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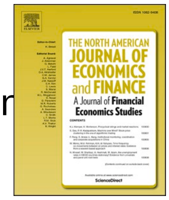

Herding in the bad times: The 2008 and COVID-19 crises

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ABSTRACT

The objective of this paper is to analyze the imitative behavior of investors in especially convulsive periods such as the 2008 financial crisis and the recent global pandemic, which could affect investors' emotions and behavior, although their different characteristics might have a different impact. The cross-sectional dispersion of returns is used to measure the level of herding in the markets of Spain and Portugal using a survivorship bias-free dataset of daily stock returns during the period January 2000 – May 2021, divided into several sub-periods classified as pre-2008 crisis, 2008 crisis, post-2008 crisis, pre-Covid-19 and Covid-19. Additionally, the existence of differences is studied between days of positive and negative returns, between days of high volatility compared to the rest, and whether the cross-sectional dispersion of returns in one market is affected by the cross-sectional dispersion of returns in the other market. The results indicate that herding appears with greater intensity prior to the crisis, disappearing in the financial crisis and reappearing, with less intensity, after it, while it is not generally detected in Covid-19 time. However, herding behavior can be observed in the market during the pandemic on high volatility days.

1. Introduction

At the beginning of the year 2020, the world witnessed the expansion of the new Covid-19 disease, first detected in China at the end of the previous year, a global emergency that pushed to the limit the health systems of many affected countries. The disease was classified as a pandemic by the World Health Organization on March 11, 2020 (World Health Organization, 2020), and most affected countries in the world, provoking governments to adopt a series of stringent measures, seeking a balance between saving lives and allowing some economic activity. The most common measures have included closure of education and work centers, social distancing measures and travel restrictions, to name just a few. Regarding the economic and financial impact of the pandemic, coronavirus is expected to result in economic recessions as did the global financial crisis, though differences can be considered as the pandemic is distinctive.

This situation could be compared to the Black Swan events, which could affect the behavior of investors through higher responses of fear, causing a panic-selling and negative narratives (Burch, Emery, & Fuerst, 2016; Chen & Siems, 2004). An epidemic, an unexpected event that substantially affected our lives, might have an emotional impact on investors and, therefore on the behavior observed in the market. Covid-19 is not the first disease to have emerged in a globalized world, however, the situation created by Covid-19 is different from others, for example SARS, in that the scope of the pandemic has been global, which gives us a unique opportunity to analyze the impact of an unexpected and deadly event on the behavior of investors in stock markets that

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more interconnected. Despite the fact that the pandemic is at a critical time in most countries, some authors have already evaluated its impact on financial markets, finding significant effects on stock returns (Shen et al., 2020), who analyze abnormal returns on global stock markets during the Public Health Emergency of International Concern announcement (COVID-19), and only the latest had a significant effect on stock markets lasting 8 days. A similar conclusion is obtained by Al-Awadhi et al. (2020) in the Chinese markets; they find that the pandemic has a negative effect on stock returns. He et al. (2020) observe that the development of the Covid-19 pandemic has had a negative impact on the European and American stock markets, although they point out that the impact could be short-term rather than long-term. In the United States, Onali (2020) examines the number of cases and deaths and finds that there is no impact on stock returns. In line with the extensive literature that examines the effects of the transmission of diverse economic and financial shocks across international markets (e.g. Bae, Karolyi & Stulz, 2003; Karolyi & Stulz, 1996), Uddin et al. (2020) analyze the dynamic connectedness of Asian markets and conclude that their interdependence grew due to the outbreak of the pandemic. Also in this vein, Akhtaruzzaman, Boubaker, and Sensoy (2020) examine how financial contagion occurs between China and G7 countries during the Covid-19 crisis, showing that they experience significant increases in conditional correlations between their stock returns.

Our paper contributes to the current literature by analyzing herding behavior in extreme market situations, namely the 2008 global financial crisis and the Covid-19 crisis, in contrast to a prior calm period in the market that takes place between these crises. These two turmoil situations have a very different nature and implications: the global financial crisis was an endogenous event of the stock market, whilst the Covid-19 was an exogenous shock to the financial system that provoked an extreme market situation. Thus, the aggregate behavior of investors in the market could be different in each of these situations, given their different psychological implications.

We construct a survivorship bias-free daily returns for the period January 2000–May 2021 for the markets of Spain and Portugal,[1] a time period long enough to contain the pre-crisis, global financial crisis, post-crisis period, coinciding with the explosion of a global pandemic period. In addition, we also cover the year when the worst of the pandemic seems to have passed. This allows us to observe the evolution of herding behavior in different market situations. We consider that conducting this research in these markets may be of interest for a number of reasons. First, having previously observed both markets (Economou et al., 2015), detecting significant herding in Portugal throughout the euro-zone sovereign debt crisis, and in Spain (Blasco et al., 2017), detecting significant herding in Spain between 2000 and 2015. This is of great importance since the first requirement for being able to deliver the study of herding and its possible market-dependent nature is that it actually exists in the market. Secondly, Spain and Portugal follow what is known as the “PIIGS” group of countries, which were heavily hit by the 2008 global financial crisis, the first market situation under study. Additionally, both countries were also hit by Covid-19, though differently, with Spain's figures being worse than those of Portugal, and so were their respective impacts on the markets of the consequences of the pandemic. As an extraordinary situation, in this case, Spain imposed stricter restrictions than Portugal did, so we can observe whether the restrictions had any impact on the imitative behavior of investors. Finally, being neighbouring countries, they present a suitable case to analyze potential contagion effects.

Herding behavior is a tendency present in the market when investors opt to imitate the trading of those they consider to be better informed, following the market consensus and ignoring their own information (Blasco, Corredor, & Ferreruela, 2012). In the existing literature, there have been several proposals of investors’ decision to follow others’ trades. The theoretical models (Banerjee, 1992; Bikhchandani, Hirshleifer, & Welch, 1992) explain that imitation is due to how information is transmitted. Reputation costs (Chevalier & Ellison, 1999; Hong, Kubik, & Solomon, 2000; Scharfstein & Stein, 1990; Zwiebel, 1995) may also lead to the appearance of herding, when the managers' performance is compared and asymmetric information about managers' ability arises under certain compensation systems as a source of incentives (Maug & Naik, 2011). Furthermore, the existence of asymmetric information also causes herding among investors (Baddeley, Curtis, & Wood, 2004). The impact of Black Swan events on investor behavior is relevant in turmoil, and numerous studies have been carried out recently for different markets. These studies have found a relatively strong link between emotion and herding behavior in turmoil markets (e.g. Blasco, Corredor, & Ferreruela, 2012; Choi & Yoon, 2020; Economou, Hassapis, & Philippas, 2018; Hudson et al., 2020; Hwang, Rubesam, & Salmon, 2021; Lakonishok, Shleifer, & Vishny, 1992; Liao, Huang, & Wu, 2011; Simões Vieira & Valente Pereira, 2015).

Mutual imitation has often been observed in extreme market conditions, in times of heightened uncertainty investors observe each other more closely and they tend to mimic the decisions of their peers (Kurz & Kurz-Kim, 2013; Schmitt & Westerhoff, 2017). In such extreme market conditions as those created by disasters and pandemics, the time for processing the amount of information is large and the uncertainty reaches its highest level. This is why some studies link herding-like behavior and crises by pointing it as an amplifying mechanism of their behavior. For instance, Brock (1999) indicates that market participants tend to imitate one another, especially clearly in bad times, which can occasionally lead to catastrophic situations. Pedersen (2009) and Brunnermeier (2009) identify “fire sales” as a risk to stability and an amplification mechanism for shocks.

Not only does research point out that the imitative behavior of investors is one of the potential explanations of simultaneous market declines. Policymakers consider that herding destabilizes markets and increases the fragility of the financial system, which make herding behavior especially worrying during crises, characterized by market inefficiency, as it makes it hard to diversify portfolios.

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[1] According to the classification of the World Federation of Exchanges 2019, Portuguese market belongs to Euronext group, capitalization in Europe, whereas Spain belongs to the BME Spanish Exchanges group.

Against this background, our study contributes to the study of herding behavior in crisis periods, and to the literatur that focuses on the cross-sectional dispersion of returns under extreme market conditions, by the pioneering works of Christie and Huang (1995) and Chang, Cheng and Khorana (2000) (hence CH and CCK). These authors propose that the phenomenon appears to be stronger under extreme market conditions, that is, when sharp rises and falls are taking place, because in such situations individuals are more likely to suppress their own beliefs and follow the market consensus. However, evidence is mixed, and while Blau (2006) finds evidence of herding at sample level even in up and down market periods of extreme market conditions, contrary to other authors who find no herding behavior when applying these measures. Among these, Caparrelli, D'Arcangelis and Cassuto (2004) examine the Italian stock market for the period 1988–2001, and their conclusions point to the herding presence in extreme market conditions. Chiang and Zheng (2010a) analyze 18 markets during the period 1988–2009 and find evidence of herding in developed markets and Asian markets, and evidence for herding in the US and Latin American markets in periods of crises. Economou, Kostakis and Philippas (2011) study four European markets (Italy, Spain, Portugal and Greece) and find herding presence mainly in the Greek and Italian markets; however, they do not find such evidence for the Spanish market, and the evidence is mixed for the case of Portugal. They also find herding effects presenting an asymmetry when considering rising and falling markets, and between days with high and low volatilit among the four. Mobarek, Mollah and Keasey (2014) document herding during crises and asymmetric market conditions in European countries. Filip, Pochea and Pece (2015) provide evidence of the existence of herding behavior of investors for all the CEE stock markets except Poland, and conclude that investors herd especially during periods of decline, while herding behavior differs in the pre-crisis and post-crisis periods with respect to the crisis. Moreover, Kabir (2017) examines herding behavior in the US financial industry during the global financial crisis 2008 and finds greater evidence of herding for commercial banks and investment banks, such herding is greater in the down market conditions of volatility. Finally, regarding the Covid-19 crisis and herd, Yarovaya, Matkovskyy and Jalan (2020) study herding behavior in cryptocurrency markets and suggest that Covid-19 does not increase

One of the factors that could condition the relation between herding and periods of stress such as crises or pandemics is the impact they have on volatility. In this sense, there seems to be a positive relationship between pandemics and market volatilit For example, Baek et al. (2020) observe that the volatility levels in the United States from the first month of 2020 reached and even exceeded those observed in October 1987, December 2008 or the end of 1929, and attribute it to several factors, including, but not limited to, the behavior and policy reactions to the pandemic. Zaremba et al. (2020) recently test the relationship between policy responses to the pandemic and stock market volatility, finding that stringent policy responses increase volatility in international stock markets. The increase in volatility is a fact that is also observed during crises (Karunanayake, Valadkhani, & O'Brien, 2010; Pati & Kanar, 2013). For instance, the 2008 crisis was associated with historically high levels of stock market volatility, which then remained high for long (Schwert, 2011). Their evidence of price adjustment (the mean reversion of volatility) are due not to the arrival of new information, which happens in complete efficient market conditions (Shefrin, 2000; Thaler, 1999), but to collective movements (Friedman, 1953), such as herding. The relationship between herding and volatility, that is, investors who imitate the investments of others, has been more recently observed by Alper and Yilmaz (2004), Avramov, Chordia and Goyal (2006), Kho and Stulz (1998), Gui and Hamid (2014), Scharfstein and Stein (1990), Lin and Yang (2015), Ysanti and Karoglou (2016), and Duarte and Bernardo (2013), among others. One reason why greater volatility in the market could modify investors' decision-making is the increase of uncertainty, which is observed under periods of stress (Kahneman & Tversky, 1979). There were earlier examples where the asymmetric herding behavior in up and down markets, periods of high and low volatility. Further, following the model of (Economou, Kostakis & Philippas, 2011), we examine whether the cross-sectional dispersion of returns in one market is affected by the cross-sectional dispersion of returns in other ones, which could pose a threat to the financial stability of the Eurozone.

The study addresses several research questions. First, has there been any change in the imitative behavior of investors in the Spanish and Portuguese stock markets? Second, has there been different herding behavior observed in periods of financial crisis with respect to periods of different stress such as a pandemic? Third, has there been different herding between days with positive and negative returns or days with high volatility different from the rest? Finally, is there some kind of influence from one country's stock market to the other in terms of herding? By answering these questions, our study also helps to explain whether the crises and the special periods in these stock markets are related to the presence of herding behavior.

The remainder of the paper is organized as follows. Section 2 presents the dataset employed in the analysis and some descriptive statistics of the Spanish and Portuguese stock markets. Section 3 describes the methodology and discusses the results, while Section 4 concludes.

2. Database

The data used for this study have been obtained from Refinitiv Datastream. Specifically, daily prices of all the stocks listed in the Spanish and Portuguese markets in the period between January 2000 and May 2021 have been used, as well as the corresponding market index (the index comprising the maximum number of firms, IBEX-35 for the Spanish market, PSI-20, for the Portuguese market). IBEX-35 is an index composed of the Spanish stock market's 35 most liquid companies listed on it. The PSI-20 (Portuguese Stock Index) is a benchmark index of the Lisbon Stock Exchange, owned by the European company of stock exchanges Euronext, and includes the 20 largest Portuguese companies in the market. All the data has been cleaned and processed following the instructions of Ince and Porter (2006) to avoid possible errors.

It is worth mentioning that the analysis carried out for the complete sample we also perform for various additional subsamples corresponding to pre-crisis, crisis, post-crisis, Covid-19[2] and post-Covid-19[3] periods so we can observe the herding in the environment that has impact on these subsamples and is identified by the sources CH and CKW. With regard to the 2008 crisis, different periods have been set according to Kang (2017). The pre-crisis period goes from January 2003 to September 2008, then the financial crisis goes from October 2008 to April 2009 and the post-crisis goes from April 2009 until 31 January 2020.

3. Methodology and results

3.1. Herding intensity

In this paper, the intensity of herding has been measured using two different measures based on the dispersion of stock returns. Following CH and CKW, the daily market return we work with throughout the study has been calculated as the average return of all the stocks on the market on day t. The descriptive statistics of market returns are shown in Table 1. It can be seen how, for the period under study, the two markets show some dissimilarities (the mean return for Portugal is four times greater than that of Spain, but the median is higher in the Spanish market, this indicates the existence of more extreme observations in Portugal). Both the maximum and minimum values are greater in Portugal, and the standard deviation also is higher in this country. In terms of asymmetry and kurtosis, the asymmetry coefficient is negative for Spain but positive for Portugal and both markets show leptokurtic distributions, Portugal's coefficient being higher than the Spanish.

We first test the herding presence by CH. These authors calculate the cross-sectional standard deviation (CSSD) of the returns of the stocks on a given market as in equation (1) and suggest that the presence of herding is proven by observing dispersion below the expected if herding did not exist.

$$CSSD_t = \sqrt{\frac{\sum_{i=1}^{N} (R_{i,t} - R_{M,t})^2}{N-1}} \tag{1}$$

where $R_{i,t}$ is the observed return of stock i at time t and $R_{m,t}$ is the equally weighted average of the N stocks on the market at time t.

The descriptive statistics of the CSSD for Spain and Portugal are presented in Table 1, where it can be noted that the values of the Spanish market are lower than those of Portugal for mean, median, maximum and standard deviation, although we cannot yet say anything about the existence of herding in the markets.

To assess whether the dispersion of returns is significantly lower during periods of extreme returns in the market, that is, whether market participants imitate the actions of others, CH propose the following regression:

$$CSSD_t = \alpha + \beta^L D^L{}_t + \beta^U D^U{}_t + \varepsilon_t \tag{2}$$

where $D^L{}_t$ is a dummy variable that takes value 1 if $R_{m,t}$ is located at the lower tail (5%, 1%) of the distribution of returns and 0 otherwise, and $D^U{}_t$ is a dummy variable that takes value 1 if $R_{m,t}$ is located at the upper tail (5%, 1%) of the distribution of returns and 0 otherwise.

It has been considered fitting to offer a graphic representation of the relationship between the average return of the market and the CSSD, given that the presence of herding would, according to CH, cause the graph to show a descending trend in the lower cross-sectional dispersion at moments of extreme market movement. Fig. 1 displays the relationship between market return and CSSD in Spain and Portugal for the complete sample and all the above-mentioned subsamples. Looking at the graphs, we notice

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[2] To delimit the Covid-19 the analyses were repeated using different starting dates for robustness reasons. Specifically, between the following events and the 27 November 2020 we take as the Covid-19 period (1) the first confirmed case (1 February 2020 Spain and 2 March 2020 Portugal); (2) the first confirmed death (13 February 2020 Spain and 16 March 2020 Portugal); (3) the stock market drop after reaching the previous maximum (20 February 2020 both countries); (4) the severity, reaching 20 points in the Oxford Government Response Stringency Index (Hale et al. 2021) (9 March 2020 Spain and 10 March 2020 Portugal); (5) the announcement of the "stay home" requirements or "lockdown" (13 March 2020 both countries) in the case of Spain, in addition (6) the period during which the restrictions were the most strict (from 8 March 2020 to 18 May 2020) has been considered, which allows us to study whether the absence of influence of the short-selling restrictions on herding behaviour observed by Bohl, Klein and Siklos (2014) during the Global Financial Crisis 2008 holds for the Covid-19. For reasons of clarity, only the results of the specification of the Covid-19 corresponding to the days between the market fall and the end of the expert-panel development (27 November 2020) are shown. However, the results for the other periods do not differ from those presented and are available upon request from the authors. In the case of Spain, the results corresponding to the period during which the restrictions were the most strict are also shown.

[3] Although Covid-19 is still active in the world, we consider that the worst of the pandemic's impact on markets ended in November 2020, coinciding with the encouraging news about vaccines from AstraZeneca, Pfizer-BioNTech and Moderna, which allowed the Ibex-35 and PSI-20 to return to pre-pandemic levels.

Table 1
Descriptive statistics of market return, CSSD and CSAD series (Spain and Portugal).

	Market return		CSSD		CSAD	
	Spain	Portugal	Spain	Portugal	Spain	Portugal
Mean	0.0003	0.0011	0.0228	0.0387	0.0132	0.0166
Median	0.0006	0.0003	0.0202	0.0266	0.0124	0.0139
Maximum	0.0907	0.1815	0.9424	1.5231	0.1666	0.3537
Minimum	−0.0982	−0.0793	0.0000	0.0000	0.0000	0.0000
Std. deviation	0.0080	0.0107	0.0188	0.0612	0.0057	0.0154
Skewness	−0.5445	4.5333	24.0963	12.6575	4.6793	9.4700
Kurtosis	15.6820	60.3073	1060.2598	233.1631	105.0897	150.1849

Note: This table reports descriptive statistics of daily market return (Rm), cross-sectional standard deviation (CSSD) and cross-sectio absolute deviation (CSAD) for the period 2000–2021.

that their relative positions with respect to market return vary. CSSD and CSAD measure dispersion across extreme movements, anticipating the non-existence of herding on the market. However, we can observe a difference between them, since in the case of Portugal we see that the dispersion is slightly higher than that observed in Spain. A similar level is found. On the other hand, looking at the subsamples, we can find differences between the pre- and post-crisis periods, with the graph for the former looking flatter than that for Spain, that is, lower levels of dispersion from the market level. However, for the Portuguese market, the graph shows the opposite situation, the post-crisis periods show lower levels of dispersion from the market level than the pre-crisis one. The graphs for the crisis and Covid-19 periods do not have enough observations to distinguish clear patterns, but we can see that the Portuguese and Spanish markets show very different characteristics.

Equation (2) has been estimated for the Spanish and Portuguese markets through the least squares method with White's variance-covariance matrix, since the presence of heteroskedasticity has been detected. The results for the Spanish market are shown in Panel A of Table 2. For herding to exist, it is necessary for the β coefficients to be negative and significant. Here, there is evidence contrary to the presence of herding, since the estimates are positive and significant for all the periods under study (complete sample, pre-crisis, post-crisis, crisis and the different Covid-19 specifications).

In the same way, we find evidence contrary to herding for the Portuguese market, as can be seen in Table 2, Panel B. The fact that herding is not detected in the market for any period, which is consistent with that seen in the previous literature (Blasco & Ferreruela, 2008a), as on many occasions this measure turns out to be too restrictive, detecting herding in markets where there are severe levels of herd behaviour. For this reason, the test is used to detect herding in specific cases of extreme movements, considering that it is at that moment that imitation takes place, it would be possible to observe it with this model.

The second measure used to test for herding is based on the cross-sectional absolute deviation of returns (CSAD), defining this variable as it starts from the conditional version of the CAPM (Black, 1972):

$$CSAD_t = \frac{1}{N}\sum_{i=1}^{N}\left|R_{i,t} - R_{M,t}\right| \quad (3)$$

where $R_{i,t}$ is the observed return of stock i at time t and $R_{M,t}$ is the equally weighted average return of the N stocks in the market at time t.

The authors argue that investors tend to herd more during periods of sharp price changes, and the increasing relationship between market return and CSAD will no longer remain linear and become non-linear and decreasing. For this reason, they use a nonlinear specification parameter to capture the nonlinear relationship between dispersion and market returns, shown below:

$$CSAD_t = \alpha + \gamma_1\left|R_{M,t}\right| + \gamma_2 R_{M,t}^2 + \varepsilon_t \quad (4)$$

The descriptive statistics of the CSAD for the Spanish and Portuguese markets are shown in Table 1. We find results similar to those obtained with the measure proposed by CH. Portugal has higher CSAD values than those of Spain in mean, median, maximum and standard deviation, therefore the market in Portugal would have a higher dispersion than that existing in Spain.

The graphs shown in Fig. 2 relate CSAD and market return for both countries (complete sample and all subsamples), allow us to draw similar conclusions to those obtained for the CSSD graphs. Thus, for the Spanish market, it is possible to point out lower dispersion from the market level, with different movements in the pre-crisis and Covid-19 periods.

The results of regression (4) for the Spanish market are shown in Table 3, Panel A. In view of these results, we can affirm that this approach does not detect herding in Spain for the entire period, while the non-linear term has a positive coefficient that is statistically significant at 1% level. Focusing on the subperiods under study, we observe that before the global financial crisis period, and after the market drop due to the Covid-19 pandemic, the coefficient is negative and significant for the quadratic term. According to these results, there is imitating behavior in the years preceding the crisis; this is not the case in the subsequent years, although herding is detected in the most

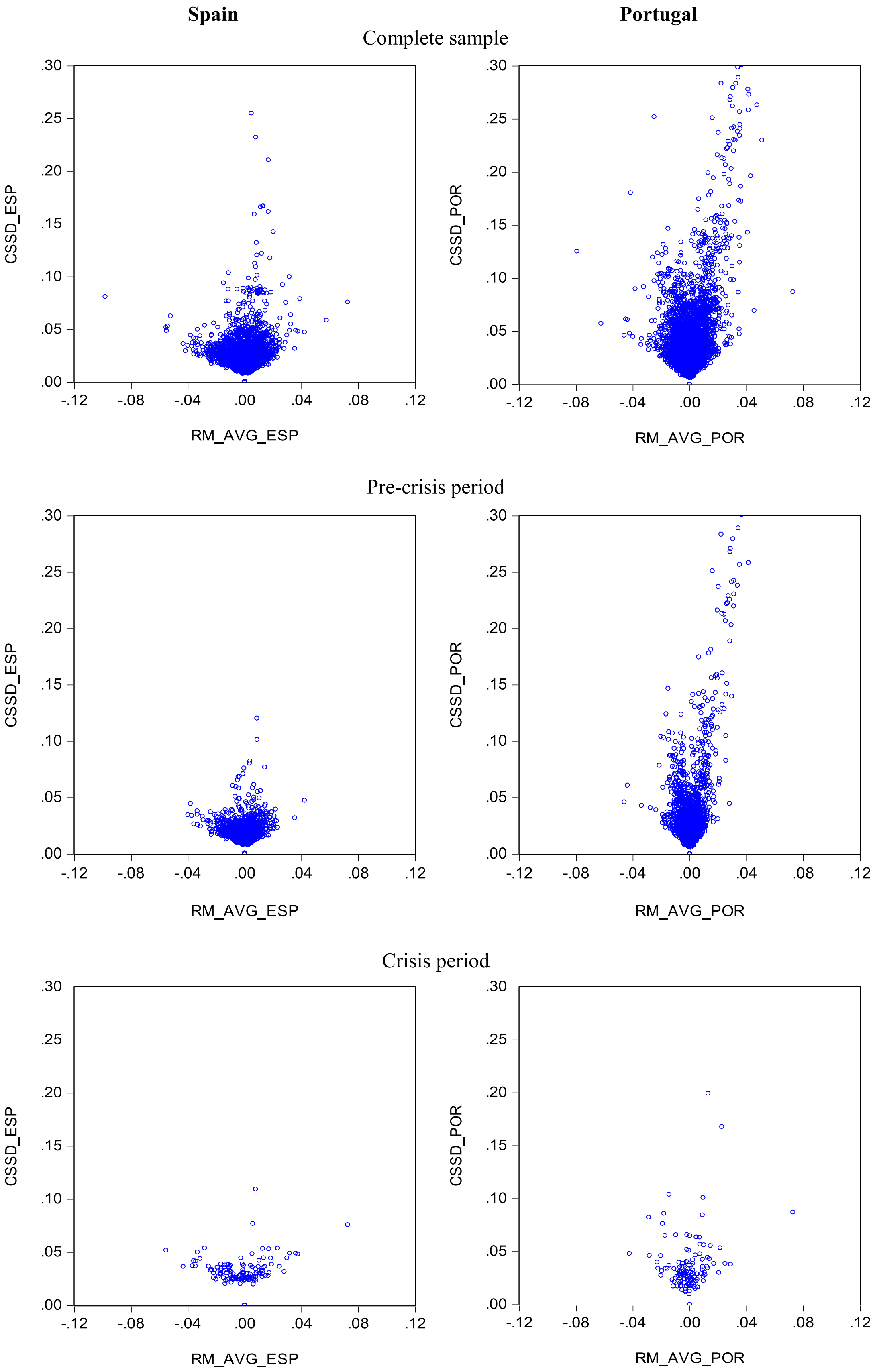


Fig. 1. CSSD-Return.

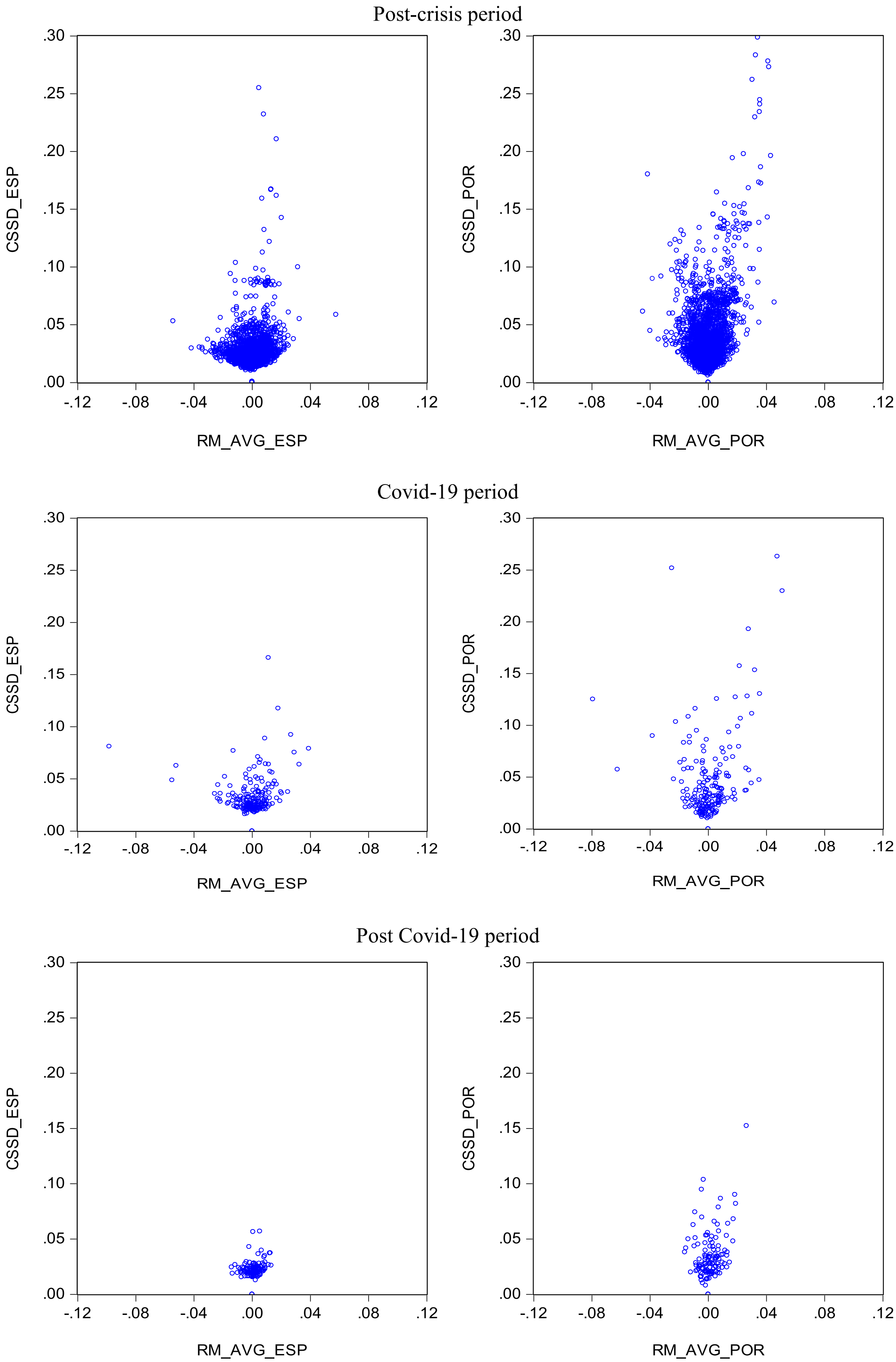


Fig. 1. (continued).

Table 2
Estimates of herding with the CSSD measure.

Panel A: Spain		α	D^L_t 5%	D^U_t 5%	α	D^L_t 1%	D^U_t 1%
Complete sample	Coef.	0.0214***	0.0069***	0.0208***	0.0222***	0.0120***	0.0446***
	t-stat	(126.4916)	(12.1389)	(5.5242)	(126.4616)	(8.1518)	(2.5804)
Pre-crisis	Coef.	0.0175***	0.0081***	0.0103***	0.0180***	0.0123***	0.0133***
	t-stat	(98.5747)	(11.6787)	(9.1875)	(101.6705)	(8.3177)	(6.6776)
Crisis	Coef.	0.0287***	0.0060***	0.0119***	0.0301***	0.0130***	0.0185***
	t-stat	(17.9788)	(2.7519)	(4.0776)	(25.4051)	(5.5254)	(4.0467)
Post-crisis	Coef.	0.0238***	0.0036***	0.0162***	0.0247***	0.0047***	0.0208***
	t-stat	(90.0439)	(4.7110)	(7.0506)	(88.4061)	(3.8050)	(4.3170)
Covid-19	Coef.	0.0301***	0.0102***	0.0753*	0.0317***	0.0254**	0.1482*
	t-stat	(23.1259)	(2.6529)	(1.8471)	(24.9469)	(2.9615)	(1.6885)
Short-selling restrictions	Coef.	0.0338***	0.0064	0.0114*	0.0358***	−0.0001	0.0079
	t-stat	(10.4865)	(1.1538)	(1.8288)	(12.6198)	(−0.0482)	(0.8981)

Panel B: Portugal		α	D^L_t 5%	D^U_t 5%	α	D^L_t 1%	D^U_t 1%
Complete sample	Coef.	0.0306***	0.0211***	0.1402***	0.0342***	0.0322***	0.4113***
	t-stat	(103.8473)	(11.4106)	(10.8052)	(88.2377)	(5.9168)	(8.7835)
Pre-crisis	Coef.	0.0272***	0.0240***	0.2257***	0.0315***	0.0274***	0.6391***
	t-stat	(61.4006)	(6.1491)	(7.1934)	(45.9693)	(3.1931)	(6.2233)
Crisis	Coef.	0.0322***	0.0167***	0.0630*	0.0353***	0.0141**	0.1823*
	t-stat	(14.3384)	(2.6360)	(1.9002)	(14.7866)	(2.0707)	(1.9502)
Post-crisis	Coef.	0.0331***	0.0172***	0.1036***	0.0361***	0.0287***	0.3069***
	t-stat	(81.7576)	(8.1900)	(7.9561)	(73.8112)	(5.0550)	(6.6734)
Covid-19	Coef.	0.0355***	0.0307***	0.0618***	0.0422***	0.0704**	0.1255***
	t-stat	(14.6488)	(2.9756)	(4.8028)	(16.4858)	(2.5229)	(2.9267)

Note: This table reports the estimated coefficients of the benchmark model Eq. (2). The sample period is January 2000–May 2021, January 2000–September 2008, October 2008–April 2009, April 2009–January 2020, February 2020–November 2021 and 18 March 2020–18 May 2020 (only in Spain). Eq. (2) has been estimated using OLS with White's variance and covariance matrix to correct for the presence of heteroskedasticity. The t-statistics are reported in parentheses. ***, ** and * represent statistical significance at the 1%, 5%, and 10% levels.

recuperation, once the worst part of the impact of Covid-19 on markets appears to be over. On the other hand, the coefficient is no longer significant [illegible] which could indicate that in times of crisis investors [illegible] suspicious of the actions carried out by others and [illegible], they would be [illegible] information [illegible] individually [illegible] market consensus. This result is consistent with the findings of Hwang and Salmon (2004), who observe that the Asian and Russian crises significantly reduced herding in the markets, although [illegible] measure [illegible] crises [illegible] market fundamentals [illegible] efficiency [illegible] post-crisis periods [illegible] information [illegible] have decreased the propensity. During the Covid-19 [illegible] subsample corresponding to short-selling restrictions, which has a negative but not significant coefficient. These results would be consistent with that observed by Bohl, Klein, and Siklos (2014), who indicate that short-selling bans can encourage herding.

In the case of the Portuguese market (see results shown in Table 3, Panel B), the results are similar to those found in the Spanish market up to the arrival of Covid-19. The [illegible] regression (4) is positive and significant for the entire sample and negative but not significant [illegible] suggesting that there is evidence of herding [illegible]. As in the Spanish market, during [illegible] the global financial crisis [illegible] higher [illegible] both markets [illegible] crisis period would be consistent with the return-generating model [illegible] crisis [illegible] pre-crisis period [illegible]. However, in the Portuguese market, the coefficient for the Covid-19 sample is positive and significant [illegible] highlight the difference between the markets over the period [illegible]. Finally, in the case of the Spanish market, herding disappears once the market recovers pre-pandemic levels.

3.1. Herding behaviour under different market conditions: bullish and bearish days

CCK also analyze asymmetry of the responses and suggest that herding could be observed when the market falls as opposed to bullish periods, due to the different psychological implications of falling prices compared to moments in which the market has a positive [illegible] period. Thus, we have carried out the joint analysis proposed by Chiang and Zheng (2010) differentiating between [illegible] the results of both markets.

$$CSAD_t = \alpha + \gamma_1 D^{UP}\left|R_{M,t}\right| + \gamma_2(1 - D^{UP})\left|R_{M,t}\right| + \gamma_3 D^{UP}(R_{M,t})^2 + \gamma_4(1 - D^{UP})(R_{M,t})^2 + \varepsilon_t \tag{5}$$

where D^{UP} is a dummy variable that takes a value of 1 if the equally weighted average market return on day t is positive and

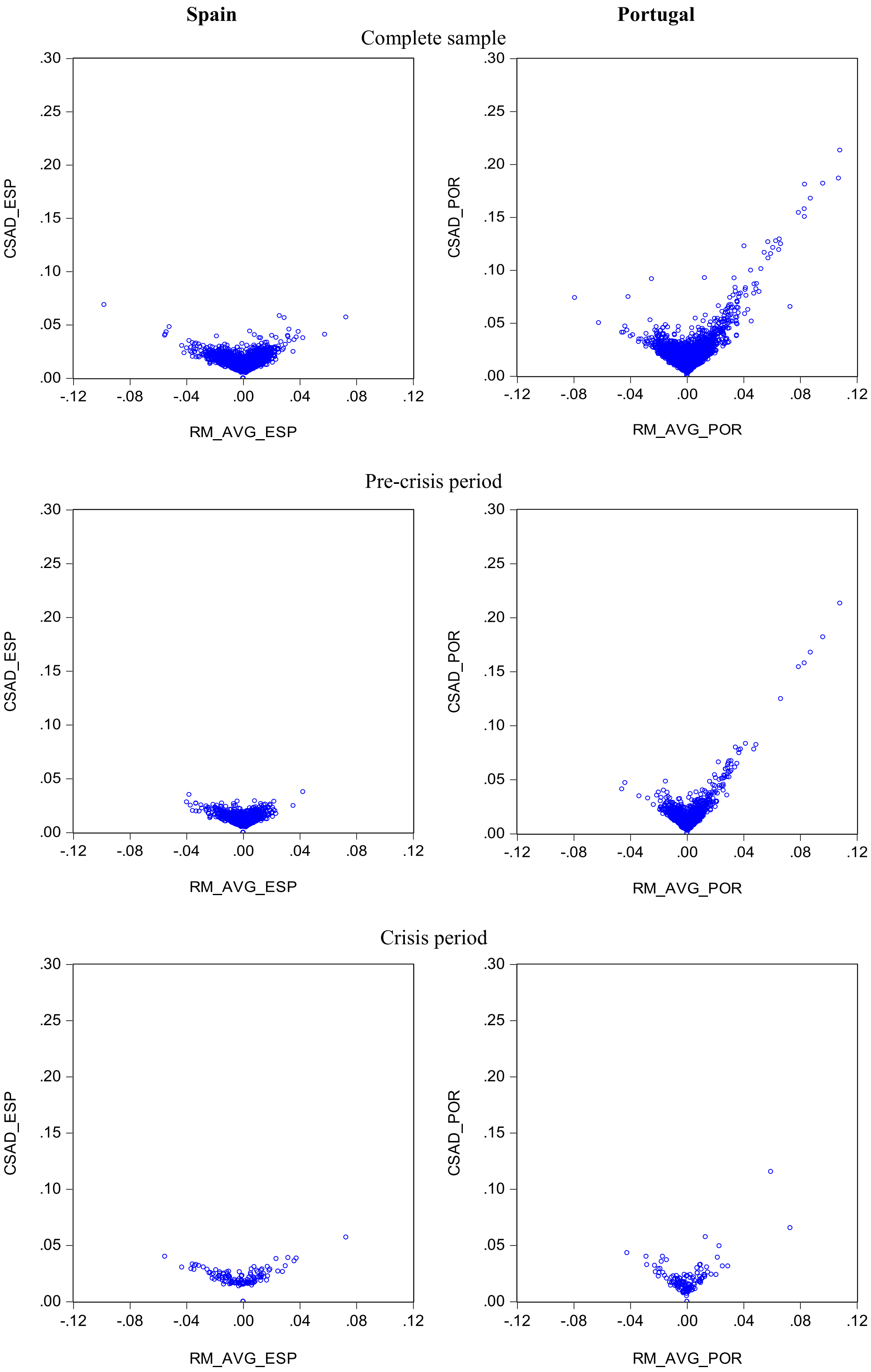
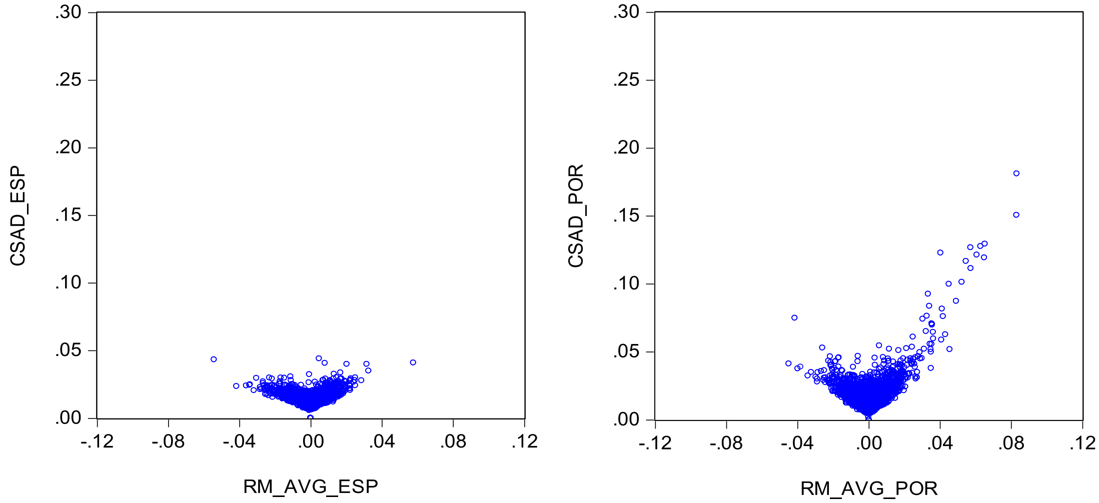
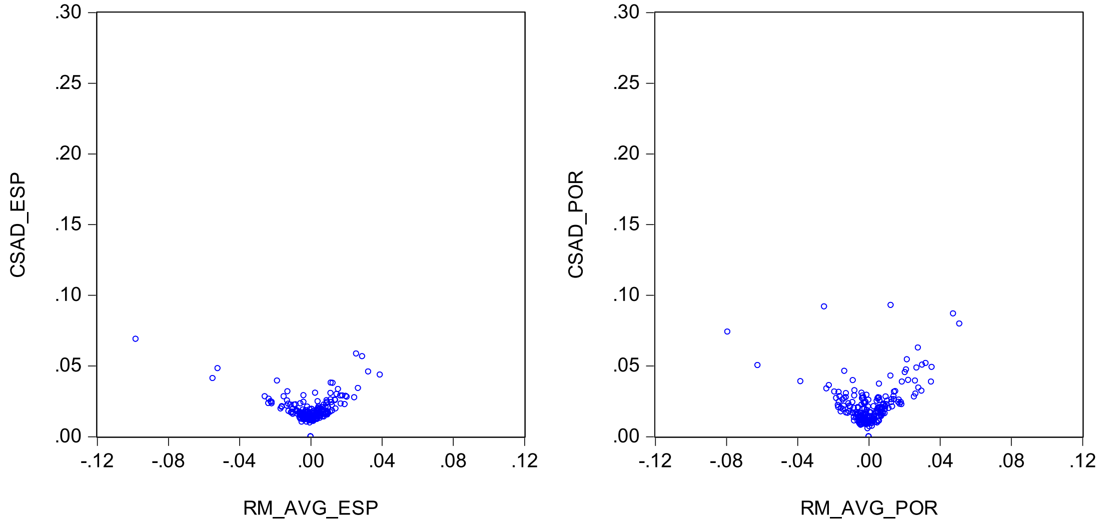


Fig. 2. CSAD-Return.

Post-crisis period



Covid-19 period



Post Covid-19 period

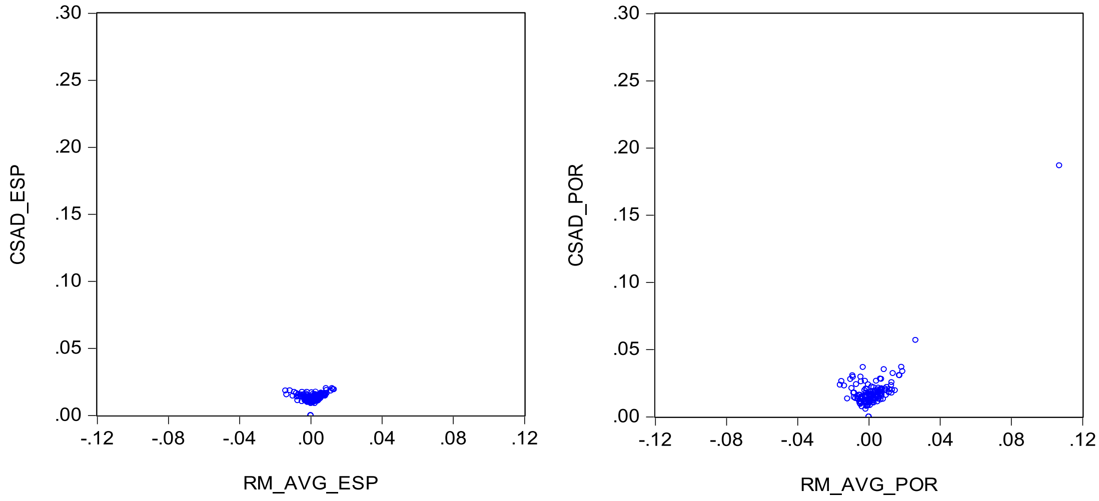


Fig. 2. (continued).

Table 3
Estimation of herding with the CSAD measure.

Panel A: Spain		α	γ_1	γ_2
Complete sample	Coef.	0.0123***	0.0074**	12.7415***
	t-stat	(85.0528)	(2.3794)	(4.8194)
Pre-crisis	Coef.	0.0081***	0.7780***	−8.1045***
	t-stat	(57.2572)	(18.4810)	(−3.8673)
Crisis	Coef.	0.0149***	0.5662***	−0.8213
	t-stat	(14.4112)	(5.5568)	(−0.4317)
Post-crisis	Coef.	0.0101***	0.7327***	−5.3898***
	t-stat	(77.8268)	(20.8671)	(−3.1568)
Covid-19	Coef.	0.0176***	0.0120***	7.1885***
	t-stat	(36.4403)	(6.4734)	(4.2039)
Short-selling restrictions	Coef.	0.0130***	1.1550***	−13.5766
	t-stat	(4.8291)	(2.9343)	(−1.2114)
Post-Covid-19	Coef.	0.0098***	1.1219***	−39.3867*
	t-stat	(12.5697)	(3.9894)	(−1.9786)

Panel B: Portugal		α	γ_1	γ_2
Complete sample	Coef.	0.0087***	1.2181***	4.5049***
	t-stat	(50.2886)	(33.8959)	(11.7819)
Pre-crisis	Coef.	0.0044***	2.0088***	−2.7013***
	t-stat	(11.1131)	(22.1426)	(−22.5978)
Crisis	Coef.	0.0111***	1.0431***	−0.0920
	t-stat	(12.0118)	(5.6133)	(−0.0150)
Post-crisis	Coef.	0.0080***	1.5287***	−0.8734***
	t-stat	(13.6361)	(15.8584)	(−15.9052)
Covid-19	Coef.	0.0106***	1.3716***	−6.9706***
	t-stat	(11.5367)	(8.6139)	(−2.7738)
Post-Covid-19	Coef.	0.0117***	0.9772***	6.1853***
	t-stat	(12.5732)	(6.1985)	(4.4618)

Note: This table reports the estimates of the coefficients of the benchmark model Eq. (4). The sample period runs from January 2007 to May 2021; January 2007–30 September 2008, October 2008–April 2009, April 2009–31 January 2020, February 2020–17 November 2020, 18 March 2020–18 May 2020 (only Spain) and 18 November 2020–31 May 2021. Eq. (4) has been estimated using OLS with White's variance and covariance matrix to correct the presence of heteroskedasticity. The t-statistics are reported in parentheses. ***, ** and * represent statistical significance at the 1%, 5%, and 10% levels.

0 otherwise.

Table 4, Panel A, shows the results of Equation (5) for the Spanish market. With the exception of the pre-crisis and post-crisis periods, the results are in line with those obtained when the analysis is carried out without distinguishing between positive and negative returns in the market, herding is detected before and after the crisis (although only bear days for the pre-crisis subsample), while during the crisis there is no evidence of herding in either bull or bear days. Also, the coefficient of the pre-crisis period is only significant with negative returns, and its intensity is greater than that of the post-crisis subsample. However, analyzing the differences between market climates in the model, the results obtained for the Covid-19 and short-selling restriction subperiods point to the existence of herding behaviour during market downturns due to the pandemic, with an asymmetric coefficient on bear days, much larger in absolute value than that for bull days. Additionally, the Wald test results for the hypothesis that the herding coefficients (γ_3 and γ_4) are equal show that in almost all market periods the probability leads to the rejection of this hypothesis, confirming the asymmetry except during the crisis (Table 5). However, as in the case where no distinction between bull and bear days was made, the period of the pandemic shows the highest levels of herding, mainly on bear days. These results are similar to those obtained by Economou, Kostakis and Philippas (2011) for the Spanish market, they find strongly significant evidence of herding on days with falling markets; however, our results suggest the existence of asymmetry when they look at the subsamples. Nevertheless, focusing on the entire period without considering subsamples results in the effect going unnoticed, which highlights the importance of separately analyzing the different market settings.

Table 4, Panel B, reports the results of Equation (5) for the Portuguese market. As in the Spanish case, the pre-crisis, post-crisis subsamples and complete sample show the same results as in Table 3, with herding being present in pre- and post-crisis subsamples during the crisis. The main novelty is that when distinguishing up and down markets, it is observed that herding has a strong asymmetric character in Portugal, mainly on bear days, both in the complete sample and in the subsamples where this collective movement is found, with significant results in all the subsamples where its existence is obtained. Herding found in the complete sample when the distinction between days in terms of market trend was not taken into account, it is important to analyze market situations, as herding could take place only on bull or bear days. In addition, the results of the Wald test for the null hypothesis that the herding coefficients (γ_3 and γ_4) are equal show that in almost all market periods the hypothesis is rejected, indicating that asymmetry is significant in the Portuguese stock market, observed to herd when the market is trending downward. These investors

Table 4
Estimates of herding behavior with the CSAD measure in climate markets.

Panel A: Spain		α	γ_1	γ_2	γ_3	γ_4
Complete sample	Coef.	0.0095***	0.7604***	0.6396***	−0.0980***	−1.4143
	t-stat	(107.8906)	(40.3967)	(26.2605)	(−39.3080)	(−1.4731)
Pre-crisis	Coef.	0.0081***	0.7450***	0.7830***	−3.9601	−9.4583***
	t-stat	(59.2332)	(16.7028)	(18.3409)	(−1.4915)	(−4.5591)
Crisis	Coef.	0.0144***	0.7472***	0.5665***	−2.4238	−2.5942
	t-stat	(13.7142)	(6.9392)	(5.1070)	(−1.6493)	(−1.1517)
Post-crisis	Coef.	0.0101***	0.8020***	0.6500***	−4.3547***	−4.7710**
	t-stat	(78.1471)	(28.5936)	(13.0951)	(−4.6319)	(−1.7677)
Covid-19	Coef.	0.0123***	0.9744***	0.7154***	−0.1264***	−1.5556*
	t-stat	(24.4736)	(10.0952)	(9.3244)	(−9.8881)	(−1.9374)
Short-selling restrictions	Coef.	0.0124***	1.2045***	1.5474***	−13.1958	−34.9104*
	t-stat	(4.3807)	(2.9807)	(2.7580)	(−1.2773)	(−1.7901)
Post-Covid-19	Coef.	0.0099***	1.0201***	1.1615***	−24.3533	−50.1613**
	t-stat	(12.4187)	(3.5185)	(3.6813)	(−1.1642)	(−2.1961)
Panel B: Portugal		α	γ_1	γ_2	γ_3	γ_4
Complete sample	Coef.	0.0085***	1.3807***	1.2197***	3.4898***	−7.0533***
	t-stat	(58.6309)	(39.3273)	(31.8542)	(9.8216)	(−4.2841)
Pre-crisis	Coef.	0.0049***	2.0996***	1.7616***	−2.8295***	−23.2629***
	t-stat	(17.2074)	(27.3348)	(24.8152)	(−27.9177)	(−7.5484)
Crisis	Coef.	0.0105***	1.3857***	1.0474***	−4.5279	−6.1501
	t-stat	(10.6187)	(5.3766)	(5.8375)	(−0.7397)	(−1.3945)
Post-crisis	Coef.	0.0084***	1.6593***	1.3537***	−0.9485***	−13.6087***
	t-stat	(18.8861)	(19.1524)	(13.4318)	(−19.1930)	(−2.7679)
Covid-19	Coef.	0.0117***	1.1190***	1.1101***	3.4497	−4.9184
	t-stat	(10.8039)	(4.6551)	(4.1953)	(0.5565)	(−1.4437)
Post-Covid-19	Coef.	0.0114***	1.0602***	1.1913**	5.4264***	−24.5495
	t-stat	(11.6393)	(6.1548)	(2.6061)	(3.5608)	(−0.7998)

Note: This table reports the estimated coefficients of the benchmark model Eq. (5). The sample periods are January 2000–May 2021, January 2000–September 2008, October 2008–April 2009, April 2009–January 2020, February 2020–7 November 2020, the March 2020–18 May 2020 (only Spain) and 8 November 2020–31 May 2021. Eq. (5) has been estimated using OLS with White's variance and covariance matrix correction, the presence of heteroskedasticity. The t-statistics are reported in parentheses. ***, ** and * represent statistical significance at the 1%, 5%, and 10% levels.

Table 5
Wald tests for equality of herding coefficients.

		$H_0: \gamma_3 = \gamma_4$	
		Spain	Portugal
Complete sample	$\gamma_3 - \gamma_4$	1.3163	10.5431***
	Chi-Sq.	(1.8821)	(141.8480)
Pre-crisis	$\gamma_3 - \gamma_4$	5.4982*	20.4334***
	Chi-Sq.	(3.4258)	(45.1968)
Crisis	$\gamma_3 - \gamma_4$	0.1704	1.6222
	Chi-Sq.	(0.0091)	(0.0615)
Post-crisis	$\gamma_3 - \gamma_4$	0.4163	12.6602***
	Chi-Sq.	(0.0267)	(6.6894)
Covid-19	$\gamma_3 - \gamma_4$	1.4291*	8.3681
	Chi-Sq.	(3.2083)	(1.9619)
Short-selling restrictions	$\gamma_3 - \gamma_4$	21.7146	–
	Chi-Sq.	(1.9093)	–
Post-Covid-19	$\gamma_3 - \gamma_4$	25.8080	29.9759
	Chi-Sq.	(2.3622)	(0.9888)

Note: This table reports the Chi-square statistics corresponding to the Wald test of the null hypothesis $\gamma_3 - \gamma_4$ in the model estimated in Eq. (5). The sample periods are January 2000–May 2021, January 2000–September 2008, October 2008–April 2009, April 2009–January 2020, February 2020–7 November 2020, the March 2020–18 May 2020 (only Spain) and 8 November 2020–31 May 2021. Eq. (5) has been estimated using OLS with White's variance and covariance matrix correction, the presence of heteroskedasticity. ***, ** and * indicate statistical significance at the 1%, 5%, and 10% levels.

could be showing a stronger herding bias than those in the Spanish market, thus they would be more concerned about the risk of a down market and more likely to exhibit herding behaviour. When comparing these results with those collected in Table 3, we can see that although the negative coefficient of the quadratic term for bearish days holds, herding during the Covid-19 period is no longer significant at usual levels.

3.1.2. Herding under different market conditions: volatility

Authors such as Gleason, Mathur, and Peterson (2004) affirm that investors' decision-making is conditioned by episodes of high volatility and specifically hypothesize that the tendency to imitate would increase with volatility, since in those situations investors find it more comfortable to follow the market consensus, making sure they achieve the average return of the market. However, in their study, they do not find any evidence during the period/market analyzed, and other authors (e.g., Economou et al., 2011) only find mixed evidence of this relation. Nonetheless, this relationship has been found by authors such as Adem and Eren (2020) or Humayun Kabir and Shakur (2018), who conclude the level of herding is significantly higher during high market volatility periods.

In this paper we aim to study whether there is a relationship between herding and market volatility in the markets under study, and also whether the 2008 and Covid-19 crises affect this relation. Given the impossibility to obtain implied market volatility, we go for other measures based on daily data; we decided to adopt the PK and GK measures for subsequent analyses.

Shan and Zhang (2006) indicate that the variance estimates with range estimators are superior to the traditional daily variance. Therefore, we use two measures of historical volatility based on the range estimators suggested by Parkinson (1980) and Garman and Klass (1980). Parkinson's measure incorporates the maximum and minimum daily prices so that it is possible to better evaluate volatility with extreme prices, since it incorporates the intraday information that is not reflected in closing prices. The expression of Parkinson's estimator is as follows:

$$\sigma_P^2 = \frac{1}{4ln2}(lnH_t - lnL_t)^2 \tag{6}$$

where H_t and L_t are, respectively, the maximum and minimum prices reached by the Ibex-35 for the Spanish market and the PSI-20 for the Portuguese.

Garman and Klass's measure, in addition to including the maximum and minimum prices, incorporates opening and closing prices. Historical volatility is calculated using the following expression:

$$\sigma_{GK}^2 = \left[\frac{1}{2}\left(ln\frac{H_t}{L_t}\right)^2 - (2ln2 - 1)\left(ln\frac{C_t}{O_t}\right)^2\right] \tag{7}$$

where H_t and L_t are, respectively, the maximum and minimum prices reached by the market index, while C_t and O_t are, respectively, the closing and opening prices of the Ibex-35 or PSI-20 on day t.

The descriptive statistics of the Parkinson and Garman and Klass measures in the Spanish and Portuguese markets are shown in Table 6. It can be concluded that both measures show similar values for each country. Overall, the Spanish market is characterized by lower volatility, with the Portuguese market showing the maximum of both measures. Both measures have a distribution characterized by a higher number of days in which volatility is below the mean, as well as by the non-normality of the series.

To address the potential asymmetries in herding behaviour in function of the market volatility that might be important for investors, the following regression is estimated:

$$CSAD_{i,t} = \alpha + \gamma_1 D^{vol}\left|R_{M,t}\right| + \gamma_2\left(1 - D^{vol}\right)\left|R_{M,t}\right| + \gamma_3 D^{vol}R_{M,t}^2 + \gamma_4\left(1 - D^{vol}\right)R_{M,t}^2 + \varepsilon_t \tag{8}$$

where D^{vol} is a dummy variable that takes a value of 1 during days characterized by high volatility and 0 otherwise. Following Tan et al. (2008), we assume that the market experiences high volatility if the volatility exceeds the previous 30-day moving average.

Table 6
Descriptive statistics of the volatility measures.

	Parkinson		Garman&Klass	
	Spain	Portugal	Spain	Portugal
Mean	0.0079	0.0082	0.0081	0.0082
Median	0.0072	0.0072	0.0075	0.0073
Maximum	0.0188	0.0240	0.0181	0.0257
Minimum	0.0025	0.0032	0.0029	0.0032
Std. deviation	0.0033	0.0039	0.0033	0.0038
Skewness	1.2552	1.6662	1.2022	1.7895
Kurtosis	4.6489	6.3259	4.3146	7.2440

Note: This table reports descriptive statistics for the two volatility measures: Parkinson (1980) and Garman and Klass (1980), for the period 2000–2021.

Table 7
Estimation of herding behavior on high volatility days vs. the rest.

Panel A: Spain-Parkinson		α	γ_1	γ_2	γ_3	γ_4
Complete sample	Coef.	0.0094***	0.6823***	0.7460***	−1.4609**	−0.0961***
	t-stat	(114.8548)	(34.8981)	(44.5733)	(−2.5221)	(−43.3485)
Pre-crisis	Coef.	0.0080***	0.7458***	0.8510***	−6.9511***	−11.1205***
	t-stat	(53.2916)	(17.1784)	(14.4249)	(−3.2993)	(−2.7027)
Crisis	Coef.	0.0151***	0.6173***	0.4744**	−1.7265	0.7571
	t-stat	(12.4178)	(5.3621)	(2.5563)	(−0.8008)	(0.1334)
Post-crisis	Coef.	0.0101***	0.6905***	0.7631***	−4.4966***	−3.5101
	t-stat	(71.1688)	(19.3990)	(12.9365)	(−2.6535)	(−0.8120)
Covid-19	Coef.	0.0125***	0.9417***	0.7678***	−3.9517***	−0.0990***
	t-stat	(25.2105)	(8.4350)	(11.8380)	(−3.4073)	(−11.5317)
Short-selling restriction	Coef.	0.0125***	1.4288***	1.3473**	−18.7788*	−30.0420
	t-stat	(3.9682)	(3.2151)	(2.3916)	(−1.6885)	(−1.5870)
Post-Covid-19	Coef.	0.0098***	1.0725***	1.1187***	−37.5066**	−31.5373
	t-stat	(11.6836)	(4.0769)	(3.1522)	(−2.0670)	(−1.1341)

Panel B: Spain-Garman-Klass		α	γ_1	γ_2	γ_3	γ_4
Complete sample	Coef.	0.0094***	0.6865***	0.7228***	−1.6556**	−0.0930***
	t-stat	(117.2744)	(31.3109)	(49.9700)	(−2.4298)	(−48.5551)
Pre-crisis	Coef.	0.0081***	0.7510***	0.7790***	−7.3819***	−6.3658*
	t-stat	(54.3931)	(16.3353)	(14.0935)	(−3.3435)	(−1.7185)
Crisis	Coef.	0.0150***	0.6045***	0.4880***	−1.4689	1.0301
	t-stat	(12.4955)	(5.0654)	(2.8530)	(−0.6955)	(0.2298)
Post-crisis	Coef.	0.0101***	0.6992***	0.7519***	−4.7998***	−4.4817
	t-stat	(74.9642)	(18.8857)	(15.5398)	(−2.6508)	(−1.4324)
Covid-19	Coef.	0.0124***	0.9704***	0.7625***	−4.2714***	−0.0983***
	t-stat	(26.1045)	(7.4988)	(15.6232)	(−3.2060)	(−15.2193)
Short-selling restriction	Coef.	0.0126***	2.8316***	0.9902**	−96.4842***	−7.8065
	t-stat	(4.6435)	(4.5949)	(2.6309)	(−3.5443)	(−0.7975)
Post-Covid-19	Coef.	0.0098***	1.0620***	1.1281***	−37.0788*	−35.1512
	t-stat	(12.1474)	(3.8169)	(3.4402)	(−1.9287)	(−1.3685)

Panel C: Portugal-Parkinson		α	γ_1	γ_2	γ_3	γ_4
Complete sample	Coef.	0.0086***	1.1279***	1.3561***	4.1949***	3.8520***
	t-stat	(56.2119)	(30.0736)	(40.0519)	(9.7302)	(8.3565)
Pre-crisis	Coef.	0.0050***	1.4972***	2.1285***	2.2333	−2.8702***
	t-stat	(18.7725)	(19.9094)	(26.1855)	(0.6760)	(−26.6162)
Crisis	Coef.	0.0116***	0.9194***	0.8571***	−2.7026*	14.6121***
	t-stat	(13.6433)	(8.7091)	(4.0932)	(−1.8281)	(4.2669)
Post-crisis	Coef.	0.0088***	1.1312***	1.5907***	4.7114***	−0.9094***
	t-stat	(17.3329)	(17.7100)	(13.3362)	(7.8756)	(−13.3542)
Covid-19	Coef.	0.0120***	1.2729***	0.8422***	−7.6502**	12.4758***
	t-stat	(12.3458)	(5.1188)	(4.6828)	(−2.0745)	(2.7835)
Post-Covid-19	Coef.	0.0126***	0.8299***	0.4953*	7.4421***	37.2992**
	t-stat	(12.4219)	(5.5505)	(1.6682)	(5.5669)	(2.5905)

Panel D: Portugal-Garman-Klass		α	γ_1	γ_2	γ_3	γ_4
Complete sample	Coef.	0.0086***	1.1667***	1.3044***	4.0212***	4.1889***
	t-stat	(55.4561)	(29.7077)	(37.9549)	(9.7124)	(8.7098)
Pre-crisis	Coef.	0.0050***	1.5313***	2.1203***	1.5677	−2.8585***
	t-stat	(18.0393)	(19.1773)	(25.6102)	(0.4454)	(−26.0292)
Crisis	Coef.	0.0106***	1.1501***	1.2411***	−1.4738	−12.2914
	t-stat	(10.6097)	(5.1457)	(4.8631)	(−0.2420)	(−1.2049)
Post-crisis	Coef.	0.0088***	1.1667***	1.5413***	4.5474***	−0.8811***
	t-stat	(15.8361)	(16.6775)	(12.0885)	(6.7357)	(−12.1055)
Covid-19	Coef.	0.0120***	1.4216***	0.7291***	−9.5912**	14.3885***
	t-stat	(12.6854)	(5.8745)	(4.2677)	(−2.5901)	(3.2919)
Post-Covid-19	Coef.	0.0126***	0.8180***	0.4642	7.5462***	39.6368***
	t-stat	(12.5168)	(5.8322)	(1.5487)	(6.0607)	(2.8796)

Note: This table reports the estimated coefficients of the benchmark model Eq. (8). The sample period is January 2000–May 2021; 1st January 2000–30th September 2008, 1st October 2008–1st April 2009, 2nd April 2009–31st January 2020, 1st February 2020–17th November 2020, 18th March 2020–18th May 2020 (only Spain) and 18th November 2020–31st May 2021. Eq. (8) has been estimated using OLS with White's variance and covariance matrix correction, to prevent heteroskedasticity. The t-statistics are reported in parentheses and ***, ** and * represent statistical significance at the 1%, 5% and 10% levels.

The analyses above were repeated with the two volatility measures considered. As before, Equation (8) has been estimated using OLS with White's variance-covariance matrix to correct for the presence of heteroskedasticity. Again, to obtain evidence of herding it is necessary that $\gamma_3 > 0$ and $\gamma_4 < 0$. If it also turns out that $\gamma_3 < \gamma_4$ we can conclude that the effects are more common on days characterized by high volatility market.

The results for both volatility measures in the Spanish market are shown in Table 7, Panel A (Parkinson's volatility measure) and B (Garman and Klass measure). When we look at the complete sample, the coefficients γ_3 and γ_4 appear negative and significant both in high volatility days and the rest, though being more intense on the days of greater volatility in the market, an asymmetry confirmed by the Wald test (Table 8). With regard to the pre-crisis and post-crisis periods, the evidence is more limited than that presented in Tables 3 and 4. In the period of the crisis, when the highest herding estimates were observed according to the results presented above, the coefficients γ_3 and γ_4 point to the existence of herding behavior, without differences between days of high volatility and the rest. During the rest, the effect would not show the existence of a significant relation, in line with what was previously observed. Hence, after the global financial crisis, herding seems to appear mainly on high volatility days.

With regard to the Covid-19 (including short-selling restrictions) and post-Covid-19 samples, it appears only on days of high volatility according to the Parkinson volatility measure. The results are practically the same when applying the measure with the Garman and Klass. These results differ from those reported by Economou, Kostakis, and Philippas (2011) for the Spanish market, as they do not find any difference between high and low volatility, though that is noted after the 2008 crisis. On the other hand, Tan et al. (2008) provide evidence suggesting that herding in Chinese equity markets occurs mainly during periods of high volatility.

Table 7, Panels C and D, report the results for the Portuguese market. Unlike the Spanish market, we find herding exclusively in calm periods for both the pre- and post-crisis periods with the two measures of volatility. However, the behavior changes during crisis periods, it being detected exclusively on days of high volatility in the period of the global financial crisis (although only in Parkinson's measure) and the Covid-19 period.

These results reveal the different behavior between two markets that, a priori, due to their geographic proximity, have similar characteristics, highlighting the impact of volatility on investor behavior, especially during periods of turmoil.

3.2. Cross-herding effects

Finally, having analyzed herding from the regulatory perspective in their respective markets, we study if markets influence each other, amplifying the impact of imitation behavior that can affect market efficiency. Thus, geographical diversification becomes more difficult. Economou, Kostakis, and Philippas (2011) report a strong positive statistically-significant relationship between the CSAD measures of the Spanish and Portuguese markets. Mobarek, Mollah, and Keasey (2014) present overwhelming evidence that cross-dispersions of returns are explained by cross-dispersions of other markets, and find that neighbouring markets report higher co-movement with the regional CSAD. This observation motivates us to follow these

Table 8
Wald test for equality of herding coefficients.

		$H_0: \gamma_3 = \gamma_4$			
		Spain		Portugal	
		Parkinson	Garman-Klass	Parkinson	Garman-Klass
Complete sample	$\gamma_3 - \gamma_4$	−1.3648**	−1.5626**	0.3428	−0.1677
	Chi-Sq.	(5.5618)	(5.2662)	(0.3221)	(0.3059)
Pre-crisis	$\gamma_3 - \gamma_4$	4.1694	−1.0161	5.1035	4.4263
	Chi-Sq.	(1.0888)	(0.0781)	(2.4111)	(1.5974)
Crisis	$\gamma_3 - \gamma_4$	−2.4836	−2.4990	−17.3147***	10.8175
	Chi-Sq.	(0.2441)	(0.4332)	(30.3200)	(1.0005)
Post-crisis	$\gamma_3 - \gamma_4$	−0.9865	−0.3181	5.6208***	5.4285***
	Chi-Sq.	(0.0532)	(0.0096)	(98.4757)	(71.8712)
Covid-19	$\gamma_3 - \gamma_4$	−3.8527***	−4.1730***	−20.1259***	−23.9797***
	Chi-Sq.	(11.1001)	(9.8501)	(17.1787)	(20.7379)
Short-selling restrictions	$\gamma_3 - \gamma_4$	11.2632	−88.6777***	–	–
	Chi-Sq.	(0.4568)	(11.9166)	–	–
Post-Covid-19	$\gamma_3 - \gamma_4$	−5.9693	−1.9275	−29.8571**	−32.0907**
	Chi-Sq.	(0.0870)	(0.0115)	(4.6169)	(5.8782)

Note: This table reports the Chi-square statistics of the Wald test for the null hypothesis $\gamma_3 - \gamma_4$ in the model estimated in Eq. (8). The sample periods are January 2000–11 May 2022, January 2000–30 September 2008, October 2008–April 2009, April 2009–31 January 2020, February 2020–7 November 2021, 8 March 2020–18 May 2020 (only Spain) and 8 November 2021–11 May 2022. Eq. (8) has been estimated using OLS with White's variance-covariance matrix to correct the presence of heteroskedasticity. ***, **, and * indicate statistical significance at 1%, 5%, and 10% levels.

and that of other authors such as Tan et al. (2008), Chiang and Zheng (2010), Chiang et al. (2013) or Chong et al. (2020), and we test whether the squared market return and the cross-sectional deviation of returns of one market have any impact on the cross-sectional absolute deviation of returns of the other, given that Spain and Portugal are two neighboring markets which suffered severe consequences of the 2008 crisis, which were included in the PIIGS group (Portugal, Italy, Ireland, Greece, and Spain) having shown similar characteristics during this period.

To examine the link of cross-sectional dispersions between markets, we estimate the following model for Spain and Portugal:

$$CSAD_{i,t} = \alpha + \gamma_1 \left|R_{Mi,t}\right| + \gamma_2 R^2_{Mi,t} + \gamma_3 R^2_{Mj,t} + \gamma_4 CSAD_{j,t} + \varepsilon_t \qquad (9)$$

where $R_{Mi,t}$ is the equally weighted average return of the stock market i at time t and $R_{Mj,t}$ is the equally weighted average return of the stock market j at time t. We have expanded the benchmark model (4) by adding the squared equally weighted average return and the cross-sectional absolute deviation of returns of market j as explanatory variable of CSAD in country i.

The results are shown in Table 9. Panel A reports the effect on the Spanish market. Like Economou, Kostakis, & Philippas (2011) and Mobarek, Mollah, & Keasey (2014), we find strongly positive significant relations when the CSAD of Portugal in Spain for the complete period and all the subsamples except the 2008 crisis. According to the coefficients, the relations become stronger in the Covid-19 short-selling restriction. This significant negative effect of the squared average return of the Portuguese market indicates that herding formation in the Spanish market is influenced by market conditions in Portugal, but not in the crisis and Covid-19 samples. Panel B of Table 9 reports the results of the Portuguese market. In this case, significant positive relations between CSAD is found in all the subsamples, whereas the squared average return of the Spanish market impacts the CSAD of the Portuguese market in the subsample prior to 2020. Even though our results show a noticeable difference regarding Portugal's CSAD explaining the Spanish market's CSAD and vice versa, as Economou, Kostakis, and Philippas (2011) already noted. As they suggest, this finding shows that international diversification in the European region may be harder to achieve as significant positive effects are time-varying in two markets. As Chiang and Zheng (2010b) argue, one possible explanation is that shocks in one market are transmitted in a simultaneous fashion across borders. Also, our results underpin the conclusions in the previous section about the difference between the 2008 crisis and the period caused by the Covid-19 pandemic. It can be concluded that, in analyzing connectivity, one cannot rule out the role of neighboring markets.

Table 9
Influence of the other market's CSAD on the estimation of herding behavior.

Panel A: Spain		α	γ_1	γ_2	γ_3	γ_4
Complete sample	Coef.	0.0098***	0.0081***	11.9807***	−2.3839***	0.1734***
	t-stat	(57.6618)	(3.0065)	(5.2540)	(−8.8693)	(12.7077)
Pre-crisis	Coef.	0.0071***	0.7310***	−7.3338***	−1.1380***	0.0897***
	t-stat	(40.3981)	(18.0929)	(−3.6719)	(−5.8659)	(8.1194)
Crisis	Coef.	0.0138***	0.5123***	0.2356	−1.2310	0.0810
	t-stat	(9.4632)	(4.6988)	(0.0942)	(−0.6526)	(1.2565)
Post-crisis	Coef.	0.0089***	0.6978***	−5.1834***	−1.2986***	0.0876***
	t-stat	(41.2385)	(20.2020)	(−3.0419)	(−5.8059)	(8.0975)
Covid-19	Coef.	0.0131***	0.0128***	6.4101***	−1.4243	0.2198***
	t-stat	(12.3152)	(7.7455)	(4.1331)	(−0.8059)	(4.0058)
Short-selling restriction	Coef.	0.0101***	0.7032**	−2.2358	−5.3042**	0.2484***
	t-stat	(3.8857)	(2.2261)	(−0.2244)	(−2.1228)	(3.7857)
Post-Covid-19	Coef.	0.0080***	0.9455***	−32.1420**	−1.7514**	0.1397***
	t-stat	(6.7328)	(4.5163)	(−2.0204)	(−2.4944)	(2.9677)
Panel B: Portugal		α	γ_1	γ_2	γ_3	γ_4
Complete sample	Coef.	0.0045***	1.2074***	4.7103***	−9.3016***	0.3650***
	t-stat	(14.1143)	(35.4242)	(11.1101)	(−7.2290)	(12.5979)
Pre-crisis	Coef.	0.0038***	1.4919***	2.8588***	−13.1030***	0.2739***
	t-stat	(11.3645)	(35.7280)	(6.5939)	(−6.8507)	(7.8508)
Crisis	Coef.	0.0061***	1.0956***	5.3706	−10.7383***	0.3078***
	t-stat	(3.5286)	(7.0282)	(1.2601)	(−3.1963)	(3.2161)
Post-crisis	Coef.	0.0056***	1.0864***	5.7487***	−9.0704***	0.3691***
	t-stat	(12.0973)	(22.0772)	(7.4467)	(−3.7997)	(9.5253)
Covid-19	Coef.	0.0073***	1.2552***	−3.9089	−3.6253	0.2311*
	t-stat	(3.8608)	(6.5411)	(−0.9995)	(−1.5599)	(1.7224)
Post-Covid-19	Coef.	0.0024	0.8358***	7.0572***	−17.1895	0.7912***
	t-stat	(1.6474)	(4.8520)	(4.8062)	(−0.8604)	(6.1893)

Note: This table reports the estimation of the benchmark model Eq. (9). The sample period is January 2000–May 2021: January 2000–30 September 2008, 1 October 2008–29 April 2010, 30 April 2010–31 January 2020, 1 February 2020–17 November 2020, 18 March 2020–18 May 2020 (only Spain), 18 November 2020–31 May 2021. Eq. (9) has been estimated using OLS with White's variance and covariance matrix correction for heteroskedasticity. The t-statistics are reported in parentheses. *, **, and *** represent statistical significance at the 1%, 5%, and 10% levels.

4. Conclusions

This study investigates the herding behavior in the South European markets of Spain and Portugal in different market periods, including the extreme movements of the 2008 crisis and the recent Covid-19 pandemic, and during different market conditions (rising vs. declining markets and high volatility vs. low volatility days) [illegible]. Finally, we test whether the common herding factor exists across these two markets in Europe.

Our results show that herding appears in both markets, but differences are observed during the subsamples analyzed and the market conditions. In both markets, herding is found in the subsample prior to and subsequent to the 2008 crisis, but not during the crisis itself. The main difference between the two markets refers to the year 2020 onwards, herding is generally detected in Spain during the pandemic [illegible], while in Portugal herding is detected during the Covid-19 subsample period but not after it. These results suggest that in times of crisis investors [illegible] information, although the differences between [illegible] global financial crisis and the pandemic between the two markets.

Additionally, for market conditions, [illegible] we find that herding presents significant asymmetries considering [illegible] Portugal and Spain [illegible] during bear days [illegible] post-Covid-19 restrictio [illegible] and post-Covid-19 samples, although [illegible] up and down markets [illegible] remained unnoticed in the Covid-19 period.

However, when we investigate herding during high volatility, the differences between the two markets appear, which could [illegible] geographical proximity, [illegible] Spain [illegible] especially during high volatility (post-Covid-19 restrictions and post-Covid-19 samples). Conversely, Portugal shows herding in all periods only during "low" volatility, while herding is detected on high volatility days during periods of turmoil (2008 crisis and Covid-19).

Finally, we study the degree of co-movement in the cross-sectional dispersion [illegible] Portugal and Spain, and found strong significant relations between the CSADs of both countries for the complete period and all the subsamples except the 2008 crisis (in the Spanish market). We also found that the situation in one market [illegible], the squared [illegible] significant [illegible] the crisis and Covid-19 samples. [illegible] especially during the contagion effect that [illegible] global financial crisis and the pandemic have a different character. While the relations between the CSADs of both countries is bi-directio [illegible] during the financial crisis, in the Covid-19 the relation [illegible] geographical [illegible] be indicating that the impact of the disease was similar in both, although Portugal was able to control the pandemic in its initial stages much more effectively than Spain [illegible]. Therefore, our results [illegible] different [illegible] participant [illegible] depending on the origin of the crisis [illegible] investors [illegible] characteristics of the [illegible] markets in which they operate.

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CRediT authorship contribution statement

Sandra Ferreruela: Conceptualization, Methodology, Software, Formal analysis, Supervision, Writing - review & editing. Tania Mallor: Data curation, Formal analysis, Validation, Writing - original draft.

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.

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