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Investigating macro herd behaviour: evidence from publicly traded German companies

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Abstract

Purpose – The purpose of this study is to examine herd behaviour under different market conditions, examine the potential impact of the firm size and stock characteristics on this relationship, and explore how herding affects market prices in the German market.

Design/methodology/approach – The authors apply a method that does not rely on theoretical models, thus eliminating the biases inherent in their application. This technique is based on the assumption that macro herding manifests itself in the synchronicity (comovement) of stock returns.

Findings – The study's findings show that herding is more pronounced in down markets and is more pronounced when market returns reach extreme levels. Additionally, the authors have found that there is stronger herding among large companies compared to small companies, and that stock characteristics considered have no effect on the degree of macro herding. Results also suggest that the contemporaneous market-wide information drives macro herding and that macro herding facilitates the incorporation of market-wide information into prices.

Practical implications – The study's results strongly support the idea of directional asymmetry, which holds that stocks react quickly to negative macroeconomic news while small stocks react slowly to positive macroeconomic news. Additionally, the study's results suggest that the contemporaneous market-wide information drives macro herding and that macro herding facilitates the rapid incorporation of market-wide information into prices.

Originality/value – To the best of the researchers' knowledge, this is the first study that examines macro herding for a major financial market using a herding measure based on the co-movement of returns that does not rely on theoretical models.

Keywords Herd behaviour, Macro herding, Size effect, Stock characteristics, Price impact

Paper type Research paper

1. Introduction

Herd behaviour was one of the earliest topics studied in social psychology. Since then, it has attracted considerable interest in economics (see, e.g. Rook, 2006) for an overview on the economic and psychological perspectives of herd behaviour) and has become widespread in the financial literature. In the financial context, researchers have studied what causes herd behaviour in various asset classes, the presence of herding in various markets, the impact of herding on financial markets, particularly the formation of bubbles, the relationship between financial crises and herd behaviour, as well as the propensity of different types of investors to engage in herding (Choijil *et al.*, 2022). The most recent studies have also examined the

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phenomenon in relation to the cryptocurrency market and COVID-19 (Kumar, 2020; Mnif and Jarboui, 2021; Shrotryia and Kalra, 2022). This study contributes to the literature examining the presence of herd behaviour and its impact on financial markets. More specifically, we investigate herd behaviour under different market conditions, examine the potential impact of the firm size and stock characteristics on this relationship, and explore how herding affects market prices in the German market.

Despite the vast range of studies on the phenomenon of herd behaviour, which is driven by cognitive factors, market information, and stock characteristics (Sachdeva *et al.*, 2023), there has yet to be a widely accepted definition in the literature. In the financial context, herd behaviour refers to a situation when investors take actions by imitating the actions of others (Spyrou, 2013). According to our view, herding corresponds to the convergence of investors' behaviour either because of widespread convention based on clear market signals (unintentional herding) or investors' ability to observe others' investment decisions (intentional herding).

In addition, the literature identifies two distinct forms of herd behaviour. One where herding encompasses a broad range of securities and another where it is confined to a single stock. The methodology applied to detect herding depends on which type of herd behaviour is the subject of the investigation. As Venezia *et al.* (2011) pointed out, to measure the herding into specific stocks, i.e. "micro herding", one should assess to what extent there is a concentration of buy or sell trades on a specific stock. Whereas to measure "macro herding", when investors herd across all stocks rather than into one stock, one should assess to what extent investors' trades are concentrated on either the buy or the sell side of the market. In this study, we aim to examine the herding of the overall market, that is, the concentration of investment decisions on the buy or the sell side for a wide range of stocks (macro herding). To this end, we employ a method that eliminates the dependence on theoretical models, as well as the biases associated with their use. This technique is based on the assumption that macro herding is reflected in the similarity of the direction of investment decisions and manifests itself in the synchronicity (comovement) of stock returns (Guo and Shih, 2008; Lee, 2017; Tessler and Venezia, 2022).

Our work addresses four research questions that have so far provided inconclusive findings in the literature on herd behaviour. The first relates to the presence of herding under different market conditions. Previous studies on the subject have investigated whether herding is prevalent in up and down markets, and if so, to what extent. These studies have already covered a wide range of markets, yet the conclusions with respect to the relationship between market condition and the development of herding have proved contradictory, due to different methods for determining market conditions, as well as for testing and measuring herd behaviour (see, Komalasari *et al.* (2021), Table 7). It is also worth noting that these studies covered different time periods, which may also have accounted for the contrasting findings. The second question revolves around the potential effect of size on herd behaviour. Even though in the literature, the size of a company has been recognized as a factor influencing herding (e.g. Andrikopoulos *et al.*, 2017; Chang *et al.*, 2000; Galariotis *et al.*, 2016; Lakonishok *et al.*, 1992; Lee, 2017; Walter and Moritz Weber, 2006; Wermers, 1999), neither theoretical considerations nor empirical evidence have provided a decisive answer as to whether herding is more pronounced among small or large firms. According to the classic reasoning, herding occurs less in large firms as they tend to be more information transparent compared with that of smaller firms and that small firms entail higher information risk due to their limited analyst coverage (Andrikopoulos *et al.*, 2017; Chong *et al.*, 2017; Lee, 2017). This argument can also be supported by the fact that small companies are mostly traded by small investors, who are more prone to imitation. Conversely, it could also be reasonable to argue that the relatively low volumes of small stocks and the homogeneity of institutional investors' strategies lead to higher herding in large companies (Andrikopoulos *et al.*, 2017). Our third research question examines if stock characteristics considered, i.e. whether a stock is a growth or a value stock, have any influence on macro herding. Financial literature has long been debating the issue of investor sentiment towards growth and value stocks. These works argued that both individual and institutional investors prefer growth stocks over value stocks in their investment decisions, which may be due to cognitive biases and inexperience of individual investors, the attraction of stock analysts towards growth stocks, the short-termism of institutional investors, or that growth stocks can easily be justified as prudent investments in contrast to many of value stocks (see, e.g. Jegadeesh *et al.*, 2004; Lakonishok *et al.*, 1992; Sharma *et al.*, 2008). Drawing on these considerations, we would expect higher levels of herding in growth stocks compared to value stocks. Finally, we focus on the question of how macro herding affects market prices, a question that has been widely studied in the literature (see, Komalasari *et al.* (2021), Table 10). This investigation helps to answer the question of whether macro herding distorts prices in the market or contributes to a faster incorporation of market-wide information into prices. Indeed, if no price reversal is observed in the periods following the emergence of herding, it suggests that herding is the result of the presence of market-wide information, which is rapidly incorporated into prices due to herding. On the other hand, if a price reversal is observed subsequently, this suggests that herding may drive prices away from their fundamental value.

Recent studies focussing on the German market have appeared to be diverse in terms of the time period covered, the sample used, and the research question addressed. Walter and Moritz Weber (2006) investigated the trading activity of German mutual funds between 1998 and 2002, and found herding and positive feedback trading among fund managers. In addition, investigating the impact of mutual fund herding on stock prices, they found that herding seems to neither destabilise nor stabilise stock prices. Kremer and Nautz (2013a) drew on the daily trade imbalance of financial institutions in the German stock market and found significant evidence of herding on a daily basis. However, they found return reversals, indicating a destabilising effect of herding on prices in the short term. Kremer and Nautz (2013b) also studied whether there are differences in the trading behaviour in small and large stocks. Their findings revealed that short-term herding does not tend to be more pronounced in small-capitalised stocks or in times of market stress. Mobarek *et al.* (2014) examined country-specific herding behaviour in European liquid constituent indices between 2001 and 2012 and found that herding is significant only during crisis and asymmetric market conditions. Moreover, they found evidence that the cross-sectional dispersions of returns can be partly explained by the cross-sectional dispersions of the other markets, with Germany having the greatest influence on the regional cross-country herding effect. Galariotis *et al.* (2016) found significant evidence of herding for high liquidity stocks using daily equity price data for the G5 markets over the time frame of January 2000 to January 201. However, the evidence for herding among DAX constituents was weaker. Finally, Espinosa-Méndez and Arias (2021) found that the COVID-19 pandemic increased herding behaviour in capital markets of Europe including the DAX.

To the best of our knowledge, this is the first study that examines macro herding for all stocks traded on the German market using a herding measure based on the comovement of returns.

The remainder of the paper is organised as follows. Section 2 and 3 presents the methodology and data used to detect herd behaviour. In Section 4, we present the empirical results, and finally, in Section 5, we draw a conclusion.

2. Materials and methods

2.1 Measuring herd behaviour

The literature provides several alternative methodologies for detecting herd behaviour. The methodology applied depends primarily on how herd behaviour is interpreted.

As Venezia *et al.* (2011) pointed out, to measure the herding into specific stocks, i.e. "micro herding", one should assess to what extent there is a concentration of buy or sell trades on a specific stock. Whereas to measure "macro herding", when investors herd across all stocks rather than into one stock, one should assess to what extent investors' trades are concentrated on either the buy or the sell side of the market. In this study, we focus on macro herding. Thus, we aim to apply a method that allows us to measure the herding of the overall market, that is, the concentration of investment decisions on the buy or the sell side for a wide range of stocks.

In literature, the most widely used measures of herding of the overall market are based on the deviation of returns (Chang *et al.*, 2000; Christie and Huang, 1995). These studies infer the presence of herd behaviour by examining the relationship between market returns and the cross-sectional dispersion of asset returns. In their seminal work, Christie and Huang (1995) argued that cross-sectional standard deviation of returns (hence CSSD) would increase with the absolute value of the market return since the predicted return of a security is the product of the market beta and the market return. However, if market participants make their investment decisions in accordance with the market consensus, considering a wide range of securities, the CSSD will take a lower value than normal, as in this case, individual returns will not diverge significantly from the overall market return. Using a dummy-variable regression model, the authors inferred the presence of herding from the negative relationship between CSSD and extreme market periods. To address the limitations of the CSSD method, Chang *et al.* (2000) later proposed a more robust proxy for herding based on the cross-sectional absolute deviation (CSAD) of returns. The authors suggested that, if investors are rational, then in accordance with CAPM, the relation between CSAD and market returns should be linear and increasingly positive. However, under herding, stock returns should converge towards the average market trend, thus, the relationship between CSAD and the average market return becomes nonlinear and negative. Chang *et al.* (2000) have used a regression approach where the nonlinearity between CSAD and the average market return is captured by the significantly negative coefficients of market return squared. Though return dispersion-based methods are widely used in the literature, several authors have underlined the limitations of these techniques, such as the model specification bias arising from the use of a theoretical model (Demirer and Zhang, 2019), the susceptibility to the presence of outliers (Economou *et al.*, 2011), and that the proposed relationship between the CSSD or CSAD and the absolute value of market return becomes ambiguous when the assumed rational asset pricing model is not the CAPM (Lee, 2017).

Recent studies have gone beyond the previous methods (e.g. Christie and Huang, 1995; Chang *et al.*, 2000) and built on them (e.g. Grinblatt *et al.*, 1995 (GTW); Lakonishok *et al.*, 1992 (LVS); Nofsinger and Sias, 1999; Venezia *et al.*, 2011 (VNS); Wermers, 1999) by constructing new techniques based on the assumption that macro herding is reflected in the similarity of the direction of investment decisions thus manifests itself in the synchronicity of stock returns (Guo and Shih, 2008; Lee, 2017; Tessler and Venezia, 2022). These methods, similarly to Christie and Huang (1995) and Chang *et al.* (2000), use the cross-sectional distribution of individual stock returns, but focus on the fraction of stocks whose prices rise, suggesting if market participants in aggregate exhibit buy (sell) herding across stocks during a certain period of time, then buyer-initiated (seller-initiated) trades will dominate across stocks on average, thus the fraction of stocks whose prices rise will be higher (lower) than the fraction expected under no herding (Lee, 2017).

Though these methods are similar in that they rely on the cross-sectional comovement of returns, they take a somewhat different approach. Lee (2017), for example, proposed a model that is based on the difference between the fraction of stocks whose prices rise and the expected value of that fraction calculated using an assumed rational asset pricing model:

$$CSC_t = U_t - U_t^P, \tag{1}$$

where U_t is the fraction of stocks whose prices rise in period t, while U_t^P is the predicted value of U_t using the CAPM or the Fama-French three-factor model. Regarding the results, Lee (2017) has concluded that the assumed asset pricing model for determining the expected value of the fraction of stocks moving in the same direction can significantly influence the outcome of detecting herd behaviour. Recently Tessler and Venezia (2022) (hereafter TV) have outlined a method [1] that does not require the use of any theoretical asset pricing model [2], thus eliminating the biases inherent in their application.

In our study, we adopted the method of TV to detect herd behaviour of the overall market, that is, when market participants trade in the same direction. By using this method, we assume that herd behaviour manifests itself in the form of synchronicity of stock price movements. First, for every week [3] t, we defined U_t by the fraction of stocks whose prices rise, that is,

$$U_t = \frac{n_t^{up}}{n_t} \tag{2}$$

where n_t^{up} is the number of stocks whose prices rise in week t, and n_t is the total number of stocks in week t.

Then, for each time window of T trading weeks, we calculated the average proportion of rising stocks as,

$$\overline{U}_t = \frac{1}{T} \sum_{t=0-T}^{t-1} U_t, \tag{3}$$

where $\overline{U}_t$ considered to be the "normal" proportion of stock price increases using observations in the rolling 156-week window [4] ending in week $t-1$. As TV suggested, a large deviation of U_t from the "normal" proportion of rising stocks on a given week ($\overline{U}_t$) indicates that stocks move simultaneously in the same direction, thus implying the presence of herd behaviour for that period. Following LVS, GTW, VNS and TV we deem large absolute deviations of U_t from $\overline{U}_t$ as signs of macro herding, i.e. $\left|U_t - \overline{U}_t\right|$.

The herding measure used in this study also takes into account whether these absolute deviations are due to chance or are systematic. To test it, VNS have developed a method that TV has adopted to the stock market environment. They assumed that the number of rising stock prices at time t, under the null hypothesis of no comovement, is binomially distributed with T "trials" and "probability of success" $\overline{U}$, where a rise in stock prices is considered a "success". Since $\left|U_t - \overline{U}\right|$ does not follow any known distribution, they suggested a normal distribution approximation of the expected value of the absolute deviations $E[\left|U_t - \overline{U}\right|]$, that was subtracted from the absolute value of $(U_t - \overline{U})$. Hence, we arrived at the following herding measure:

$$H_t = \left|U_t - \overline{U}_t\right| - E\left[\left|U_t - \overline{U}_t\right|\right] = \left|U_t - \overline{U}_t\right| - \sqrt{2\overline{U}_t\left(1 - \overline{U}_t\right) \Big/ (\pi T)} \tag{4}$$

This measure has two major benefits. First, it is more suited to the definition of macro herding than other methods widely used in the literature. Macro herding is mostly defined in terms of the direction of trades of investors. That is, herding is likely to manifest itself in the form of the synchronicity of stock price movements. This can be more effectively captured by methods based on cross-sectional comovement of returns. Second, being free from the use of asset pricing models required for detecting herd behaviour, this method minimises the biases associated with their application. As Demirer and Zhang (2019) pointed out, methods using theoretical models may be more susceptible to biases as these approaches interprets deviations from theoretical asset pricing models in the context of herding. Consequently, detecting herding may sometimes be driven by model specification bias rather than actual herding behaviour. Moreover, the results obtained from such models often depend on the type of asset pricing model employed (see, e.g. Lee, 2017).

2.2 Data

In this study, we focus on all German publicly traded companies during the period July 2005 to May 2022. To eliminate the potential distorting effect of small stocks on returns, each year we excluded firms with stock prices below 5 euros. For determining herd behaviour, we used weekly asset returns, by compounding daily holding period returns over the weekly interval. Data were obtained from Refinitiv Datastream.

3. Results

In the following, first, we examine how macro herding unfolds under different market conditions. Then we investigate whether this relationship is affected by the size of the firms and whether a company is a growth or a value stock. Finally, we focus on the impact of herding on market prices. In these analyses, we followed the same procedure as Lee (2017).

3.1 Summary statistics

Descriptive statistics for the main variables used in this study are presented in Table 1.

The period covered is from July 2005 to May 2022, i.e. a total of 883 weeks of data were used in our analysis. During this period, the number of shares covered ranged from 278 to 434, with an average number of shares per week of 366. The return of the equally-weighted market portfolio ($\overline{r}_{m,t}$) for the sample period ranged from -21.95% to 11.86%. The lowest market return was observed during the week of 06/10/2008–12/10/2008, while the highest market return was observed during the week of 22/09/2014–28/09/2014. Regarding the fraction of stocks whose prices rise, the minimum value was 2.70%, that is, less than three per cent of stock prices rose that week. This coincided with both the lowest market return and the highest herding measure. The week of 06/04/2020–12/04/2020 produced the highest

Variable	N	Mean	SD	Min	Median	Max
Number of shares	883	366	29.705	278	364	434
The return of the equally-weighted market portfolio, $\overline{r}_{m,t}$ (%)	883	0.009	2,810	−21,947	0.209	11,858
Fraction of stocks whose prices rise U_t (%)	883	47,944	15,146	2,695	50,386	84,765
Average proportion of rising stocks for each time window of T trading weeks, $\overline{U}$ (%)	883	48,045	1,818	43,865	48,141	51,585
Herding measure H_t (%)	883	9,164	8,880	−3,193	7,730	39,734

Source(s): Authors' own creation

Table 1. Descriptive statistics

proportion of stocks with price increases. During this week, nearly 85% of stock prices rose, and the equally-weighted market portfolio return was 8.41%. Finally, the herding measure reached its minimum value in the first week of April 2017, when it stood at −3.19%, accompanied by a half per cent rise in market returns. During this week, the fraction of stocks whose prices rise was 50.26%.

3.2 Herd behaviour under different market conditions

In the following, we investigate how herd behaviour unfolds under different market conditions. As Komalasari *et al.* (2021) pointed out in their literature review, following the work of Christie and Huang (1995), as well as Chang *et al.* (2000), several papers have addressed this subject, but the findings have been inconclusive so far (see, Komalasari *et al.* (2021), Table 7).

In our analysis, we followed the procedure of Lee (2017). Based on a sort on the market returns, we have divided the weeks into 20 groups. The average market return and the average herding measure were then computed for each group. Table 2 presents the results, as well as Figure 1 graphically illustrates the relationship between the average market return and the average herding measure. It should be noted that in order to examine the relationship between herd behaviour and extreme market returns, the first and twentieth groups were further subdivided into two groups.

Our results seem to confirm previous studies that found herding is more pronounced in down markets than in up markets (e.g. Chang *et al.*, 2000; Gong and Dai, 2017; Lee, 2017; Zheng *et al.*, 2017). As the second and third columns of Table 2, as well as Figure 1 illustrates, the herding measure takes higher values in the presence of negative market returns than in

Group based on the market return	Market return (%)	H_t (%)	β_g	*t*-statistics
1A (0–1%)	−12.546	28.107	0.191***	6,586
1B (1–5%)	−6.052	21.598	0.130***	8,955
1 (0–5%)	−7.351	22.900	0.145***	11,404
2	−3.701	16.202	0.074***	5,549
3	−2.403	14.552	0.057***	4,217
4	−1.764	10.128	0.010	0.738
5	−1.364	7.682	−0.016	−1,136
6	−1.039	10.204	0.011	0.797
7	−0.746	8.032	−0.012	−0.868
8	−0.453	4.529	−0.049***	−3,576
9	−0.168	3.347	−0.061***	−4,507
10	0.119	4.195	−0.052***	−3,838
11	0.32	2.535	−0.070***	−5,153
12	0.54	4.231	−0.052***	−3,809
13	0.784	5.268	−0.041***	−3,000
14	1.019	6.563	−0.027**	−1,997
15	1.281	6.928	−0.024*	−1,716
16	1.658	8.295	−0.009	−0.666
17	2.030	8.500	−0.007	−0.509
18	2.641	10.892	0.018	1,325
19	3.397	11.612	0.026*	1,878
20 (95–100%)	5.691	16.098	0.073***	5,397
20B (95–99%)	5.124	15.902	0.070***	4,418
20A (99–100%)	8.818	20.862	0.118***	3,771
Average	0.025	9.135		

Source(s): Authors' own creation

Table 2. The relationship between average weekly market return and average weekly herding measure

Source(s): Authors' own creation

Figure 1. Graphical illustration of the relationship between average weekly market return and average herding measure

the presence of positive returns. This finding supports the existence of directional asymmetry, which states that stocks react quickly to negative macroeconomic news, while small stocks display a slower reaction to positive macroeconomic news (Mcqueen *et al.*, 1996). We also find that herding is more pronounced during extreme market periods, that is when market returns take values at the extremes of the return distribution. The results in the literature on this issue are inconclusive as well. Though the majority of works have reported the presence of herding in extreme market conditions in both developed and emerging markets, some studies have reached the opposite conclusion (see, Komalasari *et al.* (2021), Table 6).

Next, we used the following dummy-variable regression model to formally test if herding is more prevalent during periods of large price movements than during other periods:

$$H_t = \mu_t + \sum_{g=1}^{24} \beta_g D_{g,t} + \varepsilon_t \tag{5}$$

where $D_{g,t}$ is equal to one if the market return in week t belongs to the g-th group based on a sort on the market return and is equal to zero otherwise.

The fourth and fifth columns of Table 2 present the results. The results of the dummy variable regression indicate that the herding measure is significantly higher at the 1% level for the bottom 20% of the market return distribution compared to other levels of returns. However, for positive market returns, the herding measure is only significant at the top 5% of the return distribution. This supports our earlier finding that herd behaviour is more significant for negative market returns than for positive market returns. The results also indicate that herding is weak or absent for returns above the median, with the exception of the top 5% of the return distribution.

3.3 Herding and size effect

In the following, we examine macro herding for portfolios of stocks formed on the basis of size. We are concerned with the question of whether size has an influence on herd behaviour and whether there is a difference in the level of herding between companies with the smallest and the largest market capitalization.

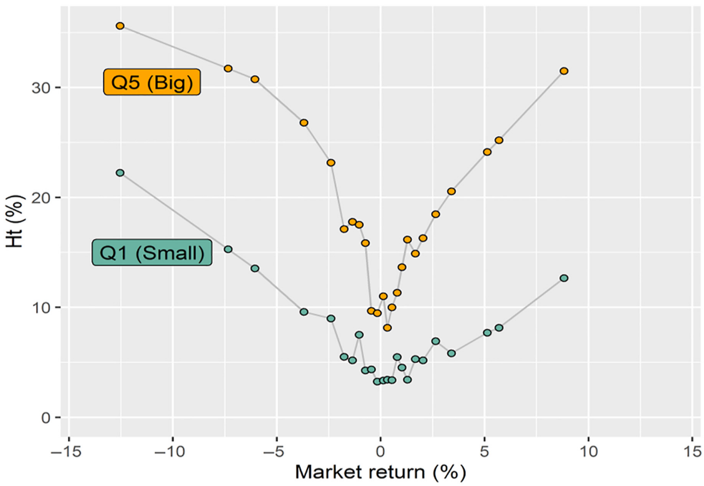
To test the size effect in relation to macro herding, we divided stocks into five groups each year based on their market capitalisation. Following the approach of Fama and French (1996), quintiles were defined based on the market capitalisation at the end of June of year t for the period of July of year t to June of year $t+1$. We then computed the herding measure for the portfolios of the smallest (Q1 Small) and largest (Q5 Big) firms. Finally, we used Eq. (5) to formally test if herding is more prevalent during periods of large price movements than during other periods. The coefficients estimated in the dummy-variable regressions are shown in the third and fourth columns of Table 3 for the groups of small and large firms, respectively. Figure 2 graphically illustrates the relationship between the average market return and the average herding measures for both groups of stocks.

Our results clearly suggest that there is stronger herding among large companies compared to small companies [5]. As shown in Figure 2, herding is higher for larger companies at all levels of market return compared to smaller firms. This contradicts the information-based herding theory, which predicts higher herding for small firms compared to large firms due to higher information risk. However, they are consistent with previous empirical studies (Andrikopoulos *et al.*, 2017; Venezia *et al.*, 2011; Walter and Moritz Weber, 2006). More importantly, our findings are in line with those of Walter and Moritz Weber (2006), who also analysed the German market. Their results did not confirm that small stocks are more vulnerable to herding behaviour and they pointed out that German fund managers are heavily engaged in trading high capitalisation stocks. However, further research is needed to provide a precise theoretical explanation for these results. We also found that under

Group based on the market return	Market return (%)	ßg Q1 (small)	ßg Q5 (Big)
1A (0–1%)	−12.546	0.164***	0.190***
1B (1–5%)	−6.052	0.079***	0.146***
1	−7.351	0.098***	0.157***
2	−3.701	0.038***	0.106***
3	−2.403	0.032***	0.067***
4	−1.764	−0.005	0.004
5	−1.364	−0.008	0.011
6	−1.039	0.016	0.008
7	−0.746	−0.018	−0.010
8	−0.453	−0.017	−0.075***
9	−0.168	−0.029**	−0.077***
10	0.119	−0.027**	−0.061***
11	0.32	−0.027**	−0.091***
12	0.54	−0.027**	−0.071***
13	0.784	−0.005	−0.057***
14	1.019	−0.015	−0.033*
15	1.281	−0.027**	−0.006
16	1.658	−0.007	−0.020
17	2.030	−0.008	−0.005
18	2.641	0.010	0.018
19	3.397	−0.002	0.040**
20	5.691	0.023**	0.089***
20B (95–99%)	5.124	0.018	0.076***
20A (99–100%)	8.818	0.068***	0.149***
Average	0.025	0.014	0.023

Source(s): Authors' own creation

Table 3. The relationship between average weekly market return and average weekly herding measure in small and large firms



Source(s): Authors' own creation

Figure 2. Graphical illustration of the relationship between weekly average market return and average herding measure for group of stocks formed on the basis of market capitalisation

extreme negative market conditions, herding is the strongest for both size groups. This suggests that size does not affect the previously explained asymmetry in herd behaviour. Furthermore, the relationship between market return and herding of small stocks is weaker for groups 19 through 20A compared to large firms. This result strongly corroborates directional asymmetry, which holds that stocks react quickly to negative macroeconomic news while small stocks react slowly to positive macroeconomic news (Mcqueen *et al.*, 1996).

3.4 Herding and stock characteristics

We now turn our attention to the relationship between stock characteristics and herd behaviour, specifically, if there is a significant difference in the level of herding between growth (high market-to-book ratio) and value stocks (low market-to-book ratio).

To test the effect of stock characteristics on macro herding, we divided stocks into five groups each year based on their market-to-book value. Quintiles were defined based on the market-to-book value at the end of June of year t for the period of July of year t to June of year $t+1$. To calculate the market-to-book value, we used the market capitalisation at the end of June of year t, and the book value of the latest fiscal year available at the end of June of year t. We then computed the herding measure for the portfolios of value (Q1 Value) and growth (Q5 Growth) firms. Finally, we used Eq. (5) to formally test if herding is more prevalent during periods of large price movements than during other periods. The coefficients estimated in the dummy-variable regressions are shown in the third and fourth columns of Table 4 for the groups of value and growth firms, respectively. Figure 3 graphically illustrates the relationship between the average market return and the average herding measures for both groups of stocks.

Our results suggest that stock characteristics considered, i.e. whether a stock is a growth or a value stock, have no effect on the degree of macro herding. As can be clearly seen in Figure 3, the herding measure calculated for the two groups of stocks is nearly equivalent at all levels of market returns. In addition, the asymmetric behaviour of macro herding has been confirmed again. The results of the dummy variable regressions show that herding behaviour is significantly higher at the 1% level among the bottom 20% of the return

Table 4.
The relationship between average weekly market return and average weekly herding measure in value and growth firms

Group based on the market return	Market return (%)	ßg Q1 (value)	ßg Q5 (growth)
1A (0–1%)	−12.546	0.177***	0.174***
1B (1–5%)	−6.052	0.121***	0.120***
1	−7.351	0.134***	0.133***
2	−3.701	0.072***	0.060***
3	−2.403	0.052***	0.078***
4	−1.764	0.004	0.009
5	−1.364	−0.011	−0.001
6	−1.039	0.010	0.012
7	−0.746	−0.023	−0.006
8	−0.453	−0.039***	−0.051***
9	−0.168	−0.051***	−0.055***
10	0.119	−0.046***	−0.054***
11	0.32	−0.051***	−0.065***
12	0.54	−0.050***	−0.051***
13	0.784	−0.023	−0.046***
14	1.019	−0.017	−0.021
15	1.281	−0.049***	−0.027*
16	1.658	−0.021	−0.016
17	2.030	0.009	−0.030**
18	2.641	0.010	0.010
19	3.397	0.025*	0.023
20	5.691	0.061***	0.090***
20B (95–99%)	5.124	0.053***	0.084***
20A (99–100%)	8.818	0.117***	0.140***
Average	0.025	0.019	0.021

Source(s): Authors' own creation

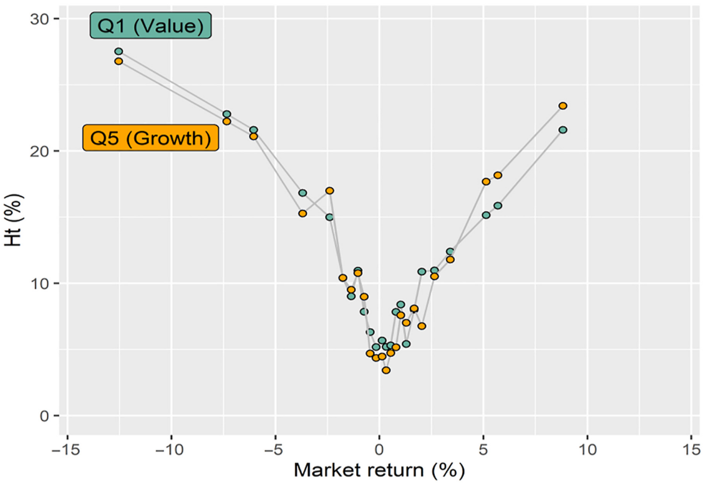


Figure 3.
Graphical illustration of the relationship between weekly average market return and average herding measure for group of stocks formed on the basis of market-to-book value

Source(s): Authors' own creation

distribution. However, herding behaviour is only significant in the top 5% of the return distribution for both groups of stocks.

Overall, our findings contradict the few studies investigating macro herding in value and growth stocks. In the Chinese stock market, Yao *et al.* (2014) have found that investors tend to conform to the market consensus when trading growth stocks, but they could not find evidence of such herd behaviour in value stocks. For US equities, Lee (2017) has found that the level of herding is generally larger for value stocks than for growth stocks, although the difference is weaker when using the FF 3-factor model. Finally, Ju (2019) concluded that investors in the Chinese A-share market herd for growth stock portfolios irrespective of market states, while they only herd for value stocks in down market. The results call for further studies.

3.5 Herding and stock market performances

In the following, we investigate how macro herding affects market prices. Specifically, we test if there is a price reversal following the emergence of herding. To conduct this analysis, we used the following regression model:

$$\overline{r}_{m,t+k} = \alpha_k + \beta_k H_t + \sum_{i=1}^{4} \gamma_{k,i} \overline{r}_{m,t+k-i} + \varepsilon_{t,k}, \tag{6}$$

where, $\overline{r}_{m,t}$ is the return of the equally-weighted market portfolio in week t, and H_t is the macro herding measure in week t. Following Lee (2017), we included four lagged market returns to control for the effects of autocorrelation in the market returns. We use this model to test the stock market performance over the herding period and thirteen periods following the herding period, i.e. for each k, where $0 \leq k \leq 13$, we estimated Eq. (6). We run the regression separately for the subsample of periods with $U_t > 0.5$, i.e. the majority of stock prices rise, and for periods with $U_t < 0.5$, i.e. the majority of stock prices decrease. In the case of the former, a negative β_k, while in the case of the latter, a positive β_k indicates a reversal in market returns and the potential market destabilising effect of herding.

As shown in Table 5, herding is only significantly correlated with the contemporaneous market return at the 1% level. In periods where the majority of stock prices decrease (the second column of Table 5), contemporaneous market returns are significantly negatively correlated with the herding measure. In contrast, in periods where the majority of stock prices rise (the fourth column of Table 5), contemporaneous market returns are significantly positively correlated with the herding measure. However, no significant parameters were found at the 1% level for the subsequent periods, indicating the absence of return reversals after the herding week.

Considering that no reversal is observed after the herding week (an exception is week 10, where a slight positive reversal is observed in the case of falling prices at the 10% significance level), our results seem to confirm that macro herding is driven by the contemporaneous market-wide information and that macro herding facilitates the rapid incorporation of market-wide information into prices.

4. Discussion

This paper examines macro herding in the German market, employing a method for the detection of herd behaviour that does not rely on theoretical models, thus eliminating the biases inherent in their application. This technique is based on the assumption that macro herding is reflected in the similarity of the direction of investment decisions and thus manifests itself in the synchronicity of stock returns. Our objective is to study macro herding under various market conditions, examine the potential effect of the firm size and stock characteristics on this relationship and explore how herding affects market prices.

	ß$_k$ ($U_t < 0.5$)	t-stat. ($U_t < 0.5$)	ß$_k$ ($U_t > 0.5$)	t-stat. ($U_t > 0.5$)
Market return in period t	−0.151***	[−15.145]	0.125***	[8.758]
Market return in period (t+1)	−0.028	[−1.490]	0.007	[0.406]
Market return in period (t+2)	−0.009	[−0.479]	0	[0.009]
Market return in period (t+3)	−0.016	[−0.897]	−0.024	[−1.273]
Market return in period (t+4)	0.019	[1.081]	−0.011	[−0.601]
Market return in period (t+5)	−0.003	[−0.240]	0.012	[0.645]
Market return in period (t+6)	0.006	[0.470]	0.02	[1.033]
Market return in period (t+7)	−0.007	[−0.496]	−0.016	[−0.883]
Market return in period (t+8)	0.008	[0.577]	0.002	[0.120]
Market return in period (t+9)	−0.014	[−1.107]	−0.001	[−0.028]
Market return in period (t+10)	0.026*	[1.771]	0.033**	[2.029]
Market return in period (t+11)	0.014	[1.011]	0.005	[0.275]
Market return in period (t+12)	0.014	[1.000]	0.008	[0.435]
Market return in period (t+13)	−0.016	[−1.118]	0.027	[1.537]

Source(s): Authors' own creation

Table 5.
Herding and stock market performances

Our results indicate that herding is stronger in down markets than in up markets and is more pronounced when market returns reach extreme levels. Additionally, we have found that there is stronger herding among large companies compared to small companies, challenging the information-based herding theory according to which herding is more pronounced for smaller firms due to lower information transparency. Further research is needed to provide a precise theoretical explanation for these results. Our results also show that under extreme negative market conditions, herding is the strongest for both size groups, but the relationship between market return and herding of small stocks is weaker for groups of the top ten per cent of the return distribution, compared to large firms. This strongly supports the idea of directional asymmetry, which holds that stocks react quickly to negative macroeconomic news while small stocks react slowly to positive macroeconomic news. We have found that stock characteristics considered, i.e. whether a stock is a growth or a value stock, have no effect on the degree of macro herding.

When investigating the impact of macro herding on market prices, we found that herding is only significantly correlated with the contemporaneous market return at the 1% level. In declining markets, contemporaneous market returns and herding measures are negatively correlated, whereas, in rising markets, the correlation between contemporaneous market returns and herding measure is positive. However, there was no evidence of reversion in the periods following the herding week. These results seem to confirm that the contemporaneous market-wide information drives macro herding and that macro herding facilitates the rapid incorporation of market-wide information into prices.

In sum, our study has added to long debated topics in the herding literature and our findings call for further investigation. One of our key findings is that large and small firms in the German market react differently to macroeconomic news. This may imply that macro herding may have a different impact on the valuation of stocks in the two groups of firms. Another key finding is that macro herding does not distort the market prices measured by the equally-weighted market portfolio. However, it would be worthwhile to further investigate whether macro herding causes distortions in prices at individual firm level, especially for small firms, which react slowly to negative macroeconomic news.

Notes

1. Building on the herding models of LSV, GTW and VNS, the authors investigated the herd behaviour of stocks markets, i.e. the contagion across markets.

2. Besides the approach described and applied in this study, there are other techniques in the literature that also do not require the use of theoretical models when measuring herd behaviour from market data. For instance, Dhaene *et al.* (2012) introduced a model-independent measure for the expected degree of herd behaviour, called the Herd Behaviour Index (HIX), while Demirer and Zhang (2019) used a modified version of the CSAD, that does not require the estimation of beta.
3. In line with Lee (2017), we used weekly frequency. Lee (2017) argued that the ability of herding to show itself may be constrained by the usage of daily data, since it may take a longer time horizon than a day to emerge.
4. We required at least 150 observations in the rolling three-year window.
5. As suggested by an anonymous reviewer, the inclusion of shares below 5 euros may alter the findings we have presented. More specifically, if we include securities with a share price of less than 5 euros in the analysis, we also include firms that are smaller in size and subject to lower information transparency, thus supposedly arriving at the same conclusion as in the literature regarding the relationship between size and herd behaviour. To address this issue, we carried out a further analysis of the relationship between firm size and herd behaviour, including firms with a share price below 5 euros in the sample. However, in order to prevent the distorting effect of illiquid stocks and shares with outlier returns (also the purpose of eliminating stocks with a price below 5 euros), we excluded companies with a share price below 1 euro. Our results remained qualitatively the same.

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