthermore, I classify the stocks in the sample according to the volatility of their returns during the sampling period (either when they are a part of S&P 500 Index, or not). I divide the sample into three roughly equal parts by stocks' volatility: high, medium and low.

Table 4 depicts the results of regression (3) separately for high and low volatility stocks. Once again, in line with with Baker and Wurgler (2006), the herding effect on the next day's stock returns is stronger pronounced for high volatility stocks. The bottom line of the two panels of the table show that for highly volatile stocks, the mean difference between β_1 and β_3 coefficient estimates with CSSD (CSAD) used as measures of market-wide herding equals -1.122 (-1.142), 75.86% (76.15%) of the differences being statistically significant, while for low volatility stocks, the mean difference between β_1 and β_3 coefficient estimates is only -0.696 (-0.713), 66.58% (67.15%) of the differences being statistically significant.

5.3. Trading strategy based on herding effect on the next day's stock returns

The results presented earlier in this Section indicated that stock returns tend to exhibit one-day reversals (drifts) following trading days characterized by high (low) levels of market-wide herding. The results are statistically and economically significant, so the need to look for a trading strategy that would take advantage of these findings is quite obvious.

In order to define such a strategy I first of all divide the sampling period (1993-2019) in two sub-periods: estimation period (1993-2015) and test period (2016-2019)[2]. Over the estimation period, I calculate the break point values allowing to split the trading days by each of the herding measures in three roughly equal sub-periods of low, medium and high cross-sectional deviation of stock returns, corresponding to the days with high, medium and low levels of herd behavior[3].

Subsequently, during the test period, I employ the break point values calculated during the estimation period, and at the end of each trading day characterized by low cross-sectional deviation of stock returns, or high market-wide herding, suggesting the expectations for the next day's reversals, I construct an equally-weighted zero-cost portfolio made of buying stocks whose prices have decreased during this given day and selling short stocks whose prices have increased during this day. Symmetrically, at the end of each trading day characterized by high cross-sectional deviation of stock returns, or low market-wide herding, suggesting the expectations for the next day's drifts, I construct an equally-weighted zero-cost portfolio made of buying stocks whose prices have increased during this given day and selling short stocks whose prices have decreased during this day. At the end of the days characterized

[2] The estimation period is intentionally taken to be significantly longer than the test one. This approach allows to estimate more correctly the break points of herding measures.
[3] The break point value between the days of low and medium cross-sectional deviation of stock returns is 2.05 (1.48) for CSSD (CSAD) measure, while the break point value between the days of medium and high cross-sectional deviation of stock returns is 3.89 (2.28) for CSSD (CSAD) measure.

by medium cross-sectional deviation of stock returns, when there are no clear expectations for the next day's reversals or drifts, I leave the portfolio composition unchanged in order to minimize stock trading fees. Table 5 concentrates the basic daily performance measures for the suggested trading strategy, based on alternatively defining the cross-sectional deviations of stock returns with CSSD and CSAD[4]. The results demonstrate that the strategy looks quite promising. If we assume no trading fees, then the mean returns based on CSSD (CSAD) are 0.212% (0.225%), or about 70% per year, and highly significant. If we assume a trading fee of 0.05% for buying and/or selling stocks, then the mean daily returns equal 0.153% (0.159%), or about 47% in yearly terms.

6. Concluding remarks

In the present study, I analyzed the predictability of stock returns based on the previous day's cross-sectional market-wide herd behavior. Assuming that herding may lead to stock price overreaction and result in subsequent price reversals, I suggested that for a given stock, daily returns should be higher (lower) following trading days characterized by negative (positive) stock's returns and high levels of herd behavior.

I analyze the daily price data for all the stocks that were making up S&P 500 Index over the period from 1993 to 2019, and use two alternative market-wide herding measures, I found corroborative evidence for the study's hypothesis. I documented that following trading days characterized by high levels of herding, stock returns tend to exhibit significant reversals, while following trading days characterized by low levels of herding, stock returns tend to exhibit significant drifts. This effect was found to be stronger pronounced for smaller and more volatile stocks. Finally, I constructed a trading strategy based on the documented effect of herding that proved to be promising.

The study's findings may be interesting for both financial theoreticians in their discussion about stock market efficiency, and practitioners in search of potentially profitable investment strategies. Potential directions for further research may include expanding the analysis to other stock exchanges, performing separate analysis for the periods of bull and bear markets and for different industries, and separately testing the suggested trading strategy for different groups of stocks.

[4] The strategy's daily performance measures are calculated based on all the trading days of the test period, including those when no changes are made to the portfolio, since the previous day's herding measures are classified as medium.

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Appendix (Tables)

Table 1: Descriptive statistics of herding measures

Statistics	CSSD	CSAD
Mean	2.2144	1.6514
Median	2.1246	1.6325
Standard Deviation	0.4875	0.4294
Minimum	0.8445	0.6581
Maximum	6.0894	3.5287
Skewness	0.8256	0.7487
Kurtosis	4.2847	3.4934
Correlation Coefficient	0.7877	

Table 2: Regression analysis of the herding effect on stock returns. Total sample: Dependent variable - r_{it}

Explanatory variables	Regression coefficients	Average coefficient estimates (percent of significantly positive/negative at 5% level)	
		Herding measure - CSSD	Herding measure - CSAD
$r_{it-1} * HM\_LOW_{t-1}$	β_1	-0.548 (0.95/58.24)	-0.561 (0.86/60.14)
$r_{it-1} * HM\_MEDIUM_{t-1}$	β_2	0.042 (5.63/4.21)	0.048 (5.85/4.15)
$r_{it-1} * HM\_HIGH_{t-1}$	β_3	0.387 (42.15/1.25)	0.394 (43.23/1.17)
Difference: $\beta_1 - \beta_3$		-0.935 (0.00/74.68)	-0.955 (0.00/75.84)

Table 3: Regression analysis of the herding effect on stock returns. Subsample analysis for high and low market capitalization stocks: Dependent variable - r_{it}

Panel A: High market capitalization stocks			
Explanatory variables	Regression coefficients	Average coefficient estimates (percent of significantly positive/negative at 5% level)	
		Herding measure - CSSD	Herding measure - CSAD
$r_{it-1} * HM\_LOW_{t-1}$	β_1	-0.346 (1.42/43.57)	-0.358 (1.30/45.21)
$r_{it-1} * HM\_MEDIUM_{t-1}$	β_2	0.036 (5.08/4.57)	0.039 (5.57/4.25)
$r_{it-1} * HM\_HIGH_{t-1}$	β_3	0.214 (30.28/2.26)	0.223 (31.12/2.32)
Difference: $\beta_1 - \beta_3$		-0.560 (0.00/51.38)	-0.581 (0.00/52.34)
Panel B: Low market capitalization stocks			
Explanatory variables	Regression coefficients	Average coefficient estimates (percent of significantly positive/negative at 5% level)	
		Herding measure - CSSD	Herding measure - CSAD
$r_{it-1} * HM\_LOW_{t-1}$	β_1	-0.694 (0.00/72.41)	-0.706 (0.00/72.96)
$r_{it-1} * HM\_MEDIUM_{t-1}$	β_2	0.045 (5.72/4.05)	0.049 (5.96/4.02)
$r_{it-1} * HM\_HIGH_{t-1}$	β_3	0.507 (53.68/0.54)	0.518 (54.11/0.45)
Difference: $\beta_1 - \beta_3$		-1.201 (0.00/81.36)	-1.224 (0.00/81.98)

Table 4: Regression analysis of the herding effect on stock returns. Subsample analysis for high and low volatility stocks: Dependent variable - r_{it}

Panel A: High volatility stocks			
Explanatory variables	Regression coefficients	Average coefficient estimates (percent of significantly positive/negative at 5% level)	
		Herding measure - CSSD	Herding measure - CSAD
$r_{it-1} * HM\_LOW_{t-1}$	β_1	-0.665 (0.00/68.56)	-0.674 (0.00/69.05)
$r_{it-1} * HM\_MEDIUM_{t-1}$	β_2	0.044 (5.68/4.12)	0.047 (5.81/4.08)
$r_{it-1} * HM\_HIGH_{t-1}$	β_3	0.457 (45.38/0.98)	0.468 (45.97/0.92)
Difference: $\beta_1 - \beta_3$		-1.122 (0.00/75.86)	-1.142 (0.00/76.15)
Panel B: Low volatility stocks			
Explanatory variables	Regression coefficients	Average coefficient estimates (percent of significantly positive/negative at 5% level)	
		Herding measure - CSSD	Herding measure - CSAD
$r_{it-1} * HM\_LOW_{t-1}$	β_1	-0.394 (1.10/48.39)	-0.405 (1.05/48.88)
$r_{it-1} * HM\_MEDIUM_{t-1}$	β_2	0.039 (5.38/4.37)	0.040 (5.59/4.21)
$r_{it-1} * HM\_HIGH_{t-1}$	β_3	0.302 (38.75/1.64)	0.308 (39.06/1.58)
Difference: $\beta_1 - \beta_3$		-0.696 (0.00/66.58)	-0.713 (0.00/67.15)

Table 5: Daily performance measures of the trading strategy taking advantage of the herding effect on the next day's stock returns

Panel A: Before trading fees		
Statistics	Herding measure employed for classification	
	CSSD	CSAD
Mean, daily %	***0.212	***0.225
Median, daily %	***0.204	***0.209
Standard Deviation, daily %	0.824	0.815
Minimum, daily %	-4.841	-4.264
Maximum, daily %	5.624	5.283
Panel B: After trading fees of 0.5% of the value of stocks bought/sold		
Statistics	Herding measure employed for classification	
	CSSD	CSAD
Mean, daily %	***0.153	***0.159
Median, daily %	***0.147	***0.150
Standard Deviation, daily %	0.794	0.785
Minimum, daily %	-5.562	-4.967
Maximum, daily %	4.987	4.496

Asterisks denote 2-tailed p-values: ***$p<0.01$