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Animal Behavior in Capital markets: Herding formation dynamics, trading volume, and the role of COVID-19 pandemic

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ABSTRACT

This paper provides new evidence on herding behavior. Using daily frequency data for 336 US listed firms over a five-year period, we investigate three important elements of financial herding behavior. First, trading volume, representing market interest, as a significant variable in capital markets apart from stock prices. Second, herding dynamics since herding formation is a dynamic process. Third, the reaction of possible financial herding to exogenous events-threats, as we use the pandemic event in order to investigate a market under stress. Even though the benchmark herding model used does not provide evidence of herding behavior, our results verify the significance of the above herding elements. We also find that trading volume and positive changes in trading volume result in increased cross-sectional absolute deviation (CSAD). Most importantly, we find that herding behavior is evident during the COVID-19 pandemic confirming that investors tend to herd during major crisis periods.

1. Introduction

Collective behaviors have been investigated under different disciplines of science and are considered important as a plausible explanation for human behavior. According to Gade, Paranjape and Chung (2015, p. 1) *"[c]ollective animal behaviors have long been a subject of interest to researchers from different fields including theoretical biology, ecology, sociology, and engineering"*, and economics is not an exemption. Herding theories have been applied in order to explain collective economic behavior. Especially in the capital markets herding metrics are relatively easy to observe and calculate. A common approach in the above direction, is to define some metrics that would enable researchers to measure performance of possible herding behaviors. For the example of birds, a metric can include the flock centroid and the flock diameter that would describe the size of the flock and the performance of possible herding; and one may visualize the radius of the flock as the maximum distance between any bird (or boid[1]) and the flock centroid (Gade et al., 2015).

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[1] The name "boid" corresponds to a shortened version of "bird-oid object", which refers to a bird-like object in artificial life programming (Reynolds, 1987).

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In Economics and Finance, herd behavior has been widely studied and documented in different market contexts.[2] It is a quite common behavioral bias that is related to correlated trading activity based on imitation irrespective of personal information, views, or analysis (see Hirshleifer and Teoh, 2003). Herding behavior can be rational when driven by payoffs related to information (Devenow and Welch, 1996), reputation (Bikhchandani and Sharma, 2000; Devenow and Welch, 1996; Scharfstein and Stein, 1990; Trueman, 1994) or compensation (Bikhchandani and Sharma, 2000; Scharfstein and Stein, 1990). However, individually rational decisions made by utility maximizing agents may result in "collectively irrational informational cascades" (Raafat, Chater and Frith, 2009). As a result, individually rational decisions may result in market inefficiency and irrational market behavior (Hwang and Salmon, 2004, 2007). Moreover, Devenow and Welch (1996) distinguished between rational and irrational herding behavior (i.e., herding driven by investor psychology and behavioral factors). Finally, spurious herding[3] (see Bikhchandani and Sharma, 2000) may also emerge when investors happen to make the same investment decisions due to style investing (Gavriilidis, Kallinterakis and Ferreira, 2013; Guney, Kallinterakis and Komba, 2017) or when employing commonly known and widely used techniques to interpret available data and information (Hirshleifer, Subrahmanyam and Titman, 1994).

Herding behavior has important implications for asset pricing and market efficiency, as well as for portfolio diversification and overall market stability (see Chiang and Zheng, 2010; Economou, Kostakis and Philippas, 2011). Asset prices may deviate from fundamental values due to imitative trading activity and in this case market efficiency does no longer hold. Moreover, herd behavior may result in under-diversified portfolios and exposure to risk that is hard to hedge. As a result, market participants need to identify such correlated trading patterns in order to adjust their asset allocation strategies accordingly. Especially during crisis periods herding may be more profound and may produce cross-market herding as well as a contagion effect (Chiang and Zheng, 2010; Economou, Hassapis and Philippas, 2018).

The outbreak of the COVID-19 pandemic created conditions of increased uncertainty and fear in the stock markets that would facilitate herding behavior. In fact, there is growing literature on the impact of herd behavior in financial markets during the COVID-19 pandemic period. Ferreruela and Mallor (2021) identified herding on high volatility days during the pandemic sub-period in Spain and Portugal, while Espinosa-Méndez and Arias (2021b) and Espinosa-Méndez and Arias (2021a) evidenced that COVID-19 increased herding behavior in the Australian stock market and five European stock markets, respectively. Jiang et al. (2022) provided evidence of herding in major Asian stock markets during the COVID-19 period, with a sharp rise of its magnitude around the stock market crash of March 2020. Wu, Yang and Zhao (2020) indicated that herding was significantly lower than usual in the Chinese stock markets during the COVID-19 pandemic, being more pronounced under specific market conditions (i.e., positive market returns, lower market trading volume and volatility). Other studies employed international stock indices to detect herding during the COVID-19 pandemic period. Kizys, Tzouvanas and Donadelli (2021) examined herding employing 72 stock market indices from both developed and emerging economies for the first quarter of 2020 providing supporting evidence of herding in international stock markets. Ghorbel, Snene and Frikha (in press) also identified herding behavior during the COVID-19 period, employing stock market indices from developed and BRICS countries (Brazil, Russia, India, China and South Africa).

In this study we are motivated by the following facts: The US capital market is the biggest and most sophisticated market in the international investment arena. Investors' herding behavior becomes central in behavioral finance literature, giving growing evidence that the "homo economicus" assumption of market efficiency is not always valid. Finally, since the beginning of 2020 Covid-19 disrupted the global economy, opening an opportunity to study stock market behavior in the form of a "natural experiment".

Our aim is to follow a synthetic research approach, bringing together significant findings from the investors' herding literature like time dynamics in herding modeling, the role of trading volume and the impact of an exogenous negative event, i.e., Covid-19. To this end, we examine for possible herding behavior in the US market, by focusing on three important elements. First, trading volume as a usually overlooked variable in investigating investor behavior in the capital markets. Price-volume relationship is important for stock price analysis and there have been offered several reasons for that (Karpoff, 1987). For example, the price–volume relation provides an insight to the structure of the financial markets; also, it is useful for event studies because if price and volume are jointly determined, then by incorporating their relationship we increase the power of the tests.[4] Second, herding dynamics, observed to be significant in some studies, possibly because of highly autocorrelated herding measures (Arjoon and Bhatnagar, 2017; Arjoon, Bhatnagar and Ramlakhan, 2020). Nevertheless, the econometric specification can be explained by the fact that herds do not form instantly. On the contrary, conventional wisdom says that herds form and dissolve gradually as herding can be proportional to the existing herding. In our study we expand the lag structure of the cross-sectional absolute deviation (CSAD) as an explanatory variable. In the financial markets it normally takes several days to observe and react to existing market behavior. Finally, we try to estimate, the reaction of possible financial herding to the exogenous event of the COVID-19 pandemic and we document an asymmetric herding behavior based on the number of new COVID-19 cases, which possibly injects sentiment, such as fear, in the investment community.

We employ the Chang, Cheng and Khorana (2000) model as well as lagged variables of the CSAD. The inclusion of the lagged values of CSAD is not only based on econometric theory to avoid autocorrelation problems in the estimation of the models. More importantly, herding, as a human behavior, is assumed to develop gradually and persist, probably inducing autocorrelation in the CSAD measure (Merli and Roger, 2014). Investors may "follow the herd" by copying the trading behavior of other investors (Graham, 1999). An

[2] See Spyrou (2013) and Kallinterakis and Gregoriou (2017) for a comprehensive review on herding behavior in different markets.

[3] According to Caparrelli, D'Arcangelis and Cassuto (2004), spurious herding behavior does not conflict with market efficiency since individuals behave similarly based on the same available information set.

[4] In some tests price changes are interpreted as the market evaluation of new information, while the corresponding volume is considered as an indication of the extent to which investors disagree about the meaning of the information (Beaver, 1968).

additional reason for herding can be positive feedback trading (Case and Shiller, 1989; Cutler, Poterba and Summers, 1989, 1991; Frankel and Froot, 1987; King and Koutmos, 2021; Koutmos, 2014). There is evidence that investors extrapolate trends, and this behavior can be reflected in a tendency towards herding based on common beliefs and imitation.[5] Even though "trend chasing" can be a wrong investment strategy, there is evidence that the subjects of psychological experiments tend to make the same mistake, they do not make random mistakes (Shleifer and Summers, 1990).

Following the approach described above, we attempt to corroborate findings of Chiang and Zheng (2010), who found no evidence of herding in the US market with the exception of the financial crisis period. This latter finding reinforces our inclination to investigate further the impact of crisis events on herding. Similar conclusions were drawn by Belhoula and Naoui (2011), who identified herding during extreme market conditions, while Galariotis, Rong and Spyrou (2015) documented similar behavior during days with important macroeconomic announcements. Voukelatos and Verousis (2019) associated herding with market stress in the options market. On the contrary Bekiros et al. (2017) provided evidence of insignificant herding during the global financial crisis (GFC).

At this point, we have to note that the nature of a crisis (endogenous or exogenous) may have a different impact on the mimicking behavior of investors (e.g., see Ferreruela and Mallor, 2021). While the 2008 GFC can be considered as an endogenous shock to the financial system, the outbreak of the COVID-19 pandemic has the characteristics of an exogenous disturbance. The latter adverse public health event might have substantially affected -perhaps even more than an endogenous shock- the risk preferences (risk aversion) of investors (Huber, Huber and Kirchler, 2021), augmenting in such a way the negative impact on their beliefs. Moreover, the COVID-19 containment measures appear to exhibit significant negative spillovers on the financial system (see Alexakis, Eleftheriou and Patsoulis, 2021). One can expect that all the above effects will alter the market sentiment (important transmission mechanism of herding), leading to herding behavior.

Our main finding is that herding behavior is observed during the pandemic period and especially on the eve of the announcement of an increased number of new COVID-19 cases. In this context, collective evidence can prove useful for fund managers and investment specialists when formulating their investment decisions especially in the light of danger factors looming ahead. We believe that our paper contributes to the ongoing debate over behavioral biases in the international markets by illuminating further the relationship between herding and the recent pandemic. We also shed new light to the impact of danger factors on herding behavior and how similar patterns could be expected in the future given extreme conditions faced globally over the last years, bearing also high likelihood that similar events will persist in the future.

The remainder of the paper is structured as follows. Section 2 provides an overview of the related research on US stock market herding. Section 3 reports the employed methodology and data. Sections 4 and 5 present the empirical results and robustness checks, respectively. Section 6 concludes the paper and provides suggestions for future research.

2. Related research on the US stock market herding

The US market has attracted researchers' interest as far as herding is concerned, with specific emphasis on different bubble and crisis periods. However, the empirical results are inconclusive. In fact, they are mixed depending mostly on the period under examination and the employed methodology. Christie and Huang (1995) were the first to introduce the concept of cross-sectional dispersion of the market returns, providing no evidence of herding in the US market for the periods July 1962 to December 1988 (daily frequency data) and December 1925 to December 1988 (monthly frequency data). Chang et al. (2000) also found no evidence of herding in the US market for the period 1963–1997. The authors introduced a nonlinear relationship of the cross-sectional absolute deviation of returns and the market return. In fact, many researchers employ various modifications of their approach to capture different market conditions and examine alternative explanatory variables. The empirical studies that follow employ a cross sectional dispersion methodology with several modifications and facilitate to some extent comparison with our own results.

More recent studies identified herding in the US market either under specific market conditions or during different time periods. For example, Chiang and Zheng (2010) examined 18 international markets and documented herding in advanced stock markets, except for the US market, for the period 4/25/1989 to 4/24/2009. However, the authors provided supporting evidence of herding in the US market during the GFC, also indicating that the US returns dispersion had a significant impact on non-US markets' herding. Belhoula and Naoui (2011) identified the joint presence of herding and positive feedback trading in the US market during periods of extreme market conditions, employing weekly frequency data for a sample of 25 Dow Jones companies from January 02, 1987, to December 11, 2009. Chen (2013) investigated 69 international stock markets and provided evidence of herding in the US market for the period 2000–2009, with no asymmetric herding effects. According to BenSaïda, Jlassi and Litimi (2015), there was no evidence of herding in the US market (S&P 100 and Dow Jones Industrial Average) over the period 1 January 2000 to 30 June 2014 or during the GFC. Even though there was no volume related asymmetric herding effect, the authors identified a bi-directional link between herding and trading volume employing VAR and Granger causality tests. Galariotis et al. (2015) tested for herding in the US market employing the S&P100 constituents from October 1989 to April 2011. Overall, there was neither evidence of herding for the whole period nor for market return asymmetries. However, there was evidence of herding during days with important macroeconomic announcements. Moreover, the authors reported fundamental herding, i.e., herding due to changes in fundamental information, during the Asian and the Russian crisis and non-fundamental herding during the GFC, while they also identified herding spillover from the US market to the UK market during the Asian crisis and the Dotcom bubble burst. Galariotis, Krokida and Spyrou (2016) provided further evidence of

[5] As Kindleberger (1978) *"Manias panics and crashes: A history of financial crises" page 15*, puts it: *"nothing can be more disturbing than seeing the man next door getting rich"*.

herding for high liquidity stocks from the US market (among five international stock markets) for the period January 2000 and January 2015 and several sub-periods. Bekiros et al. (2017) examined herding in the US market using daily and monthly frequency data for the period January 2000 - July 2015. The empirical results indicate herding being stronger using daily data. Moreover, the authors indicated that herding tends to decrease over time, being insignificant during the GFC, and supported that herding could be related to the increased volatility of the US stock market and the GFC. Voukelatos and Verousis (2019) investigated herding in the US market using daily frequency data from 1996 to 2015. Even though the empirical findings did not support the presence of herd behavior as a general investment tendency, the authors identified herd behavior on days when the options market activity reflected market stress.

Cross-market herding has also been studied in different international markets. For example, Economou et al. (2018) examined herding in the US, the UK and the German stock markets from January 2004 to July 2014 and provided evidence of herding towards the 'fear' indicator instead of the market return in the US market, as well as evidence of cross-market herding. BenMabrouk (2018), examined cross-market herding focusing on the US market and the oil market from 2000 to 2016. The author provides evidence of herding during crisis periods, with investor sentiment fuelling herding in the crude oil market and reducing herding in the stock market.

Other studies investigated industry herding since even though herding is usually absent in the whole US market, such a behavior could arise at individual industry level. Litimi, BenSaïda and Bouraoui (2016) studied the US market and individual sectors from 1985 to 2013. The authors provide evidence of herding during different financial crises and bubbles. Volume turnover and investor sentiment had a significant impact on herding that varied among sectors. In the same vein, BenSaïda (2017) also studied individual sectors, alongside with the US market for the period from 1985 to 2015 and identified herding only during financial crises and bubbles. Moreover, volume turnover did not seem to trigger herd behavior, while investor sentiment intensified herding in 4 out of 12 sectors.

BenMabrouk and Litimi (2018) indicated the absence of industry herding in the US market for the period 2000–2017. However, there is evidence of industry herding when accounting for the oil market returns, being more pronounced during oil market downturns, while oil market volatility and investor fear reduced this impact. Ukpong, Tan and Yarovaya (2021) also provided limited evidence of herding in the US market at industry level for the period January 1990 - August 2020. However, there was no evidence of herding at market level or asymmetric herding effects with respect to market return, volatility, and volume. Moreover, Andrikopoulos, Gebka and Kallinterakis (2021) focused their analysis on cannabis stocks listed in the US and Canada as well as on individual sectors in the cannabis industry, for the period 3 January 2011 to 18 September 2019. The authors documented significant herding among Canadian-listed cannabis stocks, while there was limited evidence of herding in the US-listed cannabis stocks, for days with positive average performance and high volume.

Recently, Duygun, Tunaru and Vioto (2021) tested for herding in the US and the Eurozone markets and financial industries from 2005 to 2017. The empirical results identified herding during the GFC for the US market and the financial industries, as well as evidence of herding for the US banks and insurance industries during the Eurozone crisis. Moreover, herd behavior is more likely to occur under extreme market conditions with higher volatility. Finally, the authors identified spillover effects from the insurance industry to the market as well as intentional (non-fundamental) herding for the market and the individual financial industries.

Another strand of literature focuses on individual product categories in the US market that may experience herding behavior. Philippas et al. (2013) tested for herding in the US REIT (Real Estate Investment Trusts) market for the period 2004–2011. The authors provided evidence of herding for the sub-period 2004–2009 which however could not be attributed to the GFC. Overall, herding was found to be more pronounced on days with negative market returns, while investor sentiment and adverse shocks to REIT funding also had a significant impact. Zhou and Anderson (2013) also provided supporting evidence of herding in the US REIT market for the period 1980–2010, being more pronounced during down-market days. Moreover, the authors indicated that during the GFC herding did not occur until the market was extremely turbulent. Finally, Cui, Gebka and Kallinterakis (2019) provided evidence of herding in the US closed-end fund market for the period 1992–2016, being mostly noise-related, i.e., driven by non-fundamentals, and evident only after the outbreak of the GFC. Herding was present in both up and down-market days as well as on days with high volatility, volume and economic policy uncertainty.

Overall, the empirical evidence on herding in the US market attempts to document the existence of similar instances with inconclusive evidence. Nonetheless, the literature clearly establishes an association between specific significant events and herding. As a result, we attempt to provide further insights focusing on both recent hygiene events and trading volume as potential factors influencing the tendency towards herding. We add recent and additional evidence of herding for the US market focusing on herding dynamics, trading volume and COVID-19 pandemic.

3. Methodology and data

3.1. Methodology

Chang et al. (2000) based on the cross-sectional dispersion approach of the seminal paper of Christie and Huang (1995) introduced a non-linear relationship of the cross-sectional absolute deviation (CSAD) of returns and the market return[6] to capture herding behavior, as follows:

[6] A methodology that can be associated conceptually to the centroid methodologies for birds, mentioned in the introduction.

Table 1
Descriptive statistics of the CSAD, market return and trading volume (2015–2020).

	CSAD	R_m	Log Trading Volume
Mean	3.173414	−0.005069	8.025924
Median	2.976288	−0.014237	7.978158
Maximum	8.632071	7.336835	8.873820
Minimum	1.831073	−11.11489	7.269528
Std. Dev.	0.799479	1.266843	0.217150
Skewness	2.143731	−1.244735	1.060672
Kurtosis	9.951448	16.50268	4.397674
Jarque-Bera	4196.854	11861.04	406.0383
Probability	0.000000	0.000000	0.000000
Augmented Dickey-Fuller (ADF) test *t*-Statistic	−7.490303***	−21.40422***	−4.130136***
Serial correlation at lag (Q-Stat in parentheses): 1	0.583 (513.99)***	0.087 (11.35)***	0.841 (1,070.20)***
2	0.516 (917.55)***	0.206 (75.57)***	0.796 (2,028.70)***
3	0.476 (1,260.60)***	0.028 (76.77)***	0.771 (2,929.50)***
5	0.469 (1,936.90)***	0.050 (84.04)***	0.753 (4,657.70)***
20	0.303 (4.884.60)***	0.019 (126.11)***	0.647 (15,348.00)***
Observations		1,510	

Notes: The cross-sectional absolute deviation (CSAD) is calculated as follows: $CSAD_t = \frac{\sum_{k=1}^{N}\left|R_{i,t} - R_{m,t}\right|}{N}$, where $R_{i,t}$ is the return of equity *i* on day *t*, $R_{m,t}$ is the market return on day *t*, and *N* is the number of all the equities of the sample on day *t*. *** represents statistical significance at the 1% level.

Table 2a
Herding estimations.

	Constant	$\lvert R_{m,t}\rvert$	$R^2_{m,t}$	$CSAD_{t-1}$	$CSAD_{t-2}$	$CSAD_{t-3}$	$CSAD_{t-4}$	$CSAD_{t-5}$	$Vol_{m,t}$	$\Delta Vol_{m,t}$	R^2 adj.	Akaike info criterion
Eq.2	2.7479 (75.12)***	0.4968 (9.13)***	−0.0030 (-0.49)	–	–	–	–	–			30.74%	2.03
Eq.3	0.8624 (8.51)***	0.3609 (9.45)***	−0.0100 (-1.93)*	0.3022 (9.05) ***	0.1076 (4.45) ***	0.0430 (1.79) *	0.1021 (4.08) ***	0.0799 (3.12) ***	–	–	53.23%	1.64
Eq.4	−2.3316 (-4.70)***	0.3201 (8.92)***	−0.0079 (-1.69)*	0.3139 (9.14) ***	0.1000 (3.94) ***	0.0495 (2.28) **	0.0772 (3.12) ***	0.0788 (3.19) ***	0.4079 (6.11) ***	0.9560 (6.03) ***	57.24%	1.55

Notes: This table reports the estimation results of the following equations: $CSAD_t = a + \gamma_1\left|R_{m,t}\right| + \gamma_2 R^2_{m,t} + e_t$, $CSAD_t = a + \gamma_1\left|R_{m,t}\right| + \gamma_2 R^2_{m,t} + \sum_{i=1}^{5}\gamma_{2+i}CSAD_{t-i} + e_t$, and $CSAD_t = a + \gamma_1\left|R_{m,t}\right| + \gamma_2 R^2_{m,t} + \sum_{i=1}^{5}\gamma_{2+i}CSAD_{t-i} + \gamma_8 Vol_{m,t} + \gamma_9 \Delta Vol_{m,t} + e_t$, where $CSAD_t$ is the cross-sectional absolute deviation of the individual equity returns, $R_{m,t}$ is the market return, and $Vol_{m,t}$ is the logarithm of market trading volume. Newey–West (1987) consistent *t*-statistics are reported in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% level, respectively.

Table 2b
Redundant Variable Test *t*-statistics.

	$CSAD_{t-1}$	$CSAD_{t-2}$	$CSAD_{t-3}$	$CSAD_{t-4}$	$CSAD_{t-5}$	$Vol_{m,t}$	$\Delta Vol_{m,t}$
Eq.3	12.96***	4.41***	1.75*	4.19***	3.42***	–	–
Eq.4	–	–	–	–	–	5.78***	7.89***

Notes: This table reports the redundant variable test *t*-statistics for equations (2) and (3). ***, **, and * represent statistical significance at the 1%, 5%, and 10% level, respectively.

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

$$CSAD_t = a + \gamma_1\left|R_{m,t}\right| + \gamma_2 R^2_{m,t} + e_t \tag{2}$$

where $CSAD_t$ is the cross-sectional absolute deviation of the *N* individual stock returns ($R_{i,t}$) active on day *t* and $R_{m,t}$ is the market return on day *t*, i.e., the equally weighted average return of all the individual stocks. Rational asset pricing models predict an increasing linear relationship between the CSAD and the market return, i.e., a positive and statistically significant γ_1 coefficient, as individual assets are expected to have different sensitivities to the market return (Chang et al., 2000). To the contrary, a non-linear decreasing

Table 3
Herding estimations for two sub-periods.

Constant	$\lvert R_{m,t}\rvert$	$R^2_{m,t}$	$CSAD_{t-1}$	$CSAD_{t-2}$	$CSAD_{t-3}$	$CSAD_{t-4}$	$CSAD_{t-5}$	$Vol_{m,t}$	$\Delta Vol_{m,t}$	R^2 adj.
Panel A. 5/1/2015–5/2/2020										
−2.9570 (-3.44) ***	0.1738 (2.58) ***	0.0557 (1.68)*	0.2504 (7.57) ***	0.0965 (3.65) ***	0.0638 (2.76) ***	0.0767 (3.34) ***	0.0890 (3.34) ***	0.5096 (4.67) ***	0.8057 (4.56) ***	35.53%
Panel B. 6/2/2020–31/12/2020										
−2.6393 (-1.54)	0.3726 (5.70) ***	−0.0163 (-2.03) **	0.4865 (8.11) **	0.0935 (1.90) *	–	0.1066 (2.35) **	–	0.4048 (1.95) *	1.2838 (3.47) ***	69.55%

Notes: This table reports the estimation results of the following equation: $CSAD_t = a + \gamma_1|R_{m,t}| + \gamma_2 R^2_{m,t} + \sum_{i=1}^{5}\gamma_{2+i}CSAD_{t-i} + \gamma_8 Vol_{m,t} + \gamma_9\Delta Vol_{m,t} + e_t$, where $CSAD_t$ is the cross-sectional absolute deviation of the individual equity returns, $R_{m,t}$ is the market return, and $Vol_{m,t}$ is the logarithm of market trading volume. Newey–West (1987) consistent *t*-statistics are reported in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% level, respectively.

relationship, i.e., a negative and statistically significant γ_2 coefficient, indicates that the CSAD increases at a decreasing rate, which is enough to document herding in the market under examination.

To examine herding in the US market, we employ the Chang et al. (2000) methodology augmenting the benchmark model with explanatory variables. According to Arjoon and Bhatnagar (2017) potential autocorrelation of the dependant variable may result in spurious herding results. Following Yao, Ma and He (2014), Arjoon and Bhatnagar (2017), Pochea, Filip and Pece (2017) and Kashif et al. (2021) we introduce the lagged dependent variable in our model (up to 5 lags, based on redundant variable test – Table 2b) to account for CSAD autocorrelation, as follows:

$$CSAD_t = a + \gamma_1|R_{m,t}| + \gamma_2 R^2_{m,t} + \sum\nolimits_{i=1}^{5}\gamma_{2+i}CSAD_{t-i} + e_t \tag{3}$$

We also include trading volume as an explanatory variable to account for the impact of trading volume on herding estimations, in the same spirit with Litimi et al. (2016) and BenSaïda (2017) who employ the turnover of market trading volume as a control variable. We further augment our model adding the trading volume changes[7], as follows:

$$CSAD_t = a + \gamma_1|R_{m,t}| + \gamma_2 R^2_{m,t} + \sum\nolimits_{i=1}^{5}\gamma_{2+i}CSAD_{t-i} + \gamma_8 Vol_{m,t} + \gamma_9\Delta Vol_{m,t} + e_t \tag{4}$$

where $Vol_{m,t}$ is the logarithm of market trading volume. The number of lags of CSAD included in each model estimation depends on statistical significance, i.e., only statistically significant lags are included in the final model specification.

We further test for possible herding asymmetries under different market conditions employing a single-model dummy variable approach. To this end, a dummy variable is introduced in equation (4) to capture asymmetric herding effects in "up" and "down" market returns and market volatility, as follows in equations (5) and (6), respectively:

$$CSAD_t = a + \gamma_1 D^{up}|R_{m,t}| + \gamma_2(1-D^{up})|R_{m,t}| + \gamma_3 D^{up}R^2_{m,t} + \gamma_4(1-D^{up})R^2_{m,t} + \sum\nolimits_{i=1}^{5}\gamma_{4+i}CSAD_{t-i} + \gamma_{10}Vol_{m,t} + \gamma_{11}\Delta Vol_{m,t} + e_t \tag{5}$$

where D^{up} is a dummy variable that takes the value 1 for the days with positive market returns, and 0 otherwise.

$$CSAD_t = a + \gamma_1 D^{up}_{volt}|R_{m,t}| + \gamma_2(1-D^{up}_{volt})|R_{m,t}| + \gamma_3 D^{up}_{volt}R^2_{m,t} + \gamma_4(1-D^{up}_{volt})R^2_{m,t} + \sum\nolimits_{i=1}^{5}\gamma_{4+i}CSAD_{t-i} + \gamma_{10}Vol_{m,t} + \gamma_{11}\Delta Vol_{m,t} + e_t \tag{6}$$

where D^{up}_{volt} is a dummy variable that takes the value 1 for the days with high market volatility compared to the previous 30-day moving average, and 0 otherwise.

We further investigate into herding asymmetries that could be related to market volume. In this case we remove the explanatory variables $Vol_{m,t}$ and Δ $Vol_{m,t}$ and test for herding asymmetries during "up" and "down" market volume days, as follows:

$$CSAD_t = a + \gamma_1 D^{up}_{volm}|R_{m,t}| + \gamma_2(1-D^{up}_{volm})|R_{m,t}| + \gamma_3 D^{up}_{volm}R^2_{m,t} + \gamma_4(1-D^{up}_{volm})R^2_{m,t} + \sum\nolimits_{i=1}^{5}\gamma_{4+i}CSAD_{t-i} + e_t \tag{7}$$

where D^{up}_{volm} is a dummy variable that takes the value 1 for the days with high market volume compared to the previous 30-day moving average, and 0 otherwise. Previous literature provides mixed evidence of asymmetric herding effects being present in either "up" or "down" market, volume and volatility days (see among others Chang et al., 2000; Chen, 2013; Chiang and Zheng, 2010; Cui et al., 2019; Economou et al., 2015; Economou et al., 2011; Gavriilidis et al., 2013; Gavriilidis, Kallinterakis and Tsalavoutas, 2016; Tan et al., 2008).

[7] Jlassi and BenSaïda (2014) employ the first difference of the daily trading turnover rate to perform their analysis.

Table 4
Herding estimations during up and down market days.

Constant	$D^{up}\|R_{m,t}\|$	$(1\text{-}D^{up})\|R_{m,t}\|$	$D^{up}R^2_{m,t}$	$(1-D^{up})R^2_{m,t}$	$CSAD_{t-1}$	$CSAD_{t-2}$	$CSAD_{t-3}$	$CSAD_{t-4}$	$CSAD_{t-5}$	$Vol_{m,t}$	$\Delta Vol_{m,t}$	R^2 *adj.*
Panel A. 5/1/2015–31/12/2020												
−1.9510 (-3.86)***	0.3934 (6.73)***	0.1853 (5.73)***	−0.0011 (-0.06)	0.0039 (0.87)	0.3138(9.33) ***	0.0984(4.02) ***	0.0560(2.61) ***	0.0645(2.68) ***	0.0705(3.09) ***	0.3684(5.46) ***	0.9254(6.15) ***	59.19%
Wald test γ_3-γ_4	−0.0050 (-0.29)											
Panel B. 5/1/2015–5/2/2020												
−2.6898 (-3.18)***	0.3251 (3.67)***	0.0713 (-1.19)	0.0438 (0.87)	0.0521(1.85) *	0.2572(8.16) ***	0.0932(3.66) ***	0.0652(2.81) ***	0.0654(3.03) ***	0.0830(3.25) ***	0.4799(4.51) ***	0.8062(4.81) ***	38.99%
Wald test γ_3-γ_4	−0.0083 (-0.16)											
Panel C. 6/2/2020–31/12/2020												
−2.5102 (-1.45)	0.3536 (3.74)***	0.2813 (3.86)***	−0.0031 (-0.14)	−0.0081 (-0.95)	0.4758(7.84) ***	0.1005(2.06) **	–	0.0980(2.17) **	–	0.3985(1.87) *	1.2041(3.33) ***	69.83%
Wald test γ_3-γ_4	0.0050 (0.24)											

Notes: This table reports the estimation results of the following equation: $CSAD_t = a + \gamma_1 D^{up}|R_{m,t}| + \gamma_2(1-D^{up})|R_{m,t}| + \gamma_3 D^{up}R^2_{m,t} + \gamma_4(1-D^{up})R^2_{m,t} + \sum_{i=1}^{5}\gamma_{4+i}CSAD_{t-i} + \gamma_{10}Vol_{m,t} + \gamma_{11}\Delta Vol_{m,t} + e_t$, where $CSAD_t$ is the cross-sectional absolute deviation of the individual equity returns, $R_{m,t}$ is the market return, $Vol_{m,t}$ is the logarithm of market trading volume, and D^{up} is a dummy variable that takes the value 1 for the days with positive market returns, and 0 otherwise. Newey–West (1987) consistent t-statistics are reported in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% level, respectively.

Table 5
Herding estimations during high and low market volatility days.

Constant	$D_{volt}^{up}\lvert R_{m,t}\rvert$	(1-D_{volt}^{up})$\lvert R_{m,t}\rvert$	D_{volt}^{up} $R_{m,t}^2$	(1- D_{volt}^{up}) $R_{m,t}^2$	$CSAD_{t-1}$	$CSAD_{t-2}$	$CSAD_{t-3}$	$CSAD_{t-4}$	$CSAD_{t-5}$	$Vol_{m,t}$	$\Delta Vol_{m,t}$	R^2 *adj.*
Panel A. 5/1/2015–31/12/2020												
−2.3799 (-4.77)***	0.3029 (8.21)***	0.1345 (1.80)*	−0.0072 (-1.64)	0.0610 (1.83) *	0.3114 (9.16) ***	0.1037 (4.17) ***	0.0511 (2.37) **	0.0801 (3.25) ***	0.0788 (3.00) ***	0.4181 (6.26) ***	0.9369 (5.93) ***	57.49%
Wald test γ_3-γ_4	−0.0683 (-2.03)**											
Panel B. 5/1/2015–5/2/2020												
−2.9818 (-3.44)***	0.1552 (2.04)**	0.0282 (0.17)*	0.0588 (1.63)	0.1984 (1.23)	0.2463 (7.42) ***	0.0982 (3.68) ***	0.0612 (2.64) ***	0.0766 (3.31) ***	0.0897 (3.33) ***	0.5171 (4.70) ***	0.7860 (4.52) ***	35.49%
Wald test γ_3-γ_4	−0.1396 (-0.94)											
Panel C. 6/2/2020–31/12/2020												
−3.2428 (-2.04)**	0.3274 (4.75)***	−0.0367 (-0.24)	−0.0136 (-1.69) *	0.1139 (2.28) **	0.4729 (8.02) ***	0.0960 (2.04) **	–	0.1189 (2.58) **	–	0.4963 (2.58) **	1.1775 (3.23) ***	70.08%
Wald test γ_3-γ_4	−0.1275 (-2.59)***											

Notes: This table reports the estimation results of the following equation: $CSAD_t = a + \gamma_1 D_{volt}^{up}\lvert R_{m,t}\rvert + \gamma_2(1-D_{volt}^{up})\lvert R_{m,t}\rvert + \gamma_3 D_{volt}^{up}R_{m,t}^2 + \gamma_4(1-D_{volt}^{up})R_{m,t}^2 + \sum_{i=1}^{5}\gamma_{4+i}CSAD_{t-i} + \gamma_{10}Vol_{m,t} + \gamma_{11}\Delta Vol_{m,t} + e_t$, where $CSAD_t$ is the cross-sectional absolute deviation of the individual equity returns, $R_{m,t}$ is the market return, $Vol_{m,t}$ is the logarithm of market trading volume, and D_{volt}^{up} is a dummy variable that takes the value 1 for the days with high market volatility compared to the previous 30-day moving average, and 0 otherwise. Newey–West (1987) consistent *t*-statistics are reported in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% level, respectively.

Table 6
Herding estimations during high and low market volume days.

Constant	$D^{up}_{volm}\|R_{m,t}\|$	(1-D^{up}_{volm})| $R_{m,t}$|	D^{up}_{volm} $R^2_{m,t}$	(1- D^{up}_{volm} $R^2_{m,t}$	$CSAD_{t-1}$	$CSAD_{t-2}$	$CSAD_{t-3}$	$CSAD_{t-4}$	$CSAD_{t-5}$	R^2 adj.
Panel A. 5/1/2015–31/12/2020										
0.8311 (6.63)***	0.4983 (10.26)***	0.2164 (5.42)***	−0.0229 (-3.16)***	0.0036 (0.52)	0.2858 (8.30)***	0.1222 (4.95)***	0.0479 (2.05)**	0.0990 (3.93)***	0.0947 (3.64)***	55.74%
Wald test γ3-γ4	−0.0266 (-2.70)***									
Panel B. 5/1/2015–5/2/2020										
1.2174 (9.66)***	0.3554 (2.99)**	0.0675 (0.19)*	0.0367 (0.54)	0.0621 (2.58)***	0.2123 (6.75)***	0.1017 (3.99)***	0.0504 (2.12)**	0.0799 (3.37)***	0.0904 (3.20)***	34.23%
Wald test γ3-γ4	−0.0254 (-0.38)									
Panel C. 6/2/2020–31/12/2020										
0.7070 (2.65)***	0.5215 (6.20)***	0.2996 (4.14)***	−0.0269 (-2.58)**	−0.0118 (-1.33)	0.4490 (6.94)***	0.1134 (2.53)**	–	0.1297 (2.73)***	–	67.30%
Wald test γ3-γ4	−0.0151 (-1.14)									

Notes: This table reports the estimation results of the following equation:$CSAD_t = a + \gamma_1 D^{up}_{volm}|R_{m,t}| + \gamma_2(1 - D^{up}_{volm})|R_{m,t}| + \gamma_3 D^{up}_{volm}R^2_{m,t} + \gamma_4(1-D^{up}_{volm})R^2_{m,t} + \sum_{i=1}^{5}\gamma_{4+i}CSAD_{t-i} + e_t$, where $CSAD_t$ is the cross-sectional absolute deviation of the individual equity returns, $R_{m,t}$ is the market return, and D^{up}_{volm} is a dummy variable that takes the value 1 for the days with high market volume compared to the previous 30-day moving average, and 0 otherwise. Newey–West (1987) consistent *t*-statistics are reported in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% level, respectively.

Furthermore, we repeat the aforementioned estimations of equations (4)-(7) for two endogenously defined sub-periods (5/1/2015–5/2/2020 and 6/2/2020–31/12/2020) via the Quandt–Andrews breakpoint test. Note that the second sub-period covers the COVID-19 pandemic. Note again here that in all estimated models we include only the lagged CSAD variables that are statistically significant.

Finally, we examine the COVID-19 pandemic period in the US market, as a major negative exogenous event that may create sentiment for market participants and lead to herding behavior. From the different variables related to the COVID-19 pandemic, e.g. number of cases, tests, deaths, hospitalizations, containment measures we chose the cases variable based on the number of observations and the fact that this variable may serve as predictor for the other variables. Moreover, focusing on the sub-period after the outbreak of the COVID-19 pandemic we introduce a dummy variable to identify any asymmetric herding effects on days with high or low new COVID-19 cases, as follows:

$$CSAD_t = a + \gamma_1 D^{up}_{cov}|R_{m,t}| + \gamma_2(1 - D^{up}_{cov})|R_{m,t}| + \gamma_3 D^{up}_{cov}R^2_{m,t} + \gamma_4(1-D^{up}_{cov})R^2_{m,t} + \sum_{i=1}^{5}\gamma_{4+i}CSAD_{t-i} + \gamma_{10}\quad Vol_{m,t} + \gamma_{11}\Delta Vol_{m,t} + e_t \tag{8}$$

where D^{up}_{cov} is a dummy variable that takes the value 1 for the days with high new COVID-19 cases compared to the previous 7-day or 30-day moving average, and 0 otherwise.

3.2. Data

We use daily stock price information and trading volume data through the Center for Research in Security Prices (CRSP). In particular, we consider the entire universe of CRSP and isolate firms listed in the New York Stock Exchange (NYSE) during the period 2015 to 2020. We further require that firms are classified as common stock, and thereby we eliminate 114 firms classified as closed-end funds, Americus trust components and Real Estate Investment Trusts (REIT's) by CRSP database. We further refine our data and delete observations of companies with either missing stock price or trading volume information. The application of these criteria yields a final sample of 336 firms. Table 1 provides the descriptive statistics of our dataset which consists of 1,510 daily observations. The returns of the individual firms are calculated as $R_{i,t} = 100 \times (\ln(P_{i,t}) - \ln(P_{i,t-1}))$, where $P_{i,t}$ is the closing price of firm i on day t. The Augmented Dickey-Fuller test indicates the stationarity of the employed variables, while the presence of statistically significant serial correlation in the CSAD series confirms the need to use the lagged dependent variable in the final model specification.

4. Empirical results

Table 2a reports the results of the benchmark model as well as the findings resulting from the augmented models that account for CSAD autocorrelation and trading volume for the whole period under examination (2015–2020). To begin with, the estimation of the

Table 7
Herding estimations during high and low new COVID-19 cases days.

Constant	$D_{cov}^{up}\lvert R_{m,t}\rvert$	$(1\text{-}D_{cov}^{up})\lvert R_{m,t}\rvert$	$D_{cov}^{up}\ R_{m,t}^2$	$(1\text{-}\ D_{cov}^{up})\ R_{m,t}^2$	$CSAD_{t\text{-}1}$	$CSAD_{t\text{-}2}$	$CSAD_{t\text{-}3}$	$CSAD_{t\text{-}4}$	$CSAD_{t\text{-}5}$	$Vol_{m,t}$	$\Delta Vol_{m,t}$	R^2 *adj.*
Panel A. 29/1/2020–31/12/2020, using the previous 7-day moving average for the new COVID-19 cases												
−2.2477 (-1.35)	0.3782 (4.75)***	0.2503 (2.43)**	−0.0173(-1.92) *	0.0194 (0.82)	0.4739(8.09) ***	0.0970(2.01) *	–	0.1062(2.44) **	–	0.3653(1.80) *	1.27(3.51) ***	68.51%
Wald test γ_3-γ_4	−0.0367 (-1.62)											
Panel B. 21/2/2020–31/12/2020, using the previous 30-day moving average for the new COVID-19 cases												
−3.1479 (-1.65)	0.3543 (4.42)***	0.2624 (2.57)**	−0.0152(-1.68) *	0.0243 (1.06)	0.4839(8.10) ***	0.0976(1.95) *	–	0.1154(2.54) **	–	0.4627(2.00) **	1.2490(3.29) ***	69.21%
Wald test γ_3-γ_4	−0.0396 (-1.82)*											

Notes: This table reports the estimation results of the following equation: $CSAD_t = a + \gamma_1 D_{cov}^{up}\lvert R_{m,t}\rvert + \gamma_2\left(1 - D_{cov}^{up}\right)\lvert R_{m,t}\rvert + \gamma_3 D_{cov}^{up} R_{m,t}^2 + \gamma_4 (1 - D_{cov}^{up}) R_{m,t}^2 + \sum_{i=1}^{5}\gamma_{4+i} CSAD_{t-i} + \gamma_{10} Vol_{m,t} + \gamma_{11}\Delta Vol_{m,t} + e_t$, where $CSAD_t$ is the cross-sectional absolute deviation of the individual equity returns, $R_{m,t}$ is the market return, $Vol_{m,t}$ is the logarithm of market trading volume, and D_{cov}^{up} is a dummy variable that takes the value 1 for the days with high new COVID-19 cases compared to the previous 7-day (Panel A) or 30-day (Panel B) moving average, and 0 otherwise. Data on new COVID-19 cases can be found at the Johns Hopkins Coronavirus Resource Center. Newey–West (1987) consistent *t*-statistics are reported in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% level, respectively.

Table 8
Herding estimations for two sub-periods, robustness tests.

Constant	$\|R_{m,t}\|$	$R^2_{m,t}$	$CSAD_{t-1}$	$CSAD_{t-2}$	$CSAD_{t-3}$	$CSAD_{t-4}$	$CSAD_{t-5}$	$CSAD_{norm.vol.,t}$	R^2 adj.
Panel A. 5/1/2015–31/12/2020									
0.9562 (7.10) ***	0.3334 (9.40) ***	−0.0073 (-1.55)	0.2724 (8.07) ***	0.0929 (3.69) ***	0.0392 (1.69) *	0.0914 (3.59) ***	0.0756 (2.98) ***	1.1490 (6.48) ***	55.23%
Panel B. 5/1/2015–5/2/2020									
0.9654 (6.84) ***	0.1976 (2.85) ***	0.0534 (1.55)	0.2112 (6.61) ***	0.0927 (3.60) ***	0.0575 (2.42) ***	0.0860 (3.59) ***	0.0901 (3.48) ***	3.0955 (6.83) ***	34.29%
Panel C. 6/2/2020–31/12/2020									
0.5313 (2.29)**	0.3889 (5.78) ***	−0.0156 (-1.88)*	0.4368 (7.31) **	0.0819 (1.69) *	–	0.1433 (3.16) ***	–	1.0059 (3.66) ***	67.50%

Notes: This table reports the estimation results of the following equation: $CSAD_t = a + \gamma_1|R_{m,t}| + \gamma_2 R^2_{m,t} + \sum_{i=1}^{5}\gamma_{2+i}CSAD_{t-i} + \gamma_8 CSAD_{norm.vol.,t} + e_t$, where $CSAD_t$ is the cross-sectional absolute deviation of the individual equity returns, $R_{m,t}$ is the market return, and $CSAD_{norm.vol.,t}$ is the cross-sectional absolute deviation of the normalised firm volume from the normalised mean of the market volume. Newey–West (1987) consistent *t*-statistics are reported in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% level, respectively.

benchmark Chang et al. (2000) model (Eq. (2) does not provide any evidence of herding, as coefficient γ_2 is of the expected sign, but not statistically significant. However, since herding is a dynamic phenomenon, as we correct for CSAD autocorrelation by including lagged CSAD terms, Equation (3) reveals evidence of herding, since the coefficient γ_2 is negative and statistically significant in this case. The inclusion of trading volume and volume difference transformation further sheds light to the herding dynamics. The estimation of Equation (4) indicates that both trading volume and positive changes in trading volume result in increased CSAD, since both coefficients γ_8 and γ_9 are positive and statistically significant. The necessity of the included variables is confirmed by means of the redundant variable test (Table 2b).

Focusing on the final model specification (Eq. (4), Table 3 provides the respective estimations for the two endogenously defined sub-periods. According to the results, there is evidence of herding only in the second sub-period (6/2/2020–31/12/2020), which coincides with the outbreak of the COVID-19 pandemic. In this case, coefficient γ_2 is negative and statistically significant, while trading volume holds its positive and statistically significant impact on CSAD.

Moving on to the examination of possible herding asymmetric effects, Table 4 does not document herding asymmetry during "up" and "down" market days, in line with Chen (2013) and Galariotis et al. (2015), who found no herding asymmetries with reference to market returns for the US market. This finding also holds for the two sub-periods under examination. On the contrary, Table 5 provides evidence of asymmetric herding behavior during high market volatility days but only for the second sub-period referring to the COVID-19 pandemic. Cui et al. (2019) also reported herding on days with high volatility in the US market. Moreover, the empirical results reported in Table 6 indicate the presence of herding on high volume days both for the whole period under examination and after the outbreak of the COVID-19 pandemic, while there is no evidence of herding on "up" or "down" market volume days for the first sub-period, i.e. before the outbreak of the COVID-19 pandemic. As a result, the asymmetric herding behavior with respect to volume for the whole period seems to be mostly attributed to the pandemic sub-period. Finally, Table 7 reports the empirical results for the period after the outbreak of the COVID-19 pandemic documenting herding only during days with high new COVID-19 cases compared to the previous 7-day or 30-day moving average.

5. Robustness tests

We further investigate the impact of trading volume employing an alternative explanatory variable in models (4) to (6) and (8) defined as the cross-sectional absolute deviation of the normalised firm volume from the normalised mean of the market ($CSAD_{norm.vol.,t}$). In this case respective models are structured as follows:

$$CSAD_t = a + \gamma_1|R_{m,t}| + \gamma_2 R^2_{m,t} + \sum\nolimits_{i=1}^{5}\gamma_{2+i}CSAD_{t-i} + \gamma_8 CSAD_{norm.vol.,t} + e_t \tag{9}$$

$$CSAD_t = a + \gamma_1 D^{up}|R_{m,t}| + \gamma_2(1 - D^{up})|R_{m,t}| + \gamma_3 D^{up}R^2_{m,t} + \gamma_4(1-D^{up})R^2_{m,t} + \sum\nolimits_{i=1}^{5}\gamma_{4+i}CSAD_{t-i} + \gamma_{10}CSAD_{norm.vol.,t} + e_t \tag{10}$$

$$CSAD_t = a + \gamma_1 D^{up}_{volt}|R_{m,t}| + \gamma_2(1 - D^{up}_{volt})|R_{m,t}| + \gamma_3 D^{up}_{volt}R^2_{m,t} + \gamma_4(1-D^{up}_{volt})R^2_{m,t} + \sum\nolimits_{i=1}^{5}\gamma_{4+i}CSAD_{t-i} + \gamma_{10}CSAD_{norm.vol.,t} + e_t \tag{11}$$

$$CSAD_t = a + \gamma_1 D^{up}_{cov}|R_{m,t}| + \gamma_2(1 - D^{up}_{cov})|R_{m,t}| + \gamma_3 D^{up}_{cov}R^2_{m,t} + \gamma_4(1-D^{up}_{cov})R^2_{m,t} + \sum\nolimits_{i=1}^{5}\gamma_{4+i}CSAD_{t-i} + \gamma_{10}CSAD_{norm.vol.,t} + e_t \tag{12}$$

where all variables are as previously defined.

The estimation of these models allows us to check for the robustness of our initial empirical results. Tables 8 to 11 report the results

Table 9
Herding estimations during up and down-market days, robustness tests.

Constant	$D^{up}\lvert R_{m,t}\rvert$	$(1\text{-}D^{up})\lvert R_{m,t}\rvert$	$D^{up}R^2_{m,t}$	$(1-D^{up})R^2_{m,t}$	$CSAD_{t\text{-}1}$	$CSAD_{t\text{-}2}$	$CSAD_{t\text{-}3}$	$CSAD_{t\text{-}4}$	$CSAD_{t\text{-}5}$	$CSAD_{norm.vol.,t}$	R^2 *adj.*
Panel A. 5/1/2015–31/12/2020											
1.0221 (7.07)***	0.4099 (7.33)***	0.1965 (5.99)***	−0.0011 (-0.06)	0.0046 (0.98)	0.2744(8.24) ***	0.0919(3.76) ***	0.0462(2.01) **	0.0784(3.14) ***	0.0675(2.88) ***	1.0325(5.88) ***	57.25%
Wald test γ_3-γ_4	−0.0057 (-0.34)										
Panel B. 5/1/2015–5/2/2020											
1.0039 (7.19)***	0.3507 (3.94)***	0.0845 (1.38)	0.0391 (0.77)	0.0558(1.88) *	0.2181(7.11) ***	0.0895(3.61) ***	0.0592(2.48) **	0.0752(3.31) ***	0.0842(3.37) ***	2.9687(6.71) ***	37.69%
Wald test γ_3-γ_4	−0.0167 (-0.32)										
Panel C. 6/2/2020–31/12/2020											
0.6269 (2.47)**	0.3803 (3.94)***	0.2741 (3.46)***	−0.0034 (-0.15)	−0.0053 (-0.59)	0.4283(7.09) ***	0.0912(1.88) *	–	0.1307(2.85) ***	–	0.9411(3.31) ***	69.83%
Wald test γ_3-γ_4	0.0019 (0.09)										

Notes: This table reports the estimation results of the following equation: $CSAD_t = a + \gamma_1 D^{up}\lvert R_{m,t}\rvert + \gamma_2(1-D^{up})\lvert R_{m,t}\rvert + \gamma_3 D^{up}R^2_{m,t} + \gamma_4(1-D^{up})R^2_{m,t} + \sum_{i=1}^{5}\gamma_{4+i}CSAD_{t-i} + \gamma_{10}CSAD_{norm.vol.,t} + e_t$, where $CSAD_t$ is the cross-sectional absolute deviation of the individual equity returns, $R_{m,t}$ is the market return, $CSAD_{norm.vol.,t}$ is the cross-sectional absolute deviation of the normalised firm volume from the normalised mean of the market volume, and D^{up} is a dummy variable that takes the value 1 for the days with positive market returns, and 0 otherwise. Newey–West (1987) consistent *t*-statistics are reported in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% level, respectively.

Table 10
Herding estimations during high and low market volatility days, robustness tests.

Constant	$D^{up}_{volt}\|R_{m,t}\|$	(1-D^{up}_{volt})|$R_{m,t}$|	D^{up}_{volt} $R^2_{m,t}$	(1- D^{up}_{volt}) $R^2_{m,t}$	*CSAD*$_{t-1}$	*CSAD*$_{t-2}$	*CSAD*$_{t-3}$	*CSAD*$_{t-4}$	*CSAD*$_{t-5}$	*CSAD*$_{norm.vol.,t}$	R^2 *adj.*
Panel A. 5/1/2015–31/12/2020											
0.9988 (9.02)***	0.3099 (8.46)***	0.1020 (1.30)	−0.0063 (-1.37)	0.0800 (2.30)**	0.2694 (8.11)***	0.0968 (3.96)***	0.0412 (1.79)*	0.0945 (3.75)***	0.0748 (2.81)***	1.1912 (6.83)***	55.64%
Wald test γ_3-γ_4	−0.0863 (-2.49)**										
Panel B. 5/1/2015–5/2/2020											
1.0152 (7.00)***	0.1678 (2.11)**	−0.0042 (-0.02)	0.0589 (1.56)	0.2566 (1.55)	0.2064 (6.43)***	0.0940 (3.62)***	0.0542 (2.27)***	0.0852 (3.55)***	0.0900 (3.44)***	3.1338 (6.84)***	34.38%
Wald test γ_3-γ_4	−0.1977 (-1.31)										
Panel C. 6/2/2020–31/12/2020											
0.7074 (3.38)**	0.3315 (4.76)***	−0.0931 (-0.58)	−0.0122 (-1.47)	0.1396 (2.63)***	0.4260 (7.26)**	0.0837 (1.80)*	–	0.1532 (3.38)**	–	1.0658 (4.01)***	68.32%
Wald test γ_3-γ_4	−0.1518 (-2.88)***										

Notes: This table reports the estimation results of the following equation: $CSAD_t = a + \gamma_1 D^{up}_{volt}|R_{m,t}| + \gamma_2(1 - D^{up}_{volt})|R_{m,t}| + \gamma_3 D^{up}_{volt}R^2_{m,t} + \gamma_4(1-D^{up}_{volt})R^2_{m,t} + \sum_{i=1}^{5}\gamma_{4+i}CSAD_{t-i} + \gamma_{10}CSAD_{norm.vol.,t} + e_t$, where $CSAD_t$ is the cross-sectional absolute deviation of the individual equity returns, $R_{m,t}$ is the market return, $CSAD_{norm.vol.,t}$ is the cross-sectional absolute deviation of the normalized firm volume from the normalized mean of the market volume, and D^{up}_{volt} is a dummy variable that takes the value 1 for the days with high market volatility compared to the previous 30-day moving average, and 0 otherwise. Newey–West (1987) consistent *t*-statistics are reported in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% level, respectively.

Table 11
Herding estimations during high and low new COVID-19 cases days, robustness tests.

Constant	$D^{up}_{cov}\|R_{m,t}\|$	(1-D^{up}_{cov})|$R_{m,t}$|	D^{up}_{cov} $R^2_{m,t}$	(1- D^{up}_{cov}) $R^2_{m,t}$	*CSAD*$_{t-1}$	*CSAD*$_{t-2}$	*CSAD*$_{t-3}$	*CSAD*$_{t-4}$	*CSAD*$_{t-5}$	*CSAD*$_{norm.vol.,t}$	R^2 *adj.*
Panel A. 29/1/2020–31/12/2020, using the previous 7-day moving average for the new COVID-19 cases											
0.6050 (2.65)***	0.3890 (4.73)***	0.2675 (2.62)***	−0.0162 (-1.74)*	0.0195 (0.84)	0.4254 (7.33)***	0.0867 (1.82)*	–	0.1417 (3.23)**	–	0.9604 (3.58)***	66.51%
Wald test γ_3-γ_4	−0.0357 (-1.59)										
Panel B. 21/2/2020–31/12/2020, using the previous 30-day moving average for the new COVID-19 cases											
0.4759 (2.08)**	0.3744 (4.49)***	0.2779 (2.74)***	−0.0150 (-1.59)	0.0256 (1.17)	0.4351 (7.39)***	0.0863 (1.75)*	–	0.1534 (3.42)**	–	1.0585 (3.71)***	67.21%
Wald test γ_3-γ_4	−0.0406 (-1.96)*										

Notes: This table reports the estimation results of the following equation: $CSAD_t = a + \gamma_1 D^{up}_{cov}|R_{m,t}| + \gamma_2(1 - D^{up}_{cov})|R_{m,t}| + \gamma_3 D^{up}_{cov}R^2_{m,t} + \gamma_4(1-D^{up}_{cov})R^2_{m,t} + \sum_{i=1}^{5}\gamma_{4+i}CSAD_{t-i} + \gamma_{10}CSAD_{norm.vol.,t} + e_t$, where $CSAD_t$ is the cross-sectional absolute deviation of the individual equity returns, $R_{m,t}$ is the market return, $CSAD_{norm.vol.,t}$ is the cross-sectional absolute deviation of the normalised firm volume from the normalised mean of the market volume, and D^{up}_{cov} is a dummy variable that takes the value 1 for the days with high new COVID-19 cases compared to the previous 7-day (Panel A) or 30-day (Panel B) moving average, and 0 otherwise. Data on new COVID-19 cases can be found at the Johns Hopkins Coronavirus Resource Center. Newey–West (1987) consistent *t*-statistics are reported in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% level, respectively.

for models 9 to 12 respectively. The cross-sectional absolute deviation of trading volume has a positive and statistically significant impact in all cases, indicating that when the normalized trading volume does not cluster around the normalised market trading volume of the market the cross-sectional deviation of the individual asset returns further increases. Overall, the empirical findings about herding prove to be quite robust. The Quandt–Andrews breakpoint test confirms the endogenously defined periods under examination. In fact, there is evidence of herding only during the COVID-19 pandemic sub-period, while no asymmetric effects are documented. Finally, focusing on the period after the outbreak of the COVID-19 pandemic herding is present only during days with high new COVID-19 cases compared to the previous 7-day moving average.

6. Conclusions and discussion

The present paper investigates herding from the lens of trading volume. We explore also for the existence of herding dynamics and for the impact of COVID-19 on herd behavior. According to our empirical evidence, the estimation of the basic herding model by Chang et al. (2000) does not provide any evidence of herding. The inclusion in the basic model of trading volume variables as well as the CSAD lagged values improved the model specification and the relevant statistics and revealed statistical evidence of possible herding. The inclusion of the trading volume was driven by the significance of this variable in financial theory and practice. The old Wall Street proverb *"it takes volume to make prices move"* indicates the significance of trading volume for market practitioners. In addition, Karpoff (1987) provided several reasons for the theoretical importance of the trading volume in stock price research.

Most importantly though, according to our results, herding behavior is evident during the COVID-19 sub-period, while an asymmetric behavior is documented with reference to high new COVID-19 cases. This confirms that people tend to herd in the appearance of a danger factor, as this is observed in animals in the presence of a predator.

Asset managers and portfolio investors alike could benefit from these findings as they could form relevant positions in the market anticipating events that could cause herding. Momentum seekers can be rest assured that crisis events would trigger herding and they should either follow the drift or act proactively.

Extensions of the present work could focus further towards how non-financial risks may affect herding behavior, with particular emphasis being shed on many political and hygienic events that trigger investment response.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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