Highlights

- We examine market and industry herding in the US stock market.
- We use cross-sectional absolute deviation (CSAD) method for the analysis.
- We find no evidence of herding at the market level.
- Herding becomes evident at the industry level.
- Anti-herding is present at the market and industry levels.

Determinants of Industry Herding in the US stock market

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Abstract

This article provides empirical evidence on the determinants of herding in the US using both market and industry level data. We examined herding based on market returns, volatility and trading volume, using the daily data from 1990 to 2020. The findings demonstrate that herding at the market level does not exist, however some herding becomes visible at the industry level. The results also demonstrate significant evidence of anti-herding behaviour at the market and industry level.

Keywords: industry herding; US stock markets; asymmetric behaviour

JEL Classification: G14; G40

1. Introduction

In the behavioural finance literature, herding arises when investors who are inclined to buy or sell based on their private information, overturn their decision after observing the direction of the market. Consequently, investors trade in the same direction and drive asset prices away from their fundamental values, resulting in excess market volatility (Nofsinger and Sias, 1999).

There is considerable amount of research on herding towards the market consensus in various stock markets at the market (Chen, 2020; Clements, et al., 2017; Galariotis, et al., 2016) and industry levels (Kabir, 2018; Zheng, et al., 2017; Gebka and Wohar 2013). Recently, herding has also been investigated in the excessively volatile cryptocurrency market (Philippas et al., 2020; Yarovaya et al., 2020; Vidal-Tomás, et al., 2019). While investors in the U.S. market tend to herd more at the industry level, the empirical evidence on industry herding is still sparse (Litimi, et al., 2016). BenSaida (2017) and Litimi, et al., (2016) fail to find evidence of herding in the U.S. stock market but find significant herding at the industry level during periods of market turmoil. The sparse literature motivated us to provide a deeper analysis of the determinants of industry herding. In this paper our aim is to contribute to the extant herding literature, by investigating whether industry herding is conditional upon market returns, trading volume and volatility[1]. Many studies have provided theoretical explanations on why investors herd. To provide recent insights on US industry herding, we utilise an extensive updated dataset which spans the period from 1990 until August 2020 to incorporate periods of significant volatility in the US market: the 1997 Dot Com bubble, 2008 credit market crisis and the ongoing COVID-19.

The remainder of paper is set out as follows. Section 2 describes the data and methodology utilized. Section 3 discusses the results, and Section 4 concludes the paper.

2.Data and methodology

We utilise daily prices for S&P500[2] constituents' stocks[3] between January 1990 and August 2020[4]. The stock market data was obtained from the Bloomberg Financial database. We assign of the firms to one of the 10 sectors[5] listed by Thompson Reuters Datastream.

We use a well-known and robust methodology[6] developed by Chang et al. (2000) to capture nonlinear relationships between the cross-sectional absolute deviation (CSAD) and market returns providing several advantages over original Christie and Huang (1995) model.

It is specified as follows:

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

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[1] Many studies have provided theoretical explanations on why investors herd based on these conditions. For example, herding in up markets could be due to overconfidence (Daniel, et al., 1998), in down markets could be due to loss aversion (Kahneman and Tversky, 1979), when volatility is high herding could be due to informational cascades (Homles, et al., 2013; Devenow and Welch, 1996), when volatility is low herding could be due to reputational reasons (Homles, et al., 2013; Trueman, 1994); when trading volume is high trading could due to overconfidence (Daniel, et al., 1998), when trading volume is low herding could be due to risk aversion (Kahneman and Tversky, 1979).

[2] S&P500 is used as a proxy for the US market

[3] To account for additions and deletions for every month, we have used the updated constituents of the index.

[4] The data that support the findings of this study are available from the corresponding author, [I.U], upon reasonable request.

[5] The sectors are as follows: Basic Resources, Consumer Staples, Energy, Financials, Health care, Industrials, Real Estate, Technology, Telecommunications and utilities.

[6] Hwang and Salmon (2004) provide an alternative state-space model for investigating macro herding. However, this model has a major shortcoming: it utilises monthly data which is insufficient to capture herding as a short-term phenomenon.

Where $R_{i,t}$ is the log differenced return on stock i at time t, N is the number of stocks the market and $R_{m,t}$is the cross-sectional average of market returns at time t.
Model 1, the base model used to test for herding is estimated by the following regression:

$$CSAD_t = \alpha + \gamma_1 \left| R_{m,t} \right| + \gamma_2 \; R_{m,t}^2 + \varepsilon_t \tag{2}$$

where$\left|R_{m,t}\right|$is the market (sector) return used to capture the nonlinearity in the relationship, $R_{m,t}^2$ is the squared market return, α is the constant, γ_1, and γ_2 are coefficients and ε_t is the error term at time t. Therefore, if herding is absent, then we expect $\gamma_1 > 0$ and $\gamma_2 > 0$ in equation (2).

To detect herding, the CSAD measures its presence by assessing the observed return of all stocks and the cross-sectional average return; a statistically significant negative (positive) coefficient indicates the presence (absence) of herding behaviour. Gebka and Wohar (2013), argue that positive γ_2 coefficients, also suggests the presence of 'negative herding' (anti-herding) whereby during periods of extreme price movements, the dispersion of returns is lower rather than higher than the predictions of rational asset pricing models. A number of other studies also find negative herding (Christie and Huang, 1995; Henker, et al., 2006; Babalos and Stavroyiannis, 2015; Stavroyiannis and Babalos, 2020). The level of dispersion for the model is estimated for each industry sector and the aggregate market. It is reasonable to expect that industry herding may be affected by market conditions characterised by market returns, volatility and trading volume. Consequently, we test whether herding is contingent upon high and low market returns, market volatility and volume.
To test if industry herding is contingent upon market/sector returns, we estimate model 2 which is as follows:

$$CSAD_t = \alpha + \gamma_1 D^{up} \left| R_{m,t} \right| + \gamma_2 \; (1 - D^{up}) \left| R_{m,t} \right| + \gamma_3 \; D^{up} (R_{m.t})^2 \quad + \gamma_4 \; (1 - D^{up}) (R_{m.t})^2 + \varepsilon_t \tag{3}$$

D^{up} is a dummy variable with a value of 1 for days with positive market returns and a value of 0 for days with negative market returns, α is the constant, γ_1, γ_2, γ_3, γ_4 are coefficients. The coefficients of interest are γ_3 and γ_4[7].

To test if industry herding is contingent upon market/sector volatility, we estimate model 3 which is as follows:

$$CSAD_t = \alpha + \gamma_1 D^{\sigma^2-High} \left|R_{m,t}\right| + \gamma_2 \left(1 - D^{\sigma^2-High}\right)\left|R_{m,t}\right| + \gamma_3 D^{\sigma^2-High}(R_{m.t})^2 + \gamma_4 \left(1 - D^{\sigma^2-High}\right)(R_{m.t})^2 + \varepsilon_t \quad (4)$$

WhereD^{σ^2-High} is 1 for days with high market volatility and 0 otherwise. Volatility is defined as high (low) if it is greater (lower) than the previous 30-day moving average.

To test if industry herding is contingent upon market /sector volume we estimate model 4 which is as follows:

$$CSAD_t = \alpha + \gamma_1 D^{vol-High} \left|R_{m,t}\right| + \gamma_2 \left(1 - D^{vol-High}\right)\left|R_{m,t}\right| + \gamma_3 D^{vol-High}(R_{m.t})^2 + \gamma_4 \left(1 - D^{vol-High}\right)(R_{m.t})^2 + \varepsilon_t \quad (5)$$

$D^{vol-High}$ is 1 for days with a high trading volume and 0 otherwise. Trading volume is defined as high (low) if it is greater (lower) than the previous 30-day moving average.

3.Empirical results

3.1. Empirical results for market herding

Table 3.1 presents the results from the estimation of equation (2). The results of the analysis show that the value of γ_2 is positive and statistically significant. Thus, there is no herding effect in the US market. Our results are consistent with recent evidence by BenMabrouk and Litimi (2018), Lee (2017), Galariotis, et al., (2015), and Chiang and Zheng (2010) that use the CSAD model and find no evidence of herding in the US market. It is, however, interesting that the market exhibits anti-herding, which implies that CSAD is extremely high. A possible explanation for this herding is that investors in the US market are overconfident (Barber and Odean, 1999) hence, they may attribute positive returns to their stock-picking skills rather than the prevalent market conditions (Gebka

[7] For models 2 to 4, herding exists when γ3 < 0 and γ4 < 0 and statistically significant. Anti-herding exists when

and Wohar, 2013). Consequently, they trade based on their own assessment reducing the likelihood of herd formation.

Table 3.1. Estimates of herding for the overall US market

Estimated parameters	α	γ_1	γ_2	Adj. R^2
	0.0095	0.5725	4.4819	58.23%
	(0.0000)	(0.0000)	(0.0000)	

Note: Table 3.1. reports the results from model 1. The associated p-values are reported in parentheses.

3.2. Empirical results for industry herding

On analysis of sector level data, Equation (3) is used to examine whether US investors herd at the sector level. An analysis of the regression results presented in Table 3.2 shows limited evidence of herding at the sector level. Financials, Industrials and Real Estate sectors show negative and significant γ_2 coefficients; indicating that the CSAD decreases with the size of the market return. However, the coefficients for the other 7 sectors are positive and statistically significant, indicating the presence of anti-herding. In general, our results are consistent with those of Gebka and Wohar (2013), who document evidence of anti-herding at the sector level.

Table 3.2. Estimates of herding in US sectors

Industry	α	γ_1	γ_2	Adj. R^2
Basic Materials	0.8519	-1.6436	3.4205	64.05%
	(0.0000)	(0.0000)	(0.0000)	
Consumer Staples	0.0098	0.3559	0.5082	30.13%
	(0.0000)	(0.0000)	(0.0122)	
Energy	0.0113	0.3052	1.1006	40.35%
	(0.0000)	(0.0000)	(0.0000)	
Financials	0.9295	0.1223	-0.0603	0.72%
	(0.0000)	(0.0000)	(0.0000)	

Health Care	1.5879	-0.3189	14.6923	28.05%
	(0.0000)	(0.1891)	(0.0035)	
Industrials	1.5751	1.4811	-7.4455	2.21%
	(0.0000)	(0.0000)	(0.0078)	
Real Estate	1.4603	5.4882	-28.7701	3.26%
	(0.0000)	(0.0000)	(0.0000)	
Technology	1.5127	-2.0916	25.4391	0.81%
	(0.0000)	(0.0000)	(0.0000)	
Telecoms	5.4511	-10.9214	5.4815	15.91%
	(0.0000)	(0.0000)	(0.0000)	
Utilities	3.7889	-7.5515	3.7694	19.23%
	(0.0000)	(0.0000)	(0.0000)	

Note: Table 3.2. reports the estimates from model 1. The associated p-values are reported in parentheses.

3.3. The effect of market returns on herding

To examine whether herding is contingent upon rising or declining market returns, Equation (4) is used to capture the differences in the CSADs. γ_3 and γ_4 represent the coefficients for rising and declining market conditions respectively. Table 3.3 presents the market-wide results. The evidence suggests that in rising market conditions, the coefficient γ_3 is positive and statistically significant, indicating that there is no evidence of herding.

Table 3.3. Estimates of herding in rising and declining markets, US

Estimated Parameters	α	γ_1	γ_2	γ_3	γ_4	Adj. R^2
	0.0096	0.2701	0.9344	3.6147	2.8024	73.11%
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	

Note: Table 3.3. reports the estimates from model 2. The associated p-values are reported in parentheses.

Likewise, during declining market conditions, the coefficient γ_4 is positive and statistically significant. The results also indicate that there is no evidence of herding.

Hence, herding is not contingent upon market returns. On the contrary, there is evidence of anti-herding in both market conditions.

Table 3.4 presents results for the industry sector CSADs in rising and declining price movements. In both rising and declining markets, negative statistically significant coefficients are reported in the Financials, Industrials, Real Estate, Telecoms and Utilities sectors. These results imply that market participants herd in the same industries irrespective of the state of the market.

Table 3.4. Estimates of herding for sectors in rising and declining markets, US

Industry	α	γ_1	γ_2	γ_3	γ_4	Adj.R^2
Basic Materials	0.8275	-1.2353	-1.8304	2.9628	3.7316	64.66%
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	
Consumer Staples	0.0098	0.3661	0.3400	0.6457	0.5579	30.19%
	(0.0000)	(0.0000)	(0.0000)	(0.0485)	(0.0179)	
Energy	0.0112	0.3536	0.2975	0.1684	1.2508	40.61%
	(0.0000)	(0.0000)	(0.0000)	(0.3259)	(0.0000)	
Financials	0.9294	0.1178	0.1283	-0.0630	-0.0587	0.74%
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	
Health Care	1.5878	-0.2869	-0.3370	12.8614	15.8113	0.11%
	(0.0000)	(0.3244)	(0.2419)	(0.0740)	(0.0109)	
Industrials	1.5751	1.5284	1.4540	-9.0786	-6.4755	2.19%
	(0.0000)	(0.0000)	(0.0000)	(0.0282)	(0.0557)	
Real Estate	1.4600	5.6927	5.3760	-32.6439	-26.5081	3.25%
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	
Technology	1.5138	-3.2685	-0.9999	21.0510	30.9220	3.23%
	(0.0000)	(0.0000)	(0.0010)	(0.0001)	(0.0000)	
Telecoms	0.0082	0.4876	0.4159	-0.9825	-1.6303	24.04%
	(0.0000)	(0.0000)	(0.0040)	(0.0000)	(0.0000)	
Utilities	0.0065	0.0054	0.0083	-0.0074	-0.0083	2.02%
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	

Note: Table 3.4. reports the estimates from model 2. The associated p-values are reported in parentheses.

3.4. The effect of volatility on herding

To examine whether there is a relationship between herding and volatility, we use equation (5) to capture a possible asymmetric relationship between CSAD and return volatility. The findings for the overall market are presented in Table 3.5. The results reveal that herd behaviour is absent in both low and high volatility periods, both coefficients are positive and statistically significant. This implies that there is no asymmetric relationship between herding and volatility at the market level. It is noteworthy that the γ_4 is positive and significant, providing evidence in favour of anti-herding. This implies that the market anti-herds during periods of low volatility.

Table 3.5. Estimates of herding during periods of high and low volatility for the overall US market

Estimated Parameters	α	γ_1	γ_2	γ_3	γ_4	Adj. R^2
	0.0088 (0.0000)	0.5278 (0.0000)	0.8809 (0.0000)	5.0633 (0.5725)	3.4404 (0.0000)	60.26%

Note: Table 3.5 reports the estimates from model 3. The associated p-values are reported in parentheses.

The results for the effect of high (low) volatility on herding at the sector level is presented in Table 3.6. Notably, there is no evidence of herd formation during periods of high volatility in all the sectors. We obtain positive and statistically significant coefficients in most sectors except Financials, Technology and Telecoms. This result indicates an increasing relationship between equity return dispersion and high market volatility, which is inconsistent with earlier findings of herding behaviour during low volatility periods (see *inter alia* Holmes, et al., 2013).

Table 3.6. Estimates of herding for US sectors in periods of high and low volatility

Industry	α	γ_1	γ_2	γ_3	γ_4	Adj.R^2
Basic Materials	0.2111	-0.3275	-0.0473	2.7737	3.2159	63.57%
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	
Consumer Staples	0.0115	0.0271	0.0051	5.5078	21.2684	26.77%
	(0.0000)	(0.0000)	(0.6566)	(0.0000)	(0.0000)	
Energy	0.0139	0.0116	-0.0036	2.9973	8.0262	32.42%
	(0.0000)	(0.0234)	(0.7183)	(0.0000)	(0.0000)	
Financials	0.9537	-0.0109	0.0101	-0.0034	0.1226	0.76%
	(0.0000)	(0.0308)	(0.3328)	(0.3298)	(0.0000)	
Health Care	1.5858	-0.0832	0.0794	7.7159	57.4649	0.24%
	(0.0000)	(0.4296)	(0.7127)	(0.0051)	(0.0000)	
Industrials	1.5823	-0.0540	0.2854	12.9420	92.5116	2.18%
	(0.0000)	(0.4480)	(0.0616)	(0.0000)	(0.0000)	
Real Estate	1.4960	-0.1014	0.2931	14.6122	93.0325	1.31%
	(0.0000)	(0.6034)	(0.4656)	(0.0000)	(0.0000)	
Technology	1.4991	-1.3954	-1.0051	-3.9467	-20.2229	2.48%
	(0.0000)	(0.0000)	(0.0000)	(0.0624)	(0.0761)	
Telecoms	-0.8308	1.2242	2.0584	-0.3850	-1.2190	23.91%
	(0.0014)	(0.0155)	(0.0001)	(0.1182)	(0.0000)	
Utilities	0.0069	-0.0010	-0.0013	0.0015	0.0138	0.88%
	(0.0000)	(0.0000)	(0.0024)	(0.0000)	(0.0000)	

Note: Table 3.6 reports the estimates from model 3. The associated p-values are reported in parentheses.

During low volatility periods, herding is only present in the Telecoms sector. However, anti-herding is present in all other sectors except Telecoms.

3.5. The effect of volume on herding

To investigate herd behaviour in periods of high and low trading volume, we utilise equation (5) to capture a possible asymmetric relationship between CSAD and trading volume. The results for the overall market are reported in Table 3.7. In periods of high trading volume, the γ_3 coefficient is positive and statistically insignificant, indicating that the cross-sectional dispersion is higher compared to levels suggested by rational asset pricing models. Hence, there is no asymmetric effect of herding during periods of high trading volume. We observe a positive and significant γ_4 coefficient during low trading volume periods, which indicates a tendency of investors to anti-herd. Overall, the evidence shows that using market level data, investors do not herd regardless of the trading volume hence herding is not related to trading volume.

Table 3.7. Estimates of herding during periods of high and low volume for the overall US market

Estimated Parameters	α	γ_1	γ_2	γ_3	γ_4	Adj. R^2
	0.0097	0.4315	0.5908	9.0426	3.9656	58.65%
	(0.0000)	(0.0000)	(0.0000)	(0.5725)	(0.0000)	

Note: Table 3.7 reports the estimates from model 4. The associated p-values are reported in parentheses.

To gain additional insight on whether herd behaviour exhibits an asymmetry associated with the trading volume, we examine evidence using the sector level data. The results presented in Table 3.8 shows that during high trading volume periods, the γ_3 coefficients are negative and statistically significant in Financials, Real Estate and Utilities sectors. This gives an indication that high trading volume has a limited effect on the dispersion of returns in the US sectors examined. Therefore, herding is not contingent upon high trading volume. On the contrary, we document positive and significant coefficients in Basic Materials, Energy, Health Care, Technology and Telecoms, which provides evidence in favour of anti-herding.

An analysis of herding during low volume periods shows negative and statistically significant γ_4 coefficients in the Financials, Industrials, Real estate and Utilities sectors. We document anti-herding in Basic Materials, Consumer Staples, Energy, Technology and Telecoms sectors.

In all, the results for herding conditioned on trading volume at both the market and sector level provide limited evidence in support of the presence of stronger levels of herding during high (low) volume periods. However, there is strong supportive evidence that US investors exhibit 'negative herding' as most of the coefficients during the high and low volume periods are positive and statistically significant

Table 3.8. Regression estimates for herd behaviour during high and low trading volume, US

Industry	α	γ_1	γ_2	γ_3	γ_4	Adj.R^2
Basic Materials	0.8453	-1.8018	-1.5111	3.5554	3.3194	64.08%
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	
Consumer Staples	0.0099	0.4025	0.2912	-0.0951	1.6279	30.67%
	(0.0000)	(0.0000)	(0.0000)	(0.6700)	(0.0000)	
Energy	0.0113	0.3256	0.3117	1.0466	0.5631	40.54%
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0172)	
Financials	0.9307	0.1087	0.1306	-0.0580	-0.0622	0.73%
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	
Health Care	1.5891	-0.4285	-0.3382	15.5723	16.8428	0.11%
	(0.0000)	(0.1234)	(0.3408)	(0.0040)	(0.1382)	
Industrials	1.5751	1.1329	2.0114	-1.4634	-19.4806	2.38%
	(0.0000)	(0.0000)	(0.0000)	(0.6444)	(0.0000)	
Real Estate	1.4629	5.2667	5.6180	-26.2514	-31.2197	3.26%
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	
Technology	1.5135	-2.4486	-1.6360	34.4362	11.9658	0.96%
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0511)	
Telecoms	0.0082	-10.7994	-10.8179	5.4164	5.4338	16.40%
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	
Utilities	0.0065	0.0102	0.0039	-0.0109	-0.0047	2.70%
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	

Note: Table 3.8 reports the estimates from model 4. The associated p-values are reported in parentheses.

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4.Conclusion

The aim of this study was to investigate in determinants of industry herding in the U.S market. The investigation utilised daily data from January 1990 to August 2020.

Our results show that market wide herding is absent in the US market, and limited evidence of herding becomes visible at the sector level, especially in the Financials, Real Estate, Telecoms and Utilities sectors. Further analysis revealed the absence of herding asymmetry with respect to up and down-market conditions, however, some evidence of herding emerges at the sector level in both market conditions. Our results also display that there is limited evidence of industry herding for trading volume and volatility. Notably, the results reveal significant anti-herding across at both the market and industry levels contingent upon market returns, trading volume and volatility. These findings are useful for practitioners and policy makers enhancing their understanding of the herding behaviour at industry level.

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Professor Jonathan Batten Date: 08/01/2021

Editor-in-Chief

Finance Research Letters

Dear Professor Batten,

Re: Resubmission of manuscript titled “Industry Herding in the U.S. stock market”

We would like to thank you for the letter dated 10/10/2020, and the opportunity to resubmit and revised copy of this paper. We are also grateful for the reviewer’s highly insightful and considered comments and have made every attempt to address them in the revised paper.

We believe that focusing on the comments has helped to significantly improve our paper and has allowed us to make a greater contribution to the herding literature. Our responses to each comment are appended to this letter.

We hope that the revised manuscript will be accepted for publication.

Yours truly,

Idibekeabasi

On behalf of the authors.