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Covid-19 and herding in global equity markets

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ABSTRACT

We investigate herding in ten equity markets during the COVID-19 pandemic using a methodology that considers movements in assets due to changes in fundamentals. We find heterogeneous patterns in herding across the ten countries during the pandemic, but overall, there is limited evidence of herding during this period, with only Italy, Sweden, and the United States displaying signs of herding. A cross-sectional analysis reveals that herding measures during the pandemic are negatively associated with stricter governmental actions that restrict mobility, and positively associated with economic support measures.

1. Introduction

In December 2019, a new type of coronavirus disease with high infection and fatality rates, COVID-19, was identified. Once the scale of the pandemic became clear in early 2020, asset prices declined rapidly and market volatility increased significantly. Capital markets have since reacted (and continue to react) quickly to news about the pandemic, including new variants of the virus and the effectiveness of different treatments and vaccines. In particular, the pandemic has resulted in unprecedented and heterogeneous measures being taken by governments, including actions aimed at curtailing the spread of the virus (e.g., restrictions on mobility and commercial activities) as well as actions focused on reducing the economic impacts of the pandemic (e.g., stimulus packages). Several studies have investigated the impacts of the COVID-19 crisis and the ensuing government interventions on market volatility, uncovering increased market risks and important spillover and financial contagion effects.[1]

Given the sudden and sharp changes in market sentiment, and the financial panic caused by the pandemic, an interesting question is whether the COVID-19 crisis caused investors to display herding behavior. Although, starting with Christie and Huang (1995), herding has been hypothesized to occur more during periods of market stress, empirical studies do not reach a consensus on this question. Hwang and Salmon (2004) have found that herding actually tends to decrease in periods of crises, and tends to appear "when the market is quiet and investors are confident of the direction in which markets are heading". Hwang et al. (2020) proposed a theoretical model in which overconfidence leads to herding. In that model, investors' overconfidence about the forecast of the market return leads to beta compression (i.e., herding towards the market), whereas under-confidence leads to increased beta dispersion (i.e., anti-herding).

On the one hand, a major market disruption like the pandemic increases market uncertainty and may cause investors to focus more on fundamentals in their decision making, reducing herding (Hwang and Salmon, 2004). On the other hand, some authors argue that investors are more likely to disregard their own information and imitate the behaviors of other investors during periods of market stress (Christie and Huang, 1995). One difficulty with detecting herding behavior in financial markets is that investors may appear to herd (i.e., trade similarly) simply

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[1] Tiberiu (2020) shows that COVID-19 increased the realized volatility of the S&P 500; Harjoto et al. (2020) report that the pandemic affected emerging countries and small firms most strongly; Zhang et al. (2020) reports a significant increase in market risk for the 12 countries most affected by the pandemic in early 2002; Shehzad et al. (2020) conclude that the COVID-19 crisis had a more significant impact on volatility than the 2007–2008 Global Financial Crisis; Zaremba et al. (2020) study the impact of government interventions to contain the epidemic on market volatility, concluding that non-pharmaceutical interventions significantly increased equity market volatility; Baig et al. (2020) show that market volatility increases and market liquidity decreases with the number of COVID-19 confirmed cases, and deaths; Okorie and Lin (2020) and Akhtaruzzaman et al. (2020), using different methodologies, present evidence on the contagion and spillover effects of COVID-19 on stock markets worldwide.

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because they are reacting to the same information about fundamentals, in which case the detected herding is unintentional or spurious (Bikhchandani and Sharma, 2000; Choi and Skiba, 2015). Recent studies on herding during the COVID-19 pandemic provide mixed evidence, with some studies finding evidence of herding (Kizys et al., 2020; Espinosa-Méndez and Arias, 2020), while others find either no herding (Ferreruela and Mallor, 2021; Espinosa-Méndez and Arias, 2020), or that the pandemic reduced the level of herding (Wu et al., 2020; Yarovaya et al., 2020). Bouri et al. (2021) study herding using static and rolling-window versions of the cross-sectional absolute deviation regression model of Chang et al. (2000), finding no evidence of herding during the COVID-19 period under the static model, and some evidence of herding when the rolling-window model is used.

The commonality in these recent studies is the use of the cross-sectional dispersion between individual stocks returns and the aggregate market return (Christie and Huang, 1995; Chang et al., 2000).[2] The rationale behind these methods is that, when investors mimic the actions of others, individual stock returns become less dispersed around the market return than what rational asset pricing models suggest. However, these methods have a few drawbacks. First, they do not include any mechanism to control for changes in fundamentals, making it difficult to disentangle intentional herding from movements induced by news that impact fundamentals.[3] Second, they are mostly static methods, although some studies have relied on rolling-window approaches (Bouri et al., 2021) or on time-varying parameter regressions. Lastly, the widely used regression model of Chang et al. (2000) is, in general, biased against detecting herding (Bohl et al., 2017; Stavroyiannis and Babalos, 2017).

Due to the difficulties explained above, in this paper we investigate investor's herding behavior during the COVID-19 pandemic using the methodology proposed by Hwang and Salmon (2004) (HS04). This methodology has a few advantages. First, it allows us to explicitly separate the effect of investors' reactions to fundamental variables from herding due to market sentiment. We consider a number of model specifications with different controls variables to account for fundamentals, including market-based and macro-economic related variables. Second, the state-space model specification produces an estimate of the dynamic evolution of herding, which allows us to identify the exact periods when herding (or anti-herding) behavior is present.[4] We believe that this econometric specification produces a more robust measure of herding, which is distinct from the measures that have been used in other studies, and therefore provides fresh insight into whether investors show herding behavior during the COVID-19 pandemic. Using this methodology, we investigate herding in the equity markets of ten countries (Australia, Belgium, Brazil, China, France, Italy, Japan, Sweden, the United Kingdom, and the United States). This selection includes countries with varying degrees of severity in terms of the number of COVID-19 infections and deaths, with Japan and Australia representing countries where the impact of COVID-19 was less severe. The selection also reflects differences in the stringency and timing of governmental responses to the pandemic. For example, in Brazil and the U.S., the peak in infections occurred later than in other countries, and strict lockdowns were not enforced homogeneously.

Our results reveal heterogeneous patterns in herding measures across the ten countries during the period that includes the COVID-19 pandemic, but overall, there is limited evidence of herding. The only countries for which our approach detects herding during the pandemic are Italy, Sweden, and the United States. The lack of herding for most countries during this period is in line with the results of HS04, who show that herding tends to decrease in periods of crises in the U.S. and South Korean markets, as well as the results of Hwang et al. (2020), who show that periods with high market uncertainty are characterized by adverse or anti-herding behavior, as investors lose confidence in their market forecasts.

The different herding patterns found during the COVID-19 pandemic are not surprising, once we take into account the differences in the severity of the pandemic, as well as in governmental responses across the different countries. We investigate this using a panel regression approach by regressing changes in herding in each country on variables related to the severity of the pandemic, the stringency of "lock-down style" governmental actions restricting mobility, the level of economic support measures implemented by the government, and the rate of vaccination. The results show that the implementation of stricter restrictions on mobility, which increase uncertainty and have generally a negative impact on the economy, are associated with a decrease in herding. On the other hand, measures to support the economy, such as debt relief or stimulus spending, tend to increase herding.

Our work contributes to the expanding literature on herding behavior in financial markets during the COVID-19 pandemic by providing an alternative analysis that takes into account the effect of changes in fundamentals.

The rest of the paper is organized as follows. Section 2 explains the HS04 methodology. Section 3 explains the data used. Section 4 reports the main empirical results of the paper. Section 5 concludes. The Appendix contains additional results and robustness tests.

2. Methodology

2.1. Hwang and Salmon (2004) herding model

We briefly summarize the methodology proposed by HS04 to measure herding behavior. As explained by HS04, their model has similarities with the Christie and Huang (1995) and Chang et al. (2000) models, in the sense that it also makes use of the information contained in the cross-sectional movements of the market. The difference is that the HS04 model focuses on the cross-sectional variability of factor sensitivities, rather than returns. In this model, sentiment drives investors to form biased estimates of individual assets returns and factor loadings, causing herding. The model assumes the following relationship in the presence of herding towards the market portfolio:

$$\frac{E_t^b(r_{it})}{E_t(r_{mt})} = \beta_{imt}^b = \beta_{imt} - h_{mt}(\beta_{imt} - 1), \tag{1}$$

where $E_t^b(r_{it})$ and β_{imt}^b are the short-term conditional biased market expectations of the excess returns of asset i and its beta at time t, respectively, and $h_{mt} \leq 1$ is a latent time-varying herding parameter that determines the degree of herding. If $h_{mt} = 1$, there is perfect herding towards the market portfolio, which means all individual assets move in the same direction and with the same magnitude as the market portfolio. If $h_{mt} = 0$, Eq. (1)

[2] Christie and Huang (1995) propose the cross-sectional standard deviation (CSSD) of returns as a measure of dispersion, and regress it on dummy variables that capture extreme market movements; Chang et al. (2000) propose the use of the cross-sectional absolute deviation (CSAD) of returns in a regression model that includes the absolute value and the square of the market return. These two methods have been extensively used in the herding literature, see for example Chong et al. (2020), Economou et al. (2015), Mobarek et al. (2014), and Klein (2013).

[3] We note that some studies, such as Galariotis et al. (2015), have investigated the impact of asset pricing factors and macroeconomic announcements on herding within the Chang et al. (2000) regression framework.

[4] In contrast, the regression-based models of Christie and Huang (1995) and Chang et al. (2000) only provide a binary answer; either herding is detected, or it is not. Researchers often resort to running sub-sample analyses or including period-specific dummy variables to investigate specific time periods.

states that $\beta^b_{imt} = \beta_{imt}$, i.e., there is no herding. Since the cross-sectional mean of betas (β^b_{imt} or β_{imt}) should always be equal to one, we have:

$$\begin{aligned} Std_c(\beta^b_{imt}) &= \sqrt{E_c(\beta_{imt} - h_{mt}(\beta_{imt} - 1) - 1)^2} \\ &= Std_c(\beta_{imt})(1 - h_{mt}), \end{aligned} \tag{2}$$

where E_c and Std_c represent the cross-sectional expectation and standard deviation, respectively. The first component in Eq. (2) is the cross-sectional standard deviation of the equilibrium betas, and the second is a direct function of the herding parameter.

HS04 use a state-space model to extract h_{mt} from $Std_c(\beta^b_{imt})$. First, by taking the logarithm of Eq. (2), we obtain:

$$\log[Std_c(\beta^b_{imt})] = \log[Std_c(\beta_{imt})] + \log(1 - h_{mt}). \tag{3}$$

Second, HS04 assume that $Std_c(\beta_{imt})$ does not exhibit any systematic movement, i.e., $\log[Std_c(\beta_{imt})] = \mu_m + \nu_{mt}$, where $\mu_m = E[\log[Std_c(\beta_{imt})]]$ and $\nu_{mt} \sim iid(0, \sigma^2_{m\nu})$. Denoting $H_{mt} = \log(1 - h_{mt})$ and assuming it follows an AR(1) process, we can write the state-space model below:

$$\log[Std_c(\beta^b_{imt})] = \mu_m + H_{mt} + \nu_{mt} \tag{4}$$

$$H_{mt} = \phi_m H_{mt-1} + \eta_{mt}, \tag{5}$$

where $\eta_{mt} \sim iid(0, \sigma^2_{m\eta})$. Eqs. (4) and (5) represent a state-space model, which can be estimated using the Kalman filter. In this model, the focus is on the dynamic structure of the latent herding variable H_{mt}. Note that, if $\sigma^2_{m\eta} = 0$, Eq. (5) becomes $\log[Std_c(\beta_{imt})] = \mu_m + \nu_{mt}$, and there is no herding. Therefore, a significant value of $\sigma^2_{m\eta}$ supports the existence of herding (or anti-herding), meaning that $H_{mt} \neq 0$ for all t. One restriction is that the herding process H_{mt} should be stationary; since we do not expect herding to be an explosive process, we should have $|\phi_m| < 1$.

One advantage of the HS04 methodology is the possibility of adding control variables to Eq. (4) in order to account for the effect of fundamental or macroeconomic variables. This allows the econometrician to control for potential decreases in return dispersion because investors are reacting similarly to perceived changes in fundamentals, in which case, the herding may be spurious or unintentional (Bikhchandani and Sharma, 2000; Choi and Skiba, 2015). Of course, the choice of control variables used in the model may impact the results. For robustness, we consider several specifications. Model 1 consists of the state-space model without any control variables, i.e., the observation equation is given by (4). In Model 2, we include as control variables the excess market return (r_{mt}) and the log of the market volatility ($\log(\sigma_{mt})$), calculated using daily returns in each month. The inclusion of the excess market return and its volatility, which are specific to each country, helps capture the overall changes in fundamentals at the level of each local market. Thus, Model 2 is represented as follows:

$$\log[Std_c(\beta^b_{imt})] = \mu_m + H_{mt} + \theta_1 r_{mt} + \theta_2 \log(\sigma_{mt}) + \eta_{mt}. \tag{6}$$

In Model 3, we include, in addition to the variables in Model 2, the change in the term spread (ΔTS_t), where TS_t is defined as the difference between the U.S. 10-year Treasury bond rate and the U.S. 3-month Treasury bill rate, and the change in the credit spread (ΔCS_t), where CS_t is defined as the difference between the rate on Moody's AAA and BAA rated corporate bonds as independent variables.[5] Although these variables are U.S.-specific, they may be important due to the prominent role of the U.S. in the global economy, and the fact that many studies suggest that the U.S. market influences (leads) other markets (see, e.g, Jayasuriya (2011) and the references therein). Studies on herding also suggest an important role for the U.S. stock market in explaining herding in other markets (Chiang and Zheng, 2010; Chong et al., 2020), so if herding behavior is partly explained by reactions to fundamentals, the inclusion of U.S. macroeconomic variables may be relevant. Thus, Model 3 is represented as follows:

$$\begin{aligned} \log[Std_c(\beta^b_{imt})] = \mu_m + H_{mt} + \theta_1 r_{mt} + \theta_2 \log(\sigma_{mt}) \\ + \theta_3 \Delta TS_t + \theta_4 \Delta CS_t + \nu_{mt}. \end{aligned} \tag{7}$$

Finally, in Model 4, which is the specification for which our main results are reported, we add to Model 2 the Economic Policy Uncertainty Index (EPU) and the Amihud et al. (2015) illiquidity measure ($Illiq$). The EPU is added as a proxy for overall economic uncertainty in each country, whereas the $Illiq$ measure allows to control for the impact of illiquidity or trading volume patterns on herding.[6] Model 4 follows the specification:

$$\begin{aligned} \log[Std_c(\beta^b_{imt})] = \mu_m + H_{mt} + \theta_1 r_{mt} + \theta_2 \log(\sigma_{mt}) \\ + \theta_3 EPU_t + \theta_4 Illiq_t + \nu_{mt}. \end{aligned} \tag{8}$$

2.1.1. Estimation of betas and their cross-sectional standard deviation

In order to estimate the state-space models, we first need to obtain estimates of the cross-sectional standard deviation of individual stocks' betas at each month. This is done in two steps. In the first step, for each country and each month, we estimate individual betas using daily returns (a minimum of 70% of valid returns is required), using the current and lagged returns to minimize the impact of non-synchronous price movements (Lewellen and Nagel, 2006):

$$r_{it} = \alpha_{it} + \beta^{k3}_{i,0} r_{mt} + \beta^{k3}_{i,1} r_{mt-1} + \beta^{k3}_{i,2}[(r_{mt-2} + r_{mt-3} + r_{mt-4})/3] + \varepsilon_{it} \tag{9}$$

from which betas ($\beta^{k3}_i = \beta^{k3}_{i,0} + \beta^{k3}_{i,1} + \beta^{k3}_{i,2}$) and their heteroscedasticity-robust standard errors are calculated.[7] In the second step, the cross-sectional standard deviation of the estimated betas is calculated as:

$$Std(\hat{\beta}^b_{imt}) = \sqrt{\frac{\sum_{i=1}^{N_t} (\hat{\beta}^b_{mt} - \overline{\hat{\beta}^b_{mt}})^2}{N_t}}, \tag{10}$$

where $\overline{\hat{\beta}^b_{mt}} = \frac{1}{N_t} \sum_{i=1}^{N_t} (\hat{\beta}^b_{mt})$ and N_t is the number of assets in month t.

2.2. CSAD methodology

For comparison purposes, we also carry out analyses using cross-sectional absolute deviation (CSAD) regression models.[8] The CSAD measure is calculated as follows:

$$CSAD_t = \frac{1}{N_t} \sum_{i=1}^{N_t} |r_{it} - r_{mt}|. \tag{11}$$

We consider two specifications. The first one is the Chang et al. (2000) model. These authors note that, under the CAPM, the expected CSAD increases linearly with the market return.

5 We opted to work with the first difference in the term and credit spreads because both variables were non-stationary according to an Augmented Dickey–Fuller test (not reported).

6 We thank an anonymous reviewer for this suggestion.

7 A similar approach is used in recent papers on herding, see e.g. Raimundo Júnior et al. (2020) and Hwang et al. (2020).

8 We thank an anonymous reviewer for the suggestion to include this analysis.

Fig. 1. Heterogeneity in severity of COVID-19 pandemic and governmental responses.

They then propose a model in which $CSAD_t$ is regressed onto the absolute value of the market return, as well as its square:

$$CSAD_t = \gamma_0 + \gamma_1 |r_{mt}| + \gamma_2 r_{mt}^2 + \varepsilon_t. \tag{12}$$

In this model, a negative and statistically significant γ_2 indicates the presence of herding.

The second specification we consider is the one proposed by Chiang and Zheng (2010), who proposed a modified regression that also includes the market return:

$$CSAD_t = \gamma_0 + \gamma_1 r_{mt} + \gamma_2 |r_{mt}| + \gamma_3 r_{mt}^2 + \varepsilon_t. \tag{13}$$

Chiang and Zheng (2010) show that the inclusion of r_{mt} allows the model to account for asymmetric investor behavior under different market conditions. A negative and statistically significant γ_3 indicates the presence of herding. We estimate both regression models for each country using daily values of the CSAD measure in different sample periods. We calculate standard errors using the Newey–West method to correct for heteroscedasticity and autocorrelation in the residuals.

3. Data

We obtain daily return and volume data for common stocks for each of the ten countries from Compustat's Global Security database. Our data spans the period from January 2001 to August 2021. To ensure consistency and comparability, we apply the same rule to define the universe of stocks in each country. Specifically, at each month, we rank all common stocks based on their market capitalization in descending order and include in our universe the number of stocks that comprise 90% of the total market capitalization of that country. The market portfolio return is calculated as the market-capitalization weighted average of the returns of the stocks in the universe at each month.[9] In addition to ensuring a consistent definition of the market portfolio across all countries, this approach also alleviates survivorship bias concerns and ensures replicability of our analyses. All returns are in the local currency, to avoid differences induced by exchange rate volatility.

The data on the 10-year and 3-month U.S. Treasury rates, which are used to create the term spread variable, are obtained from Refinitiv. We download the rates on AAA and BAA corporate bonds, used to calculate the credit spread, from the Federal Reserve Economic Data (FRED) website.

Our strategy to select the countries used in this study was based on the examination of key variables of interest regarding the governments' responses to the COVID-19 pandemic (stringency of measures limiting people's behaviors, extent and duration of economic support measures, and vaccinations) as well as the impact of the pandemic, including the mortality rates and disparity in the dates when the waves of infections occurred. We obtain the number of total COVID-19 deaths per 1 million inhabitants, the Oxford Government Response Stringency and Economic Support Indices from the Oxford Covid-19 Government Response Tracker.[10] Data on total number of vaccinations per one hundred thousand inhabitants is downloaded from the Our World in Data website.[11] Data on the Economic Policy Uncertainty index are downloaded from the Economic Policy Uncertainty website.[12] The methodology is described in Baker et al. (2016).

4. Empirical results

We start by comparing the 10 countries in terms of the severity of the pandemic and the governmental measures in response to the crisis. Fig. 1 shows the number of confirmed COVID-19 deaths per one million people, the Oxford Government Response Stringency and Economic Support indices, and the total number of vaccinations per 100 thousand people. the corresponding averages and standard deviations are shown in Table 1. The stringency index measures the strictness of governmental policies that restrict people's behavior, such as for example, school and workplace closures, restrictions on public gatherings, stay-at-home requirements, and restrictions on traveling. The economic support index records measures such as income support (including, for example, stimulus spending) and debt relief.

There are stark differences in terms of severity of the pandemic (total COVID-19 deaths/million), with Belgium, Brazil, Italy,

9 This approach is similar to how MSCI defines their universe of stocks for global equity indices, see for example (Asness et al., 2013). In Table A.1 in the Appendix, we compare our market portfolio calculations with the corresponding MSCI index for each country. Our indices are very highly correlated and show similar average returns and volatilities, compared to the MSCI indices.

10 https://www.bsg.ox.ac.uk/research/research-projects/coronavirus-government-response-tracker

11 https://ourworldindata.org/covid-vaccinations

12 https://www.policyuncertainty.com/

Table 1
Heterogeneity in severity of COVID-19 pandemic and governmental responses.

		Australia	Belgium	Brazil	China	France	Italy	Japan	Sweden	UK	USA
Total deaths per million	Ave	26.24	1414.77	1118.35	2.95	892.52	1142.85	44.22	885.04	1150.74	982.29
	Std	14.46	673.42	895.98	0.74	585.25	739.79	45.78	470.06	665.83	679.98
Economic support	Ave	42.50	63.75	82.50	45.00	52.50	71.88	44.38	25.00	56.25	90.00
	Std	36.36	23.61	31.52	19.62	19.70	27.17	23.81	21.84	25.49	30.78
Stringency index	Ave	61.25	70.44	39.95	54.03	58.43	55.32	71.32	61.07	59.68	62.36
	Std	18.30	14.90	12.17	19.83	20.63	18.38	9.64	20.45	19.78	21.62
Vaccinations per 100 thousand	Ave	20.30	53.72	30.48	46.87	48.88	50.05	25.83	46.62	70.88	65.21
	Std	26.61	54.60	31.97	54.50	49.10	49.52	38.07	46.05	49.34	43.44

The table reports averages and standard deviations of variables per country. The sample period is from January 2020 to August 2021, except for the "Vaccinations per 100 thousand", for which the sample period is from December 2020 to August 2021.

Table 2
Properties of the cross-sectional standard deviation of market betas.

	Log cross-sectional standard deviation of OLS betas									
	Australia	Belgium	Brazil	China	France	Italy	Japan	Sweden	UK	USA
Mean	−0.783	−0.841	−0.917	−0.667	−0.828	−0.814	−0.698	−0.980	−0.666	−0.431
Standard deviation	0.299	0.300	0.247	0.285	0.276	0.306	0.236	0.300	0.313	0.296
Skewness	0.318**	0.019**	0.324**	−0.041	0.126***	0.729***	0.228***	−0.074**	1.757**	0.612***
Excess kurtosis	3.506***	3.194	4.278***	2.808	2.903	6.570***	3.335	2.578	13.391***	5.269***
Jarque–Bera statistics	6.509**	0.387	20.199***	0.428*	0.729***	146.260***	3.293*	1.966	1183.300***	65.362***
Median # Stocks	133	26	53	921	73	57	707	67	180	712

Note: The table reports statistics of the cross-sectional standard deviations of betas for each country. Market betas are estimated using daily data on all stocks in the universe on each month. The sample period is from January 2001 to August 2021. We obtain a total number of 248 monthly cross-sectional variances of betas. (***) denotes a significance level of 1%, (**) indicates 5%, and (*) indicates 10%.

Table 3
Estimates of state-space models for herding measures for all countries.

Variables	Australia	Belgium	Brazil	China	France	Italy	Japan	Sweden	UK	USA
μ_m	−2.914***	−2.026***	−2.102***	−2.856***	−2.006***	−2.116***	−2.410***	−2.538***	−2.294***	−2.593***
$\sigma_{m\upsilon}$	0.177***	0.218***	0.124***	0.112***	0.171***	0.185***	0.142***	0.183***	0.163***	0.142***
ϕ_m	0.933***	0.943***	0.685***	0.894***	0.950***	0.909***	0.820***	0.980***	0.950***	0.947***
$\sigma_{m\eta}$	0.054***	0.073***	0.109***	0.069***	0.064***	0.077***	0.074***	0.044***	0.062***	0.083***
r_{mt}	−0.174	0.309	3.097*	−0.124	10.769***	0.714**	9.025	12.520	1.098	28.878***
$\log \sigma_{mt}$	−0.461***	−0.259***	−0.282***	−0.496***	−0.253***	−0.286***	−0.373***	−0.358***	−0.347***	−0.453***
EPU_t	0.123***	−0.043	−0.019	−0.019	−0.009	−0.006	−0.141***	−0.044	0.140***	0.006
$Illiquid_t$	0.034	−1.460	−0.050	−1.306	0.746	1.318	−1.750**	−1.450	1.307	1.269
Proportion of signal	0.201	0.270	0.403	0.256	0.236	0.284	0.274	0.165	0.228	0.307

Note: In each month from January 2001 to August 2021, we use daily data on individual stocks to estimate market betas. The cross-sectional standard deviation of the estimated betas is used to estimate the state-space model below

$$
\begin{aligned}
\log[Std_c(\beta^b_{imt})] &= \mu_m + H_{mt} + \theta_1 r_{mt} + \theta_2 \log(\sigma_{mt}) + \theta_3 EPU_t + \theta_4 Illiq_t + \nu_{mt} \\
H_{mt} &= \phi_m H_{mt-1} + \eta_{mt},
\end{aligned}
$$

where $\nu_{mt} \sim iid(0, \sigma^2_{m\upsilon})$, $\eta_{mt} \sim iid(0, \sigma^2_{m\eta})$, r_{mt} denotes the return on the market portfolio, $\log \sigma_{mt}$ is the log of the market volatility, EPU_t is the Economic Policy Uncertainty index, and $Illiq_t$ is the Amihud et al. (2015) illiquidity measure. (***) denotes a significance level of 1%, (**) indicates 5%, and (*) indicates 10%. The proportion of signal is calculated as $(\sigma_{m\eta}/SD \log CX\beta)$, where $SD \log CX\beta$ is the time-series standard deviation of the log-cross-sectional standard deviation of betas.

and the UK showing the highest average mortality rates (all above 1,000/million), and China, Australia and Japan showing much lower rates. The graphs for the stringency and economic support indices show that all countries implemented both types of measures, but to different degrees and in different moments. The average level of the economic support index varies from 25.0 in Sweden to 90 in the USA. There is less variability regarding the stringency of "lock-down style" governmental actions restricting mobility: the average value varies from 39.95 in Brazil to 71.32 in Japan. A similar pattern holds for the average number of newly vaccinated people. A non-parametric Kruskal–Wallis test rejects the null hypothesis of equality of the mean values of each of the four variables across countries at the 1% significance, confirming the heterogeneity.

Table 2 summarizes the statistical properties of the estimated cross-sectional standard deviations of stocks betas on the relevant market portfolio. The table shows that $Std(\hat{\beta}^b_{imt})$ varies significantly across countries, is positively skewed and leptokurtic. The Jarque–Bera test rejects the normality assumption for all countries. Table A.2 in the Appendix reports additional statistics for betas. As expected, the average betas are close to one in all countries.

Table 3 reports estimates of the state-space Model 4 for each country. The estimates of ϕ_m are statistically significant for all countries and show that the latent herding variable, H_{mt}, is highly persistent. Moreover, the estimates of $\sigma_{m\eta}$ are highly significant for all countries, and therefore we can conclude that there is a degree of herding (and consequently, adverse or anti-herding) towards the market portfolio in all markets. The proportion of signal in the state-space model, which is a measure of the percentage of the total variability in the cross-sectional standard deviation of betas which is explained by herding, shows that herding explains between 17% to 40% of the total variation in $Std(\hat{\beta}^b_{imt})$.

The coefficients on the market return (r_{mt}) are positive for 8 out of 10 countries, and significant at the 5% level or lower for France, Italy, and the U.S. On the other hand, the coefficients on the log-market volatility ($\log(\sigma_{mt})$) are negative and significant at the 1% level for all countries. These results are in line with those found by HS04 for the U.S. and South Korean markets: $Std_c(\beta^b_{imt})$

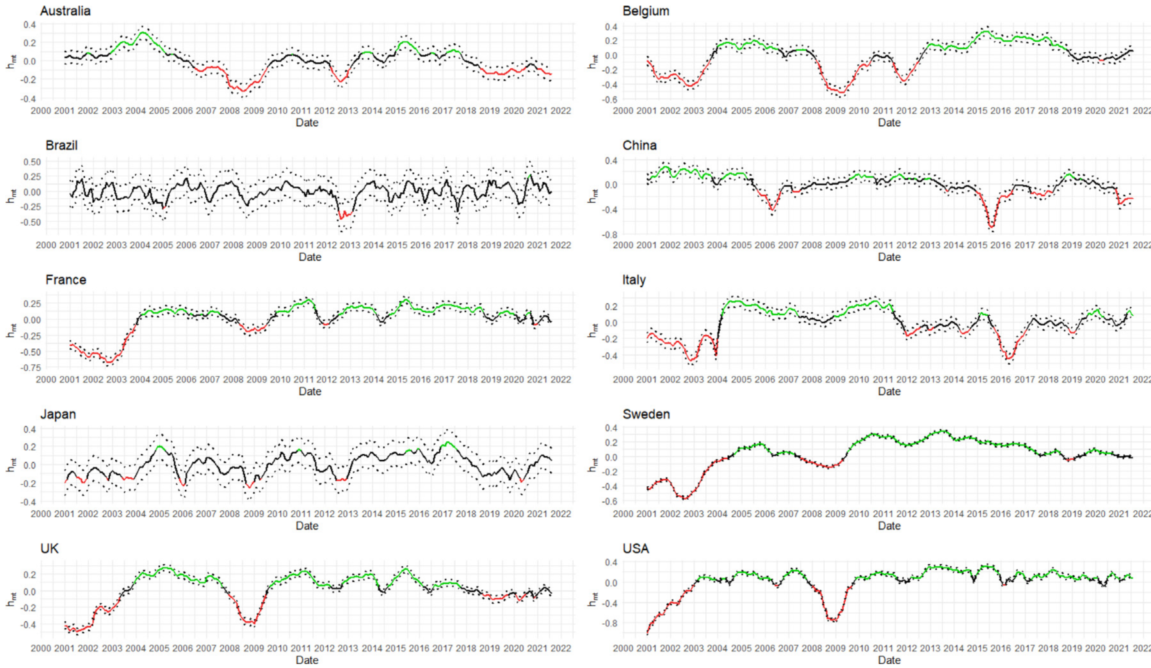

Fig. 2. Herding towards the market factor: 2001 to 2021.

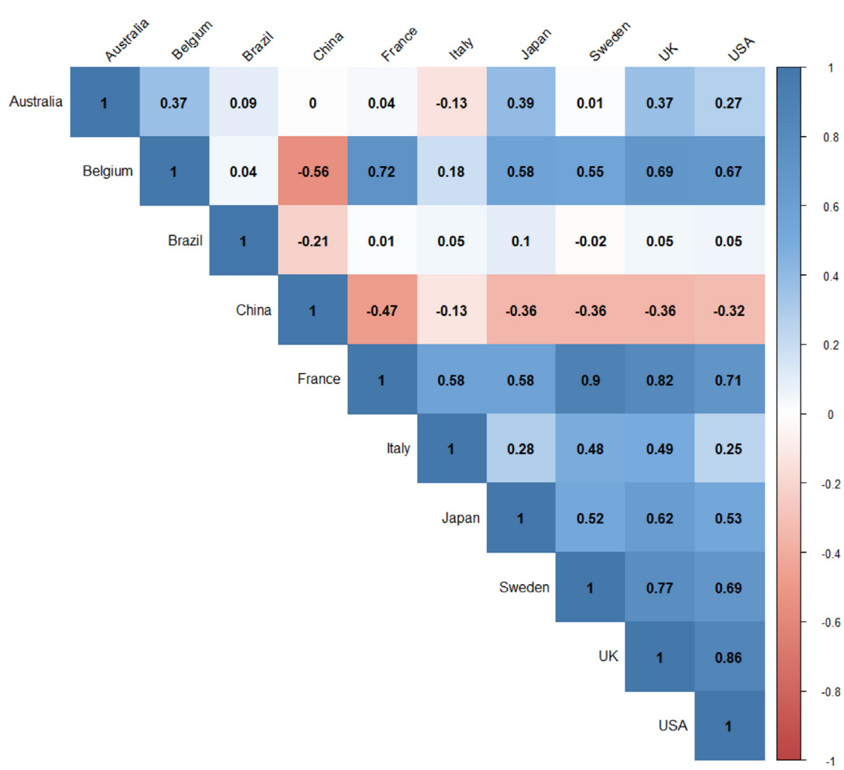

Fig. 3. Correlation among herding in the countries.

decreases when the market is riskier and falling but increases when markets are less risky and rising. As noted by HS04, this finding explains why empirical studies that rely only on cross-sectional deviation measures usually find that herding occurs during market crises. The coefficients on *EPU* are significant for Australia, Japan, and the UK, while *illiq* is only significant (at the 5% level) for Japan. Similar results were found in Raimundo Junior et al. (2020).

Tables B.1–B.10 in the Appendix report results for Models 1, 2, and 3. The additional control variables in Model 3, (credit and term spreads) are generally not significant. We note that the herding patterns extracted from all state-space models with control variables are very similar.

Fig. 2 shows the evolution of the herding measure, $h_{mt} = 1-\exp(H_{mt})$, for each of the markets, as well as the associated 95% confidence bands. When h_{mt} is significantly positive, there is a

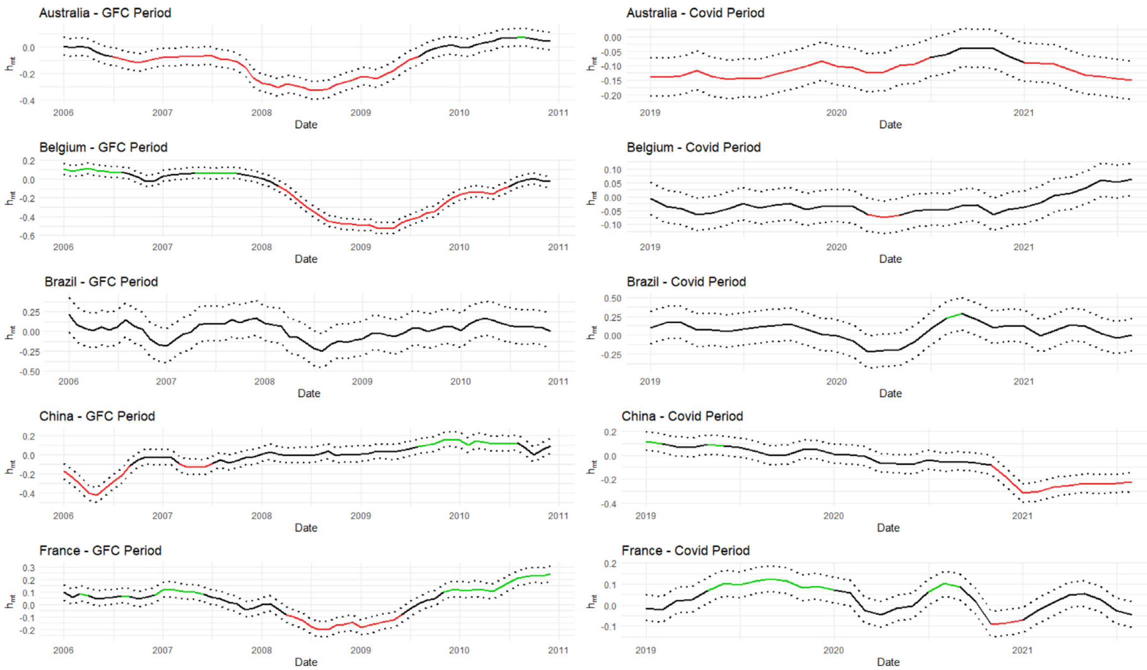

Fig. 4. Herding towards the market factor in 10 markets in 2006–2008 and 2019–2021.

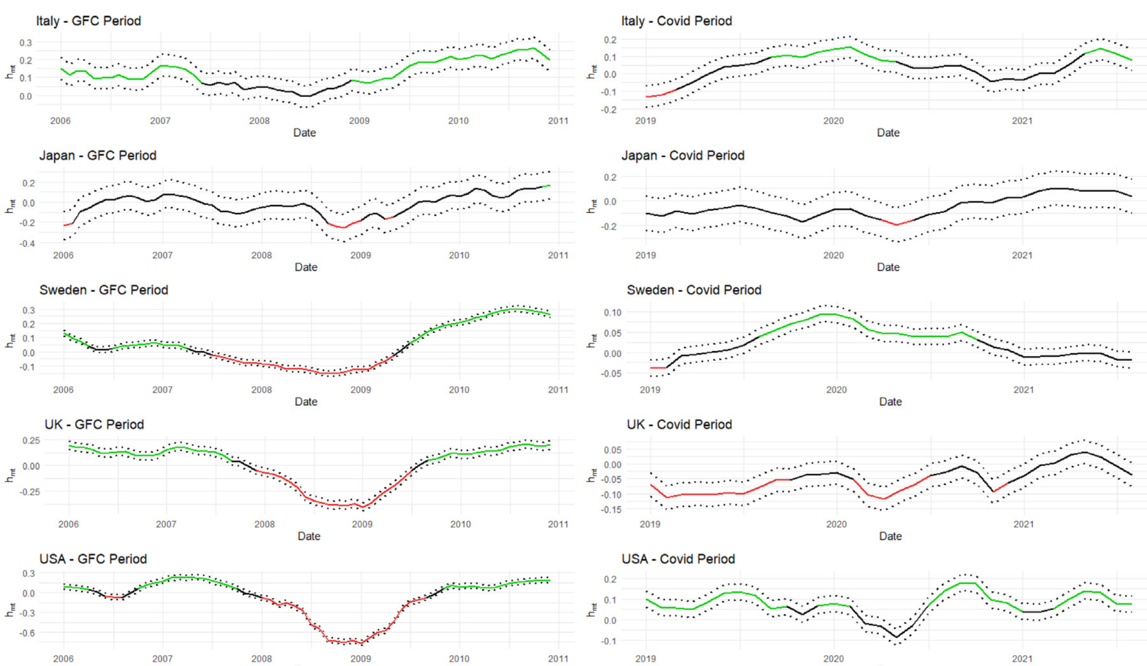

Fig. 5. Herding towards the market factor in 10 markets in 2006–20010 and 2019–2021.

degree of herding in the market (indicated in green on the graph). On the other hand, a significantly negative h_{mt} indicates adverse or anti-herding, meaning that assets' betas diverge from that of the market portfolio (indicated in red on the graph). The graphs show a few salient features. First, all countries go through periods of herding and anti-herding. Second, the highest value of h_{mt} is much lower than one, suggesting that there was not an extreme degree of herding towards the market portfolio during the sample period. Third, consistently with HS04, h_{mt} tends to increase in the periods preceding crises or market turbulence, and to decrease during crises, as investors focus more on fundamentals. This can be seen for most countries during the GFC of 2007–2008, but also for more country-specific events, such as the Chinese stock market crash in mid-2015. Fig. 3 shows the contemporaneous correlations between the herding measures across countries. With a few exceptions, the correlations are mostly positive, but not very high, suggesting a degree of comovement in herding patterns in the stock markets of the ten countries. Correlations are particularly higher among European countries. Interestingly, herding in China is negatively correlated with herding in all other countries.

4.1. *Herding during the GFC and the COVID-19 pandemic*

In Figs. 4 and 5, we explore in more detail the herding patterns in the ten countries during periods that include two crises,

Table 4
Panel regression analysis of changes in herding on the number of COVID-19 deaths and policy responses against the pandemic.

	Dependent variable:
	Δh_{mt}
New deaths per million	0.007*
	(0.004)
Economic support index	0.0002**
	(0.0001)
Stringency index	−0.0003*
	(0.0002)
New vaccinations	0.016
	(0.021)
Constant	−0.001
	(0.010)
Observations	200

Note: The independent variables used in the regression are the number of new COVID-19 deaths per 1 million inhabitants, the Oxford government response economic support and stringency Indices, and the proportion of new vaccinated inhabitants in each month. (***) denotes a significance level of 1%, (**) indicates 5%, and (*) indicates 10%.

the Global Financial Crisis (GFC) of 2007–2008 (left-hand side) and the COVID-19 pandemic (right-hand side). We first analyze the period that includes the GFC and its aftermath, from January 2006 to December 2010. In the year that precedes the GFC (2006), most countries exhibit positive h_{mt}, at least during some months. All European countries, as well as the U.S., show significant herding during this period. During the GFC, from 2007 to 2008, h_{mt} typically decreases and goes into negative territory for most countries, as market uncertainty forces investors to focus more on fundamentals. With the exception of Brazil, all countries show significant anti-herding at some point during the 2007–2008 period. As uncertainty begins to decrease and markets enter the recovery bull market of 2009, h_{mt} increases again and herding becomes significant in several countries. Although there are variations across countries, the pattern is quite clear: herding behavior is present in the period preceding the GFC; it subsequently decreases or even becomes anti-herding ($h_{mt} < 0$) during the worst period of the crisis, as investors lose confidence and turn more towards fundamentals, and then herding intensifies again once the recovery is under way.

Turning to the right-hand side of Figs. 4 and 5, we would like to answer the question: did herding exist in any of the ten countries during the COVID-19 pandemic? The graphs show the estimated herding for the ten countries from January 2019 to August 2021 (the end of our sample). It is clear that, in contrast with the GFC period, herding patterns during the COVID-19 pandemic are much more heterogeneous across countries. China, France, Italy, Sweden, and the U.S. exhibit significant herding in the period that precedes the outbreak of the pandemic. On the other hand, Australia, Belgium, Japan, and the UK show either anti-herding or no significant herding in this period. Focusing on the period from the beginning of the pandemic in January 2020, we note that, for the markets of Australia, Belgium, China, Japan, and the U.K., herding is never present. The only countries where herding appears more strongly during the pandemic are Italy, Sweden, and the U.S. Brazil shows a very short period of significant herding in the second half of 2020, whereas in France, herding appears during the second half of 2020, but quickly reverses leading into 2021.

The U.S. displays an interesting and distinct pattern during the 2019–2021 period, with significant herding in the period preceding the pandemic, which briefly disappears in the second half of 2019. A plausible explanation for this unique pattern is the market uncertainty regarding the possible impeachment of President Donald Trump. The investigations began formally in July 2019 and reached public attention in mid-September 2019, which coincides exactly with the trough in h_{mt} shown in the graph. h_{mt} decreases and becomes negative in early 2020, but then starts to increase still in the first half of 2020, a period that coincides with the passing of various economic stimulus packages amounting to trillions of dollars and which was followed by a significant rise in U.S. stocks.[13] Herding behavior in the U.S. becomes significant from the second half of 2020. This pattern suggests once again that events that increase market uncertainty, regardless of their nature (i.e., political or public-health related), cause investors to refocus on fundamentals and therefore decrease herding. On the other hand, government actions focused on stimulus reduce uncertainty and induce investors to herd as the market rises.

4.2. Comparison with CSAD regression models

The results thus far suggest limited evidence of herding during the COVID-19 pandemic. As discussed previously, recent studies on herding during the pandemic have found mixed evidence, so it is naturally interesting to contrast the results of our state-space model with those obtained with the CSAD regression models. We calculate CSAD for each country following Eq. (11). Fig. B.6 shows the evolution of the CSAD measure for all countries. Clear increases in the CSAD measure can be observed during periods of market turmoil, such as the GFC and the early stage of the COVID-19 pandemic. Tables B.11 and B.12 in the Appendix report estimated coefficients for each country for the regression models of Chang et al. (2000) and Chiang and Zheng (2010), respectively. We report results for the full sample, the period including the GFC, from January 2007 to December 2008, and two periods including the COVID-19 pandemic: the more volatile period from January to April 2020 (Covid_1), and the period starting in January 2020 until the end of our sample (Covid_2).

We start by discussing the results from the Chang et al. (2000) model on Table B.11. When the entire sample is considered, China is the only country for which there is evidence of herding (a negative and statistically significant γ_2 in Eq. (12)). Several countries show signs of anti-herding (positive and statistically significant γ_2). During the GFC, the model suggests evidence of herding in Australia (although only at the 10% significance level) and again in China (at the 5% level). During the more turbulent Covid_1 period, γ_2 is negative and statistically significant in Australia, Belgium, Brazil, France, and the UK. However, if we consider the longer period from the beginning of the pandemic until the end of our sample, the only country for which there is evidence of herding is Belgium.

Table B.12 reports results obtained with the Chiang and Zheng (2010) model, which reveal a few differences with respect to the Chang et al. (2000) model. When the entire sample period is considered, we now find, in addition to herding in China, evidence of herding (negative and statistically significant γ_3 in Eq. (13)) for Brazil, which under the Chang et al. (2000) model showed significant anti-herding. During the GFC period, the evidence of herding in China persists, while the coefficient for Australia is no longer significant. Finally, during either of the two periods that include the COVID-19 pandemic, the evidence of herding is much weaker in comparison with that obtained with the Chang et al.

[13] The Coronavirus Preparedness and Response Supplemental Appropriations Act, which included $8.3 billion in emergency funding to combat the COVID-19 pandemic, was enacted on March 6, 2020. The Coronavirus Aid, Relief, and Economic Security Act (CARES), a $2.2 trillion economic stimulus, was signed into law on March 27, 2020. It included $300 billion in one-time cash payments to individuals, with most single adults receiving $1,200 and families with children receiving more. See https://en.wikipedia.org/wiki/U.S._federal_government_response_to_the_COVID-19_pandemic.

Table A.1
Comparison of market portfolio returns constructed in this study with MSCI indices.

	Correlation	Average return	Average return (MSCI)	Standard dev.	Std. deviation (MSCI)
Australia	84.47%	0.04%	0.03%	1.42%	1.03%
Belgium	88.82%	0.03%	0.01%	1.70%	1.40%
Brazil	86.77%	0.06%	0.04%	2.07%	1.64%
China	98.61%	0.03%	0.02%	1.53%	1.56%
France	90.67%	0.03%	0.02%	1.43%	1.37%
Italy	91.90%	0.02%	0.00%	1.54%	1.47%
Japan	88.18%	0.02%	0.01%	1.29%	1.32%
Sweden	89.81%	0.05%	0.03%	1.30%	1.40%
UK	88.17%	0.02%	0.01%	1.32%	1.16%
USA	99.81%	0.04%	0.04%	1.21%	1.23%

Note: The table reports statistics of the returns of the market indices used in this study and the corresponding MSCI market indices. The sample period is from January 2001 to August 2021 and all statistics are based on the daily returns. Daily returns on MSCI indices are obtained from Refinitiv. The second column of the table reports the correlation between our indices and the corresponding MSCI index. The remain columns report the daily average return and standard deviations of the indices used in this study, and the corresponding MSCI indices.

Table A.2
Properties of the market betas.

	Australia	Belgium	Brazil	China	France	Italy	Japan	Sweden	UK	USA
Average	0.936	0.804	0.936	0.901	0.950	0.947	0.940	0.908	0.970	1.004
Standard deviation	1.193	0.980	1.104	0.972	0.992	0.980	1.065	1.024	1.001	0.869
Maximum	1.400	1.680	2.400	1.518	1.505	1.888	1.503	2.228	1.706	2.200
Minimum	−0.187	−0.905	0.015	0.011	−0.312	0.015	−0.100	0.120	−0.234	0.350
Median (N stocks)	133	26	53	921	73	57	707	67	180	712

Note: The table reports cross-sectional statistics of individual stock betas for each country. Market betas are estimated using daily data on all stocks in the universe on each month. The sample period is from January 2001 to August 2021. We obtain a total number of 248 monthly cross-sections of betas for each country.

Table A.3
Correlation matrix of variables used in panel regression.

	New deaths per million	Economic support	Stringency	New vaccinations per 100 thousand
New deaths per million	1.00	0.12	0.41	0.05
Economic support	0.12	1.00	0.33	0.03
Stringency	0.41	0.33	1.00	0.05
New vaccinations per 100 thousand	0.05	0.03	0.05	1.00

(2000) model, with negative γ_3 coefficients that are significant only for a few countries, and at the 10% significant level.

These results highlight some of the challenges associated with the detection of herding using the CSAD regression methodologies. First, the significance of the herding coefficients show a strong dependence on the sample period chosen. Second, since the model is static, it can only indicate whether herding or anti-herding is present in the period used to run the regression, but it cannot shed light on the dynamic nature of herding behavior. In contrast, the state-space approach yields dynamic estimates of herding, purged from the potential effects of unintended herding due to investors' reactions to fundamentals. Although fundamentals can be incorporated into CSAD regressions (e.g., Galariotis et al., 2015), the model remains static in nature.

4.3. Herding, COVID-19 mortality, and government response

An interesting question is whether differences in herding patterns in different markets can be explained by the severity of the pandemic in each country, as well the governmental measures implemented in response to the pandemic, which have been heterogeneous, as seen in Table 1.[14] We investigate this by estimating a panel regression of the change in the estimated latent herding measure in each country, Δh_{mt}, on the number of new COVID-19 deaths per million, the Oxford government response economic support and stringency indices, and the number of new vaccinations per one hundred thousand people.[15] The panel regression specification includes random effects by country.[16]

The results, reported in Table 4, show that the severity of the pandemic, in terms of new COVID-19 deaths per million, seems to be associated with increases in the level of herding, although the coefficient is significant only at the 10% level. The stringency index has a negative and statistically significant impact (at the 10% level) on Δh_{mt}, and therefore it decreases the overall level of herding. In contrast, the coefficient on the economic support index is positive and significant at the 5% level, showing that measures that provide economic support tend to increase the level of herding. Changes in vaccinations do not seem to have an impact on herding. We note that the positive association between new deaths per million and changes in herding is likely confounded with the effects of economic support and stringency measures, as increases in mortality likely trigger more measures to support the economy and restrict movements. In untabulated results, we repeated the panel analysis by adding the interactions between new deaths per million and the two government response indices.

14 See also Zaremba et al. (2020) and the references therein.

15 Table A.3 in the Appendix reports the correlations among these variables across all countries.

16 We tested for fixed versus random effects using the Durbin–Wu–Hausman test, which rejected the fixed effects specification in favor of the random effects one.

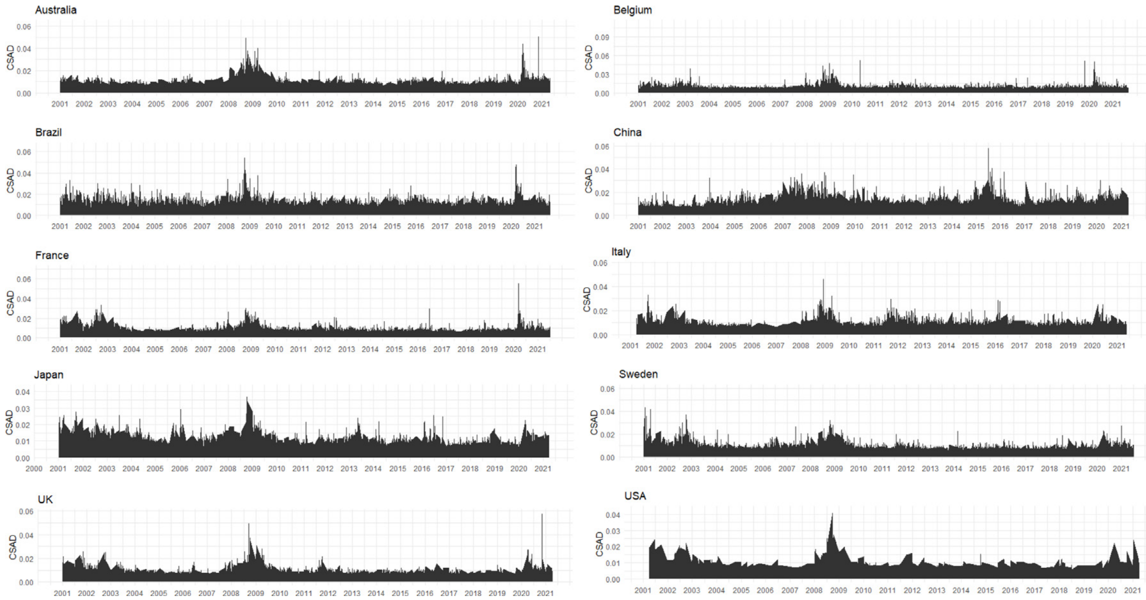

Fig. B.6. CSAD measure of the 10 countries.

Table B.1
Estimates of state-space models for herding measures — Australia.

Variables	Model 1	Model 2	Model 3
μ_m	-0.780^{***}	-2.917^{***}	-2.896^{***}
σ_{mv}	0.200^{***}	0.191^{***}	0.189^{***}
ϕ_m	0.790^{***}	0.928^{***}	0.923^{***}
$\sigma_{m\eta}$	0.135^{***}	0.062^{***}	0.065^{***}
r_{mt}		-6.858	-0.310
$\log\sigma_{mt}$		-1.090^{***}	-1.080^{***}
ΔCS_t			0.133
ΔTS_t			-0.011
Log likelihood	0.180	23.026	38.592
AIC	0.201	-0.144	-0.246
SIC	0.260	-0.056	-0.133
Proportion of signal	0.208	0.450	0.218

Note: In each month from January 2001 to August 2021, we use daily data on individual stocks to estimate market betas. The cross-sectional standard deviation of the estimated betas is used to estimate the state-space model below

$$\log[Std_c(\beta^b_{imt})] = \mu_m + H_{mt} + \sum_j \theta_h c_{jt} + v_{mt}$$
$$H_{mt} = \phi_m H_{mt-1} + \eta_{mt},$$

where $v_{mt} \sim iid(0, \sigma^2_{mv})$, $\eta_{mt} \sim iid(0, \sigma^2_{m\eta})$, and c_{jt} denotes the control variables included in Models 2 and 3. r_{mt} denotes the return on the market portfolio, $\log\sigma_{mt}$ is the log of the market volatility, ΔCS_t is the change in the credit spread, and ΔTS_t is the change in the term spread. (***) denotes a significance level of 1%, (**) indicates 5%, and (*) indicates 10%. The proportion of signal is calculated as $(\sigma_{m\eta}/SD\log\beta)$.

Table B.2
Estimates of state-space models for herding measures — Belgium.

Variables	Model 1	Model 2	Model 3
μ_m	-0.837^{***}	-1.954^{***}	-1.958^{***}
σ_{mv}	0.250^{***}	0.230^{***}	0.230^{***}
ϕ_m	0.891^{***}	0.930^{***}	0.933^{***}
$\sigma_{m\eta}$	0.076^{***}	0.074^{***}	0.075^{***}
r_{mt}		5.429	0.318
$\log\sigma_{mt}$		-0.567^{***}	-0.569^{***}
ΔCS_t			-0.569
ΔTS_t			0.006
Log likelihood	-33.821	-21.054	-9.843
AIC	0.320	0.229	0.143
SIC	0.379	0.317	0.257
Proportion of signal	0.247	0.253	0.249

Note: In each month from January 2001 to August 2021, we use daily data on individual stocks to estimate market betas. The cross-sectional standard deviation of the estimated betas is used to estimate the state-space model below

$$\log[Std_c(\beta^b_{imt})] = \mu_m + H_{mt} + \sum_j \theta_h c_{jt} + v_{mt}$$
$$H_{mt} = \phi_m H_{mt-1} + \eta_{mt},$$

where $v_{mt} \sim iid(0, \sigma^2_{mv})$, $\eta_{mt} \sim iid(0, \sigma^2_{m\eta})$, and c_{jt} denotes the control variables included in Models 2 and 3. r_{mt} denotes the return on the market portfolio, $\log\sigma_{mt}$ is the log of the market volatility, ΔCS_t is the change in the credit spread, and ΔTS_t is the change in the term spread. (***) denotes a significance level of 1%, (**) indicates 5%, and (*) indicates 10%. The proportion of signal is calculated as $(\sigma_{m\eta}/SD\log\beta)$.

Confirming our intuition, the number of new deaths per million is no longer significant, whereas the coefficients on the economic support and stringency indices retain their signs and statistical significance.

4.4. Potential implications for investors and policy makers

The COVID-19 pandemic has been unlike previous episodes of market stress or increased volatility seen in financial markets. First, it is a truly exogenous shock to financial markets, unlike, for instance, the GFC. Second, different countries were impacted differently in terms of both severity and timing. And third, governmental responses have been heterogeneous, with countries implementing different measures to different degrees. Some measures have arguably a direct impact on financial markets (e.g., direct economic stimulus), while others may have indirect or even no impact (e.g., stringency of lockdowns). One important question is what implications the heterogeneous herding patterns that we document may have for investors, as well as regulators and policy makers.[17]

[17] We thank an anonymous reviewer for the suggestion to discuss the policy implications of our findings.

Table B.3
Estimates of state-space models for herding measures — Brazil.

Variables	Model 1	Model 2	Model 3
μ_m	−0.913***	−2.143***	−2.145***
$\sigma_{m\upsilon}$	0.1729***	0.158***	0.157***
ϕ_m	0.802***	0.737***	0.737***
$\sigma_{m\eta}$	0.105***	0.087***	0.087***
r_{mt}		4.187*	0.214*
$\log\sigma_{mt}$		−0.689***	−0.690***
ΔCS_t			−0.130
ΔTS_t			0.006
Log likelihood	22.236	53.326	79.539
AIC	−0.154	−0.401	−0.576
SIC	−0.095	−0.313	−0.463
Proportion of signal	0.439	0.366	0.290

Note: In each month from January 2001 to August 2021, we use daily data on individual stocks to estimate market betas. The cross-sectional standard deviation of the estimated betas is used to estimate the state-space model below

$$\log[Std_c(\beta^b_{imt})] = \mu_m + H_{mt} + \sum_j \theta_h c_{jt} + \nu_{mt}$$
$$H_{mt} = \phi_m H_{mt-1} + \eta_{mt},$$

where $\nu_{mt} \sim iid(0, \sigma^2_{m\upsilon})$, $\eta_{mt} \sim iid(0, \sigma^2_{m\eta})$, and c_{jt} denotes the control variables included in Models 2 and 3. r_{mt} denotes the return on the market portfolio, $\log\sigma_{mt}$ is the log of the market volatility, ΔCS_t is the change in the credit spread, and ΔTS_t is the change in the term spread. (***) denotes a significance level of 1%, (**) indicates 5%, and (*) indicates 10%. The proportion of signal is calculated as $(\sigma_{m\eta}/SD\log\beta)$.

Table B.4
Estimates of state-space models for herding measures — China.

Variables	Model 1	Model 2	Model 3
μ_m	−0.662***	−2.849***	−2.832***
$\sigma_{m\upsilon}$	0.174***	0.111***	0.113***
ϕ_m	0.932***	0.900***	0.910***
$\sigma_{m\eta}$	0.069***	0.081***	0.066***
r_{mt}		−2.423	−0.105
$\log\sigma_{mt}$		−1.151***	−1.142***
ΔCS_t			0.178*
ΔTS_t			−0.006
Log likelihood	63.441	116.902	121.539
AIC	−0.660	−0.939	−0.915
SIC	−0.589	−0.851	−0.802
Proportion of signal	0.273	0.231	0.221

Note: In each month from January 2001 to August 2021, we use daily data on individual stocks to estimate market betas. The cross-sectional standard deviation of the estimated betas is used to estimate the state-space model below

$$\log[Std_c(\beta^b_{imt})] = \mu_m + H_{mt} + \sum_j \theta_h c_{jt} + \nu_{mt}$$
$$H_{mt} = \phi_m H_{mt-1} + \eta_{mt},$$

where $\nu_{mt} \sim iid(0, \sigma^2_{m\upsilon})$, $\eta_{mt} \sim iid(0, \sigma^2_{m\eta})$, and c_{jt} denotes the control variables included in Models 2 and 3. r_{mt} denotes the return on the market portfolio, $\log\sigma_{mt}$ is the log of the market volatility, ΔCS_t is the change in the credit spread, and ΔTS_t is the change in the term spread. (***) denotes a significance level of 1%, (**) indicates 5%, and (*) indicates 10%. The proportion of signal is calculated as $(\sigma_{m\eta}/SD\log\beta)$.

Table B.5
Estimates of state-space models for herding measures — France.

Variables	Model 1	Model 2	Model 3
μ_m	−0.079***	−2.087***	−2.088***
$\sigma_{m\upsilon}$	0.045***	0.176***	0.176***
ϕ_m	0.949***	0.925***	0.927***
$\sigma_{m\eta}$	0.058***	0.080***	0.087***
r_{mt}		11.115***	0.570***
$\log\sigma_{mt}$		−0.653***	−0.652***
ΔCS_t			−0.071
ΔTS_t			0.010
Log likelihood	1.040	27.843	−1.232
AIC	0.025	−0.185	0.074
SIC	0.083	−0.097	0.187
Proportion of signal	0.217	0.265	0.260

Note: In each month from January 2001 to August 2021, we use daily data on individual stocks to estimate market betas. The cross-sectional standard deviation of the estimated betas is used to estimate the state-space model below

$$\log[Std_c(\beta^b_{imt})] = \mu_m + H_{mt} + \sum_j \theta_h c_{jt} + \nu_{mt}$$
$$H_{mt} = \phi_m H_{mt-1} + \eta_{mt},$$

where $\nu_{mt} \sim iid(0, \sigma^2_{m\upsilon})$, $\eta_{mt} \sim iid(0, \sigma^2_{m\eta})$, and c_{jt} denotes the control variables included in Models 2 and 3. r_{mt} denotes the return on the market portfolio, $\log\sigma_{mt}$ is the log of the market volatility, ΔCS_t is the change in the credit spread, and ΔTS_t is the change in the term spread. (***) denotes a significance level of 1%, (**) indicates 5%, and (*) indicates 10%. The proportion of signal is calculated as $(\sigma_{m\eta}/SD\log\beta)$.

Table B.6
Estimates of state-space models for herding measures — Italy.

Variables	Model 1	Model 2	Model 3
μ_m	−0.799***	−2.000***	−1.972***
$\sigma_{m\upsilon}$	0.218***	0.194***	0.188***
ϕ_m	0.933***	0.928***	0.926***
$\sigma_{m\eta}$	0.076***	0.070***	0.070***
r_{mt}		14.074**	0.720***
$\log\sigma_{mt}$		−0.618***	−0.600***
ΔCS_t			0.210*
ΔTS_t			0.033*
Log likelihood	−11.981	14.811	23.284
AIC	0.135	−0.074	−0.123
SIC	−0.194	0.013	−0.009
Proportion of signal	0.256	0.233	0.232

Note: In each month from January 2001 to August 2021, we use daily data on individual stocks to estimate market betas. The cross-sectional standard deviation of the estimated betas is used to estimate the state-space model below

$$\log[Std_c(\beta^b_{imt})] = \mu_m + H_{mt} + \sum_j \theta_h c_{jt} + \nu_{mt}$$
$$H_{mt} = \phi_m H_{mt-1} + \eta_{mt},$$

where $\nu_{mt} \sim iid(0, \sigma^2_{m\upsilon})$, $\eta_{mt} \sim iid(0, \sigma^2_{m\eta})$, and c_{jt} denotes the control variables included in Models 2 and 3. r_{mt} denotes the return on the market portfolio, $\log\sigma_{mt}$ is the log of the market volatility, ΔCS_t is the change in the credit spread, and ΔTS_t is the change in the term spread. (***) denotes a significance level of 1%, (**) indicates 5%, and (*) indicates 10%. The proportion of signal is calculated as $(\sigma_{m\eta}/SD\log\beta)$.

As shown in Table 3, in general, the cross-sectional standard deviation of betas decreases with market volatility (the coefficients of $\log\sigma_{mt}$ are negative) and increases with market returns (the coefficients on r_{mt} are mostly positive). Even after taking into account these effects and those of other macroeconomic or market conditions through additional control variables, herding (and anti-herding) exists and is significant in all countries, which suggest that herding can occur in different market regimes. The herding patterns during and immediately after the GFC in Figs. 4 and 5 suggest that the period of increased market stress from mid-2007 to 2008 is mostly associated with reduction in herding and anti-herding, whereas the recovery period starting in early 2009 shows, for most countries, an increase in herding behavior. This is in line with the findings of HS04, who document that herding is present "when the market is quiet and investors are confident of the direction in which markets are heading". While herding patterns during the pandemic are less homogeneous, we still find that herding usually decreases (or there is anti-herding) during the early stages of the pandemic, when uncertainty is much higher. A possible implication for investors is that sudden

Table B.7
Estimates of state-space models for herding measures — Japan.

Variables	Model 1	Model 2	Model 3
μ_m	-0.698^{***}	-2.410^{***}	-2.410^{***}
σ_{mv}	0.195^{***}	0.156^{***}	0.156^{***}
ϕ_m	0.811^{***}	0.869^{***}	0.869^{***}
$\sigma_{m\eta}$	0.077^{***}	0.062^{***}	0.062^{***}
r_{mt}		10.263	0.476
$\log \sigma_{mt}$		-0.869^{***}	-0.869^{***}
ΔCS_t			0.022
ΔTS_t			0.005
Log likelihood	18.192	66.552	75.939
AIC	−0.120	−0.531	−0.547
SIC	−0.061	−0.425	−0.434
Proportion of signal	0.259	0.208	0.208

Note: In each month from January 2001 to August 2021, we use daily data on individual stocks to estimate market betas. The cross-sectional standard deviation of the estimated betas is used to estimate the state-space model below

$$\log[Std_c(\beta^b_{imt})] = \mu_m + H_{mt} + \sum_j \theta_h c_{jt} + \nu_{mt}$$
$$H_{mt} = \phi_m H_{mt-1} + \eta_{mt},$$

where $\nu_{mt} \sim iid(0, \sigma^2_{m\nu})$, $\eta_{mt} \sim iid(0, \sigma^2_{m\eta})$, and c_{jt} denotes the control variables included in Models 2 and 3. r_{mt} denotes the return on the market portfolio, $\log \sigma_{mt}$ is the log of the market volatility, ΔCS_t is the change in the credit spread, and ΔTS_t is the change in the term spread. (***) denotes a significance level of 1%, (**) indicates 5%, and (*) indicates 10%. The proportion of signal is calculated as $(\sigma_{m\eta}/SD \log \beta)$.

Table B.8
Estimates of state-space models for herding measures — Sweden.

Variables	Model 1	Model 2	Model 3
μ_m	-0.908^{***}	-2.502^{***}	-2.494^{***}
σ_{mv}	0.238^{***}	0.191^{***}	0.190^{***}
ϕ_m	0.981^{***}	0.969^{***}	0.971^{***}
$\sigma_{m\eta}$	0.040^{***}	0.053^{***}	0.052^{***}
r_{mt}		14.624	0.720^{***}
$\log \sigma_{mt}$		-0.830^{***}	-0.824^{***}
ΔCS_t			0.384
ΔTS_t			0.019
Log likelihood	−14.877	24.850	37.190
AIC	0.159	−0.159	−0.235
SIC	0.218	−0.071	−0.122
Proportion of signal	0.134	0.177	0.173

Note: In each month from January 2001 to August 2021, we use daily data on individual stocks to estimate market betas. The cross-sectional standard deviation of the estimated betas is used to estimate the state-space model below

$$\log[Std_c(\beta^b_{imt})] = \mu_m + H_{mt} + \sum_j \theta_h c_{jt} + \nu_{mt}$$
$$H_{mt} = \phi_m H_{mt-1} + \eta_{mt},$$

where $\nu_{mt} \sim iid(0, \sigma^2_{m\nu})$, $\eta_{mt} \sim iid(0, \sigma^2_{m\eta})$, and c_{jt} denotes the control variables included in Models 2 and 3. r_{mt} denotes the return on the market portfolio, $\log \sigma_{mt}$ is the log of the market volatility, ΔCS_t is the change in the credit spread, and ΔTS_t is the change in the term spread. (***) denotes a significance level of 1%, (**) indicates 5%, and (*) indicates 10%. The proportion of signal is calculated as $(\sigma_{m\eta}/SD \log \beta)$.

Table B.9
Estimates of state-space models for herding measures — UK.

Variables	Model 1	Model 2	Model 3
μ_m	-0.649^{***}	-2.342^{***}	-2.333^{***}
σ_{mv}	0.264^{***}	0.212^{***}	0.213^{***}
ϕ_m	0.849^{***}	0.891^{***}	0.892^{***}
$\sigma_{m\eta}$	0.096^{***}	0.087^{***}	0.086^{***}
r_{mt}		23.136	1.062^{***}
$\log \sigma_{mt}$		-0.839^{***}	-0.833^{***}
ΔCS_t			0.118
ΔTS_t			0.004
Log likelihood	−51.995	−8.793	49.815
AIC	0.472	−0.125	−0.337
SIC	0.531	0.213	−0.222
Proportion of signal	0.320	0.280	0.286

Note: In each month from January 2001 to August 2021, we use daily data on individual stocks to estimate market betas. The cross-sectional standard deviation of the estimated betas is used to estimate the state-space model below

$$\log[Std_c(\beta^b_{imt})] = \mu_m + H_{mt} + \sum_j \theta_h c_{jt} + \nu_{mt}$$
$$H_{mt} = \phi_m H_{mt-1} + \eta_{mt},$$

where $\nu_{mt} \sim iid(0, \sigma^2_{m\nu})$, $\eta_{mt} \sim iid(0, \sigma^2_{m\eta})$, and c_{jt} denotes the control variables included in Models 2 and 3. r_{mt} denotes the return on the market portfolio, $\log \sigma_{mt}$ is the log of the market volatility, ΔCS_t is the change in the credit spread, and ΔTS_t is the change in the term spread. (***) denotes a significance level of 1%, (**) indicates 5%, and (*) indicates 10%. The proportion of signal is calculated as $(\sigma_{m\eta}/SD \log \beta)$.

Table B.10
Estimates of state-space models for herding measures — USA.

Variables	Model 1	Model 2	Model 3
μ_m	-0.430^{***}	-2.436^{***}	-2.441^{***}
σ_{mv}	0.100^{***}	0.158^{***}	0.158^{***}
ϕ_m	0.315^{***}	0.866^{***}	0.865^{***}
$\sigma_{m\eta}$	0.201^{***}	0.100^{***}	0.101^{***}
r_{mt}		32.119^{***}	1.476^{***}
$\log \sigma_{mt}$		-0.963^{***}	-0.965^{***}
Δ Credit spread			0.004
ΔTS_t			−0.007
Log likelihood	−34.790	36.156	64.379
AIC	0.328	−0.255	−0.456
SIC	0.387	−0.167	−0.341
Proportion of signal	0.668	0.334	0.337

Note: In each month from January 2001 to August 2021, we use daily data on individual stocks to estimate market betas. The cross-sectional standard deviation of the estimated betas is used to estimate the state-space model below

$$\log[Std_c(\beta^b_{imt})] = \mu_m + H_{mt} + \sum_j \theta_h c_{jt} + \nu_{mt}$$
$$H_{mt} = \phi_m H_{mt-1} + \eta_{mt},$$

where $\nu_{mt} \sim iid(0, \sigma^2_{m\nu})$, $\eta_{mt} \sim iid(0, \sigma^2_{m\eta})$, and c_{jt} denotes the control variables included in Models 2 and 3. r_{mt} denotes the return on the market portfolio, $\log \sigma_{mt}$ is the log of the market volatility, ΔCS_t is the change in the credit spread, and ΔTS_t is the change in the term spread. (***) denotes a significance level of 1%, (**) indicates 5%, and (*) indicates 10%. The proportion of signal is calculated as $(\sigma_{m\eta}/SD \log \beta)$.

reversals in herding patterns may help identify changes from one market regime to another.

In terms of policy implications, our panel analysis reveals that governmental actions may have an impact on herding behavior in financial markets. In particular, actions that provide direct stimulus to the economy seem to increase herding, while actions that restrict people's behavior, such as more stringent lockdowns, increase uncertainty and therefore decrease herding. This is in line with the findings of Zaremba et al. (2020), that non-pharmaceutical interventions significantly increased equity market volatility. Regulators should therefore weigh the public health benefits of the latter type of measure, as well as the economic benefit of the former type of measure, against potential short-term distortions and decreased market efficiency in financial markets.

Table B.11
Regression results - Chang et al. (2000) model.

	Full sample		GFC		Covid$_1$		Covid$_2$	
	$\lvert r_{mt}\rvert$	r_{mt}^2	$\lvert r_{mt}\rvert$	r_{mt}^2	$\lvert r_{mt}\rvert$	r_{mt}^2	$\lvert r_{mt}\rvert$	r_{mt}^2
Australia	0.228***	0.436	0.323***	−1.284*	0.702***	−4.415**	0.228***	0.045
Belgium	0.283***	0.845	0.290***	1.345	0.521***	−2.214**	0.412***	−1.134*
Brazil	0.158***	0.718***	0.176***	0.636*	0.371*	−0.925*	0.255***	−0.056
China	0.322***	−1.872***	0.240***	−2.332**	0.106	0.082	0.138***	−0.266
France	0.214***	0.641*	0.230***	0.240	0.634***	−0.3248*	0.374***	−0.678
Italy	0.148**	1.263***	0.077*	1.809**	−0.341*	11.008***	0.122	2.041
Japan	0.198*	0.884*	0.206***	0.547	0.468	−5.746	0.176*	1.486
Sweden	0.164***	0.712*	0.169***	0.414	0.375*	−3.877	0.086*	1.486
UK	0.189***	1.174*	0.110	1.601	1.080**	−18.608*	0.213*	2.640
USA	0.077	6.841*	0.102	7.228*	0.723	16.557	0.307	4.441

The table reports the estimated coefficients of the regression model:

$$CSAD_{i,t} = \gamma_0 + \gamma_1 |r_{mt}| + \gamma_2 r_{mt}^2 + \varepsilon_{it},$$

where $CSAD_{i,t}$ denotes the cross-sectional absolute deviation of returns for country i on day t. The entire sample includes data from January 2001 to August 2021. GFC denotes the period including the Global Financial Crisis, from January 2007 to December 2008. Covid$_1$ denotes the period from January to April 2020. Covid$_2$ denotes the period from January 2020 to August 2021. Standard errors are adjusted using the Newey–West method. (***) denotes a significance level of 1%, (**) indicates 5%, and (*) indicates 10%.

Table B.12
Regression results - Chiang and Zheng (2010) model.

	Full sample			GFC			Covid$_1$			Covid$_2$		
	r_{mt}	$\lvert r_{mt}\rvert$	r_{mt}^2	r_{mt}	$\lvert r_{mt}\rvert$	r_{mt}^2	r_{mt}	$\lvert r_{mt}\rvert$	r_{mt}^2	r_{mt}	$\lvert r_{mt}\rvert$	r_{mt}^2
Australia	0.032*	0.262***	0.482	0.005***	0.288***	−0.752	0.027	0.683***	−4.032*	0.032*	0.258*	0.522
Belgium	0.018***	0.326***	0.708***	0.004	0.368***	0.639	0.067*	0.388***	−0.556	0.079**	0.497***	−1.540*
Brazil	0.028***	0.156***	−0.765***	0.029***	0.180***	0.607*	0.087***	0.338***	−0.391	0.068***	0.229***	−0.361
China	−0.063***	0.341***	−2.203***	−0.076***	0.227***	−2.266***	−0.016	0.114	−0.200	−0.012	0.147***	−0.496
France	0.026***	0.216***	0.615*	0.036***	0.275***	−0.064	0.109**	0.658***	−2.531*	0.087***	0.349***	−0.046
Italy	0.014**	0.152***	1.194***	0.012	0.088	1.661*	0.033	−0.430	13.485*	0.026	0.083	3.193
Japan	0.014*	0.199***	0.906**	0.006	0.210***	0.495	0.009	0.469	−5.872	0.020	0.160	2.159
Sweden	0.019**	0.182***	0.593*	0.021**	0.180***	0.257	0.017	0.368*	−3.852	0.036*	0.068	1.899
UK	0.010***	0.186***	1.303**	0.032*	0.115*	1.669*	0.036	1.001**	−16.451*	0.089*	0.148	4.345
USA	−0.001	0.109*	6.351*	0.015	0.113	6.979*	0.084	0.604	28.034	−0.189	0.867	−29.883

The table reports the estimated coefficients of the regression model:

$$CSAD_{i,t} = \gamma_0 + \gamma_1 r_{mt} + \gamma_2 |r_{mt}| + \gamma_3 r_{mt}^2 + \varepsilon_{it},$$

where $CSAD_{i,t}$ denotes the cross-sectional absolute deviation of returns for country i on day t. The entire sample includes data from January 2001 to August 2021. GFC denotes the period including the Global Financial Crisis, from January 2007 to December 2008. Covid$_1$ denotes the period from January to April 2020. Covid$_2$ denotes the period from January 2020 to August 2021. Standard errors are adjusted using the Newey–West method. (***) denotes a significance level of 1%, (**) indicates 5%, and (*) indicates 10%.

5. Conclusion

In this paper, we investigate herding patterns in ten global equity markets during the COVID-19 pandemic. Although previous studies have found some evidence of investor herding during the pandemic, the methods used in these studies to infer herding are based only on measures of the dispersion between individual stock returns and the return on the market portfolio, and therefore do not control for movements in fundamentals. In contrast to these studies, we investigate herding during the pandemic using the methodology proposed by Hwang and Salmon (2004), which allows us to obtain dynamic estimates of herding conditioning on fundamentals. Using this methodology, we uncover heterogeneous herding patterns across the ten countries during the COVID-19 pandemic. Overall, we find little evidence of herding during the pandemic, with the exceptions of Italy, Sweden, and the U.S. In comparison with the COVID-19 period, we find much more commonality in the herding patterns of the ten countries during the Global Financial Crisis (GFC) of 2007–2008, which perhaps is due to the differences in the severity of the pandemic and the resulting governmental responses across the countries.

Using a panel regression approach, we investigate the relationship between herding, the severity of the pandemic, and measures taken by governments to contain the pandemic and support the economy. We find that a measure of the stringency of governmental measures to contain the pandemic, such as school and work closures and travel bans, is associated with decreases in herding behavior, whereas measures to support the economy tend to increase herding. Our study contributes to the growing literature on the impact of COVID-19 in financial markets, and the link between crises and investors' herding. An interesting question, which we leave for future research, is the investigation of differences in herding patterns during the pandemic across different industries.

CRediT authorship contribution statement

Alexandre Rubesam: Conceptualization, Methodology, Data curation, Formal analysis, Writing – original draft, Investigation, Visualization, Writing – review & editing. **Gerson de Souza Raimundo Júnior:** Conceptualization, Methodology, Software, Formal analysis, Writing – original draft, Visualization, Investigation.

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Appendix A. Additional tables

See Tables A.1–A.3.

Appendix B. Additional results by country

See Tables B.1–B.12 and Fig. B.6.

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