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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 imitation behavior of investors in especially convulsed periods, such as the 2008 financial crisis and the recent global pandemic, both of which could affect investors' emotions and behavior, although both have different characteristics and might have different implications. 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, in turn divided into several sub-periods classified as pre-2008 crisis, 2008 crisis, post-2008 crisis, Covid-19 and post Covid-19. Additionally, the existence is studied of differences between days of positive and negative returns, or 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 in periods prior to the crisis, disappearing during the financial crisis and reappearing, although with less intensity, after it, while it is not generally detected in Covid-19 times. 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 worldwide expansion of the new Covid-19 disease, first detected in China at the end of the previous year, started a global health emergency and 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 Organisation, 2020), and affected most countries in the world, provoking government responses of various degrees of stringency, seeking a balance between saving lives and allowing some economic activity. The most common measures have included the closure of educational and work centers, social distancing measures and travel restrictions, along with stimulus packages, to mention just a few. Regarding the economic and financial impact of the pandemic, the coronavirus crisis is expected to result in a business cycle recession and a global financial crisis, although different scenarios are being considered as the pandemic is still active.

This situation could be compared to other Black Swan events, which modify the behavior of investors through their responses to fear, causing sharp panic-selling among international investors (Burch, Emery, & Fuerst, 2016; Chen and Siems, 2004). An epidemic, as an unexpected event that substantially modifies the life and routine of investors, could have a similar impact on emotions and therefore on the behavior observed in the markets. Covid-19 is not the first disease to have emerged in times of globalized markets. However, the situation created by Covid-19 is different from, for example, SARS, in that the scope of the pandemic has been global, which gives us a unique opportunity to gauge the impact of an unexpected and dreaded disease on the behavior of investors in stock markets that are

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more interconnected than ever. Despite the fact that the pandemic is still active in most countries, some authors have already evaluated its impact on financial markets, finding significant effects on stock returns. Schell et al., 2020, who analyze abnormal returns of global stock markets during six Public Health Risk Emergency of International Concern announcements, including Covid-19, find that only the latter had a significant negative effect on stock markets lasting at least 30 days. A similar conclusion is obtained by Al-Awadhi et al. (2020) in the Chinese market, as they find that this pandemic disease has a negative effect on stock market returns. He et al. (2020) observe that the development of the Covid-19 pandemic also 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 market returns. In line with the extensive strand of the literature that examines contagion effects on the transmission of adverse economic and financial shocks across international markets (see Bae, Karolyi, & Stulz, 2003; Karolyi & Stulz, 1996), Uddin et al. (2020) analyze the connected dynamics 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 period, showing that they experience a significant increase in conditional correlations between their stock returns.

Our paper contributes to the literature by directly analyzing investor behavior during extreme market situations, namely the 2008 global financial crisis and the Covid-19 period, in contrast to the a priori calmer periods in the markets that take place between these crises. These two turmoil situations actually have a very different nature and implications, since the global financial crisis was an endogenous event for the stock markets, while the Covid-19 pandemic was an exogenous shock to the financial system that provoked an extreme market situation. Thus, the aggregate behavior of investors in the markets could show different features in each of these situations, given their different psychological implications.

We construct a survivorship-bias-free dataset of daily returns for the period January 2000–May 2021 for the markets of Spain and Portugal[1], a time period long enough to contain a pre-crisis moment, a global financial crisis, a post-crisis period, a period coinciding with the explosion of a global pandemic and a period that coincides with the slow recovery of the markets once the worst of the pandemic seems to have passed. This allows us to observe the evolution of investor behavior in different market situations. We consider that conducting this research in these two markets may be of interest for a number of reasons. First, herding has been previously observed in both markets (Economou et al., 2015, detect significant herding in Portugal following the outbreak of the euro-zone sovereign debt crisis, and Blasco et al., 2017, detect significant herding in Spain between 2000 and 2015). This fact is of great importance since the first requirement for being able to delve into the study of herding behavior and its possible state of the market-dependent nature is that it does actually exist in a market. Secondly, both Spain and Portugal are part of what was known as the "PIIGS" group of countries, hence they were hit hard by the 2008 global financial crisis, one of the market situations under study. Additionally, both countries were also hit by Covid-19, although to a different degree, with Spain's figures being worse than those of Portugal, and their respective capital markets suffered the consequences of the worst of the pandemic. As an extraordinary circumstance, in this last period Spain imposed restrictions on short sales, while Portugal did not, so we can observe whether this fact has had any impact on the imitation effect shown by investors. Finally, as neighboring countries, they represent a suitable setting to analyze potential contagion effects.

Herding behavior is said to be present in a market when investors opt to imitate the trading practices of those they consider to be better informed or the market consensus, rather than acting upon their own information and beliefs (Blasco, Corredor, & Ferreruela, 2012a). In the existing literature, many reasons have been proposed for investors to decide to follow others' actions. The theoretical models of Banerjee (1992) and Bikhchandani, Hirshleifer and 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, because when there is managerial concern for reputation and asymmetric information on ability, some managers may prefer to imitate others and refrain from undertaking innovations and assume uncertainty. Compensation systems can also affect investment decisions (Maug & Naik, 2011). Furthermore, the existence of scarce or asymmetric information can also cause herding to increase among investors (Baddeley, Curtis, & Wood, 2004). The impact of Black Swan events on investor behavior is a relevant factor in numerous studies carried out in recent years for different market settings. These studies have found a relatively strong link between emotions and herding behavior, mainly through market sentiment (e.g. Blasco, Corredor, & Ferreruela, 2012b; 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 one another's actions more closely and have a tendency to mimic the decisions of their peers (see Kurz & Kurz-Kim, 2013, or Schmitt & Westerhoff, 2017). In such extreme market conditions as those created by crises and pandemics, the cost and time of processing the amount of information generated is higher than usual, thus increasing the incentives to herd. In this vein, some studies linking herding-like behavior and crises do so by pointing to imitation as an amplifying mechanism for behaviors due to panic. For instance, Brock (1999) indicates that those market participants more prone to imitate others are especially concerned about the short term, which can occasionally boost panic situations. Pedersen (2009) and Brunnermeier (2009) also identify "fire sales" as a risk for stability and an amplification mechanism for negative shocks.

Not only do researchers point out that the imitating behavior of investors is one of the potential explanations for simultaneous market declines. Policymakers also agree in that herding destabilizes markets and increases the fragility of the financial system, which

[1] According to the classification of the World Federation of Exchanges for 2019, the Portuguese market belongs to Euronext, the first group by capitalization in Europe, whereas the BME Spanish Exchange is the sixth group.

makes herding behavior especially worth detecting and characterizing, as it reduces market efficiency and makes it harder to diversify portfolios.

Against this background, our study contributes to the study of herding behavior and, more precisely, to the strand of the literature that focuses on the cross-sectional dispersion of stock returns in extreme market conditions, by applying the pioneering measures of Christie and Huang (1995) and Chang, Cheng and Khorana (2000) (henceforth CH and CCK). These authors presuppose that, if the phenomenon appears, it would be stronger under extreme market conditions, that is to say, 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, the evidence is mixed, and while Baur (2006) finds no evidence of herding in a sample of eleven developed stock markets during periods of extreme market conditions, other authors document significant herding behavior during crises when applying the said measures. Among these, Caparrelli, D'Arcangelis and Cassuto (2004) examine the Italian stock market for the period 1988–2001, and their conclusions support the idea that herding is present in extreme market conditions. Chiang and Zheng (2010a) analyze 18 markets during the period 1988–2009 and find evidence of herding in developed markets as well as in Asian markets, and evidence for herding in the US and Latin American markets during periods of financial crises. Economou, Kostakis and Philippas (2011) study four European markets (including Spain and Portugal) and find that herding effects are present mainly in the Greek and the Italian market; however, they do not find such evidence for the Spanish market, and the evidence is mixed for the case of Portugal. They also find that herding effects present significant asymmetries when considering rising and falling markets and also between days with high and low volatility, among other factors. Mobarek, Mollah and Keasey (2014) document significant herding behavior during crises and asymmetric market conditions in some 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, at sector level, and conclude that investors herd especially during periods of decline, while their behavior is different in the pre-crisis and post-crisis periods compared with the crisis period. More recently, Kabir (2017) examines the herding behavior of investors in the US financial industry during the global financial crisis of 2008 and finds a greater influence of the crisis on spurious herding for commercial and investment banks, with such herding increasing in the down market and with conditional volatility of returns. Finally, regarding the Covid-19 crisis and herding, Yarovaya, Matkovskyy and Jalan (2020) study this behavior in cryptocurrency markets and suggest that Covid-19 does not increase it.

One of the factors that could condition the relationship between investor behavior 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 volatility. For example, Baker et al. (2020) observe that the volatility levels in the United States in the first months of 2020 reached or even exceeded those observed in October 1987, December 2008 or the end of 1929, and attribute the impact to several factors including, but not limited to, the behavioral and policy reactions to the pandemic. Zaremba et al. (2020) directly investigate the relationship between policy responses to the pandemic and stock market volatility, finding that stringent policy responses increase return volatility in international stock markets. The increase in volatility is an effect that is also observed during crises (Karunanayake, Valadkhani, & O'Brien, 2010; Patev & Kanaryan, 2003). For instance, the 2008 crisis was associated with historically high levels of stock market volatility, which did not remain high for long (Schwert, 2011). There is evidence of price adjustments (and therefore, volatility) that are due not to the arrival of new information, as would happen in a completely efficient market, but to market conditions (Shefrin, 2000; Thaler, 1991) or collective phenomena (Friedman, 1953) such as herding. The relationship between volatility and investors who imitate other investors has been more recently described by Alper and Yilmaz (2004), Avramov, Chordia and Goyal (2006), Choe, Kho and Stulz (1998), Di Guilmi, He and Li (2014), Froot, Scharfstein and Stein, (1992), Huang, Lin and Yang, (2015), Karanasos, Yfanti and Karoglou (2016), and Ouarda, El Bouri and Bernard (2013), among others. One reason why greater volatility in the market could modify investor decision-making is because, in times of rising uncertainty, investors tend to overvalue losses and underestimate profits (Kahneman & Tversky, 1979). Therefore, we also examine whether there is asymmetric herding behavior in up and down markets, and periods of high and low volatility. Furthermore, following (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 the other, which could pose a threat to the financial stability of the Eurozone.

The study is founded on several main research questions. First, are there any changes in the imitating behavior observed in investors in periods of turmoil in the Spanish and Portuguese stock markets? Second, is there any difference in the herding behavior observed in periods of financial crisis with respect to periods of crisis of different origin such as a pandemic? Third, are there any differences between days with positive and negative returns, or do days of high volatility differ somewhat from others? Finally, is there some kind of influence of one country's stock market on the other in terms of herding? By answering these questions, our study can also help to explain whether recent widespread collapses in the stock markets may be related to the presence of herding behavior.

The remainder of the paper is organized as follows: Section 2 presents the details of the dataset employed in the analysis with 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 the study have been obtained from Refinitiv Datastream. Specifically, the daily closing prices of all the stocks listed on the Spanish and Portuguese markets in the period between 1st January 2000 and 31st May 2021 have been used as well as the corresponding market index data (opening, closing, maximum and minimum price of Ibex-35, for the Spanish market, and of PSI-20, for the Portuguese market). Ibex-35 is the main stock index of the Spanish stock market, made up of the 35 most liquid companies listed on it. The PSI-20 (Portuguese Stock Index) is the main benchmark of the Lisbon Stock Exchange, controlled by the European company of stock markets Euronext. It is made up of the 20 largest Portuguese companies in the market. All the data from Datastream have been cleaned and processed following the instructions of Ince and Porter (2006) to avoid possible errors.

It is worth mentioning that all the analyses have been carried out for the complete sample, as well as for five additional subsamples corresponding to pre-crisis, crisis, post-crisis, Covid-19[2] and post Covid-19[3] periods, so that we can observe whether the change in the environment has some impact on the results obtained, as intuited by authors such as CH and CCK. With regard to the 2008 crisis, the different periods have been set according to Kabir (2017). The pre-crisis period goes from 1st January 2000 to 30th September 2008, the financial crisis goes from 1st October 2008 to 1st April 2009 and the post-crisis period runs from 2nd April 2009 until 31st January 2020.

3. Methodology and results

3.1. Herding intensity

In this paper, the intensity of herding behavior has been assessed through two different measures based on the dispersion of stock returns. Following CH and CCK, the daily market returns we worked with throughout the study have been calculated as the average return of all the stocks listed on the market on day *t*. The descriptive statistics of market returns for both markets are shown in Table 1. It can be seen how, for the period under study, the returns of the two markets show some dissimilarities (the mean return for Portugal is four times bigger than that of Spain, but the median is higher in the Spanish market, thus indicating the existence of more extreme observations in Portugal). The spread between the maximum and minimum values is greater in Portugal, and the standard deviation is also bigger in this country. In terms of asymmetry and kurtosis, the asymmetry coefficient is negative for Spain but positive in Portugal and both markets show a leptokurtic distribution of returns, but Portugal's coefficient is much bigger than the Spanish.

We first use the herding measure proposed by CH. These authors calculate the cross-sectional standard deviation (CSSD) of the returns of the stocks listed on a given market as seen in equation (1) and suggest that in the presence of herding this dispersion would be lower than expected if such behavior 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 return of the *N* stocks listed on the market at time *t*.

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

To assess whether the dispersion of returns is significantly lower or not during periods of extreme returns in the markets, that is, whether market participants imitate the actions of others or not, CH propose the following regression:

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

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

It has been considered of interest to graphically represent the relationship between the average return of the market and the CSSD, given that in the presence of herding, and always according to CH, the ends of the graph should show a descending line, reflecting the lower cross-sectional dispersion at moments of extreme market movements. 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 can notice

[2] To delimit the Covid-19 period, the analyses were repeated using different starting dates for robustness reasons. Specifically, the days between the following events and the 27th November 2020 were taken as the Covid-19 period: (1) the first confirmed case (1st February 2020 in Spain and 2nd March 2020 in Portugal), (2) the first confirmed death (13th February 2020 in Spain and 16th March 2020 in Portugal), (3) the stock market drop after reaching the previous maximum (20th February 2020 in both countries), (4) the overcoming of the 2000 point barrier on the Oxford Government Response Stringency Index (Hale et al., 2021), (9th March 2020 in Spain and 10th March 2020 in Portugal) and (5) the announcement of the "stay at home" requirements, also known as "lockdown" (13th March 2020 in both countries). In the case of Spain, in addition, (6) the period during which there were restrictions on short selling (from 18th March 2020 to 18th May 2020) has been considered, which allows us to study whether the absence of influence of short selling restrictions on herding behavior observed by Bohl, Klein and Siklos (2014) during the Global Financial Crisis of 2008 holds for the Covid-19 period. For reasons of clarity, only the results of the specification of the Covid-19 period corresponding to the days between the stock market fall and the return of the indexes to pre-pandemic levels (27th November 2020) are shown. However, the results for the other variants do not differ from those presented here and are available upon request from the author. In the case of Spain, the results corresponding to the period in which there were restrictions on short selling are also shown.

[3] Although Covid-19 continues to be active around 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 both Ibex-35 and PSI-20 to return to pre-pandemic levels.

Table 1
Descriptive statistics for 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
St. 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 returns (Rm), daily cross-sectional standard deviations (CSSD) and daily cross-sectional absolute deviations (CSAD) for the period 2000–2021.

that there is a positive relationship between returns (in absolute value) and CSSD in both markets. Dispersion increases on extreme movements days, anticipating the non-existence of herding in either of the markets. However, we can observe a clear difference between them, since in the case of Portugal it can be seen that the dispersion is slightly higher than that observed in Spain for similar levels of return. On the other hand, looking at the subsamples, we can see small differences between the pre- and post-crisis periods, with the graph for the former looking flatter than the latter in Spain, that is, lower levels of dispersion for the same return level. However, for the Portuguese market, the graphs point in the opposite direction, as the one for the post-crisis period seems to show lower levels of dispersion for the same return levels than the pre-crisis one. The graphs for the crisis and Covid-19 periods do not have enough observations to distinguish clear patterns, but what can be seen is that the Portuguese and the Spanish markets show very different characteristics.

Equation (2) has been estimated for both the Spanish and Portuguese markets through the least squares method, with White's variance and covariance matrix, since the presence of heteroskedasticity has been detected. The results obtained for the Spanish market are shown in Panel A of Table 2. For herding to exist, it is necessary for the beta coefficients to be negative and significant. Here, there is evidence contrary to the presence of herding, as the betas are either positive or non-significant for all the periods under study (complete sample, pre-crisis, crisis, post-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 either market for any period with this measure should not discourage us since, as has been seen in the previous literature (Blasco & Ferreruela, 2008), on many occasions this measure has turned out to be too restrictive, not detecting herding in markets where other measures have been able to reveal it. For this measure to detect it, herding has to specifically focus on extreme moments, a starting condition that implies that if the imitation took place at other times, it would not be possible to observe it with this model.

The second measure we use is that proposed by CCK based on the cross-sectional absolute deviation of the returns (CSAD). To define this variable, the authors start from the conditional version of CAPM of Black (1972):

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

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 listed on the market at time t.

These authors argue that, if investors follow the market consensus during periods of sharp price changes, the linear and increasing relationship between market return and CSAD will no longer be maintained and can become non-linear and even decrease. For this reason, they use a nonlinear specification using a parameter that captures these nonlinearities in the relationship between dispersion and market return, as shown below:

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

The descriptive statistics of the CSAD series 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 presents higher CSAD values than those of Spain in mean, median, maximum and standard deviation, and therefore the imitating behavior, a priori, should be lower than that existing in Spain.

The graphs shown in Fig. 2 relate CSAD and market return for both countries (complete sample and subsamples) and allow us to draw similar conclusions to those obtained for the CSSD graphs. The point cloud is flatter for the Spanish market, pointing to lower dispersion for the same return level, with differences more noticeable in the pre-crisis and post Covid-19 periods.

The results of regression (4) for the Spanish market are shown in Table 3, Panel A. In view of the results shown in the table we can affirm that, with this approach, herding is not detected in Spain for the entire period as a whole, since the non-linear term has a positive coefficient that is statistically significant at a 1% level. Focusing on the subperiods under study, we observe that both prior to the global financial crisis, in the period after it, and after the market drop due to the Covid-19 pandemic, herding is detected, given that negative and significant coefficients are obtained for the quadratic term. According to the coefficients, there is a greater intensity of imitating behavior in the years preceding the crisis than in those subsequent to it, although the highest herding intensity is detected in the most

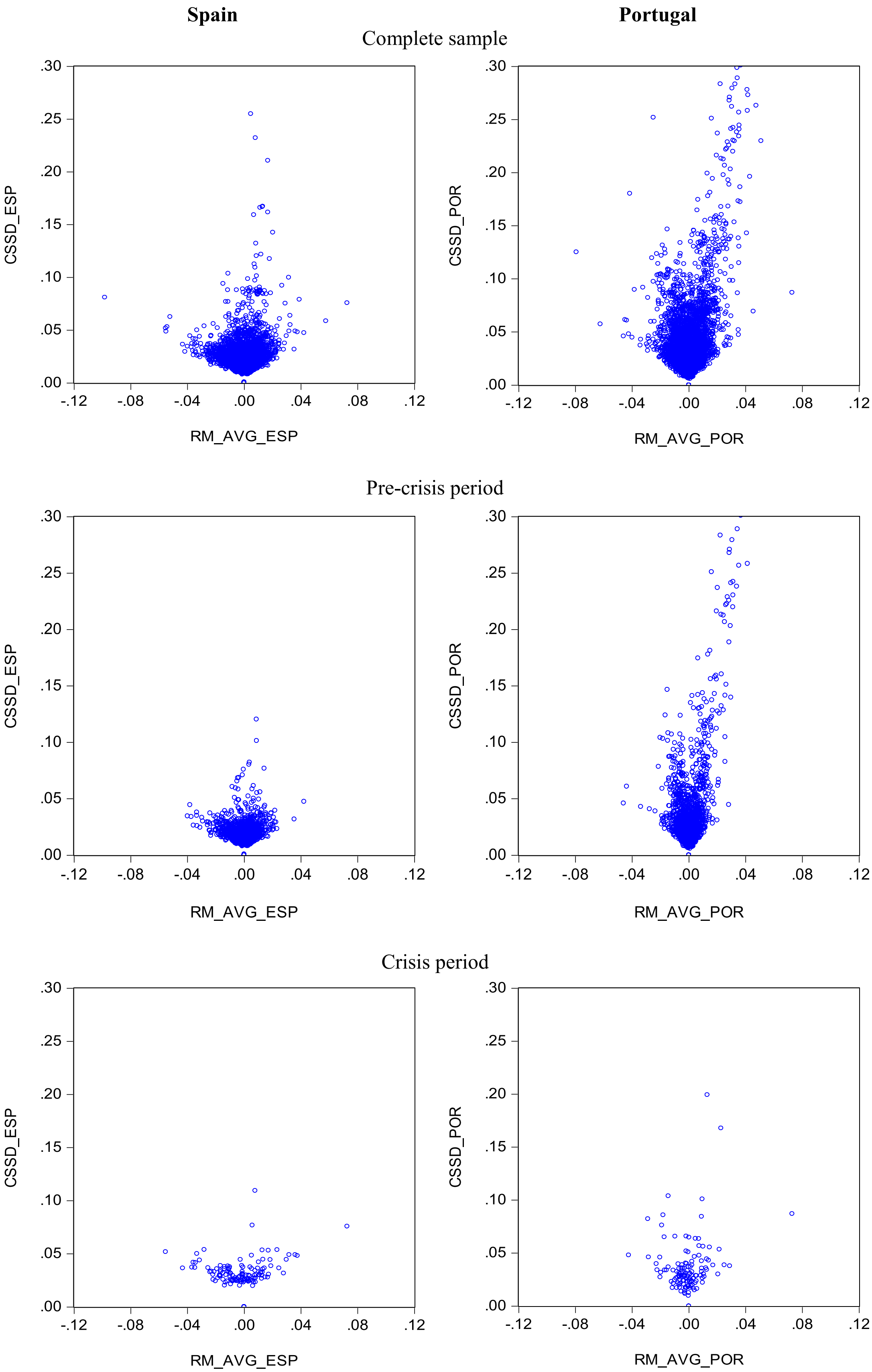

Fig. 1. CSSD-Return.

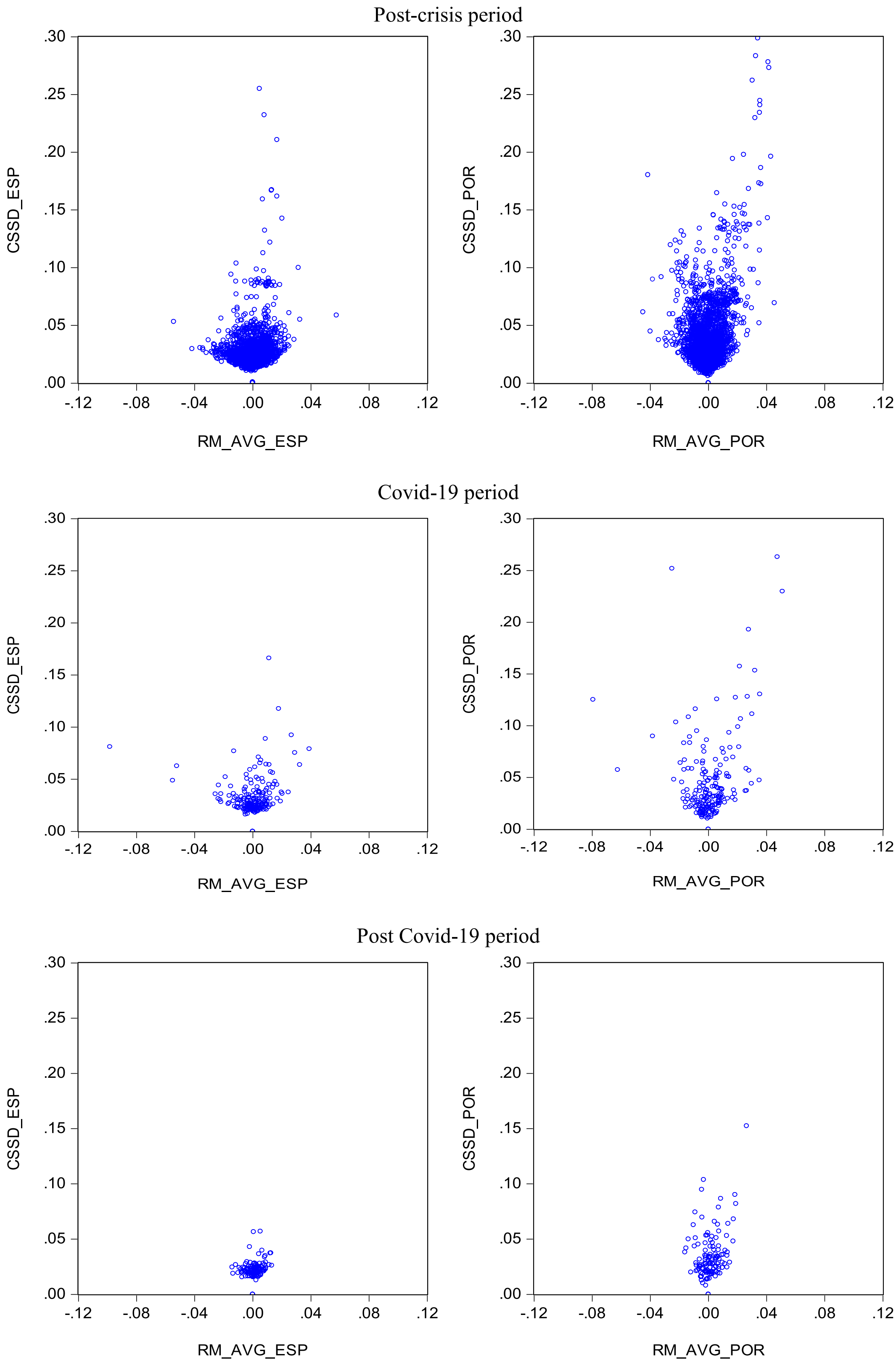

Fig. 1. (*continued*).

Table 2
Estimates of herding behavior 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 for the benchmark model Eq. (2). The sample periods are January 2000–May 2021, 1st January 2000–30th September 2008, 1st October 2008–1st April 2009, 2nd April 2009–31st January 2020, 20th February 2020–27th November 2021 and 18th March 2020–18th May 2020 (only in Spain). Eq. (2) has been estimated using OLS with White's variance and covariance matrix, due to the presence of heteroskedasticity. The T-statistics are reported in parentheses. ***, ** and * represent statistical significance at the 1%, 5%, and 10% levels.

recent period, once the worst part of the impact of Covid-19 on financial markets appears to be over. On the other hand, the coefficient is no longer significant during the crisis period, revealing the absence of imitating behavior, which could indicate that in times of crisis investors in this market are suspicious of the actions carried out by others and imitate to a lesser extent, that is, they would be negotiating following their own information, or maybe individually imitating other specific investors, but not the market consensus. This result is consistent with the findings of Hwang and Salmon (2004), who observe that both the Asian and Russian crises significantly reduced the herding detected in the markets. It might also help explain why the CH measure fails to detect herding given that crisis periods, instead of enhancing imitating behavior, seem to help markets return to fundamentals and efficiency. It may also shed light on the lower herding intensity detected in the post-crisis period: investors may not have regained confidence in the quality of the information provided by the market consensus or, thanks to having followed their own information during a previous period, they may have decreased their propensity to imitate. During the covid-19 period, the existence of herding is not detected, nor is it found in the subsample corresponding to the restrictions on short selling, which has a negative but not significant coefficient. This result would be consistent with that observed by Bohl, Klein and Siklos (2014), who indicate that short selling bans can encourage adverse herding.

In the case of the Portuguese market (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 quadratic term in regression (4) is positive and significant for the entire sample period and negative but not significant for the crisis, suggesting that there is no evidence of herding in those periods. As in the Spanish market, herding is detected before and after the global financial crisis, with higher intensity prior to the crisis. In both markets, the results for the crisis period would be consistent with a return-generating model in which investors' expectations impose a higher risk premium during a crisis period and are slow to return to the pre-crisis period risk premium after the crisis. However, in the Portuguese market, the coefficient for the Covid-19 subsample is negative and significant, thus indicating the presence of herding in that period, and highlighting the differences between both markets and both periods of turmoil. Finally, unlike the case of the Spanish market, herding disappears once the market index recovers its pre-pandemic levels.

3.1.1. *Herding behavior under different market conditions: bullish vs. bearish days*

CCK also analyze the asymmetry in the responses of investors and suggest that greater herding could be observed at times when the market falls as opposed to the bullish periods, given the different psychological implications of moments of falling prices compared to moments in which the market has a positive change in prices. Thus, we have carried out the joint analysis proposed by Chiang and Zheng (2010) differentiating between both scenarios in order to see whether the results hold for these two markets.

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

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

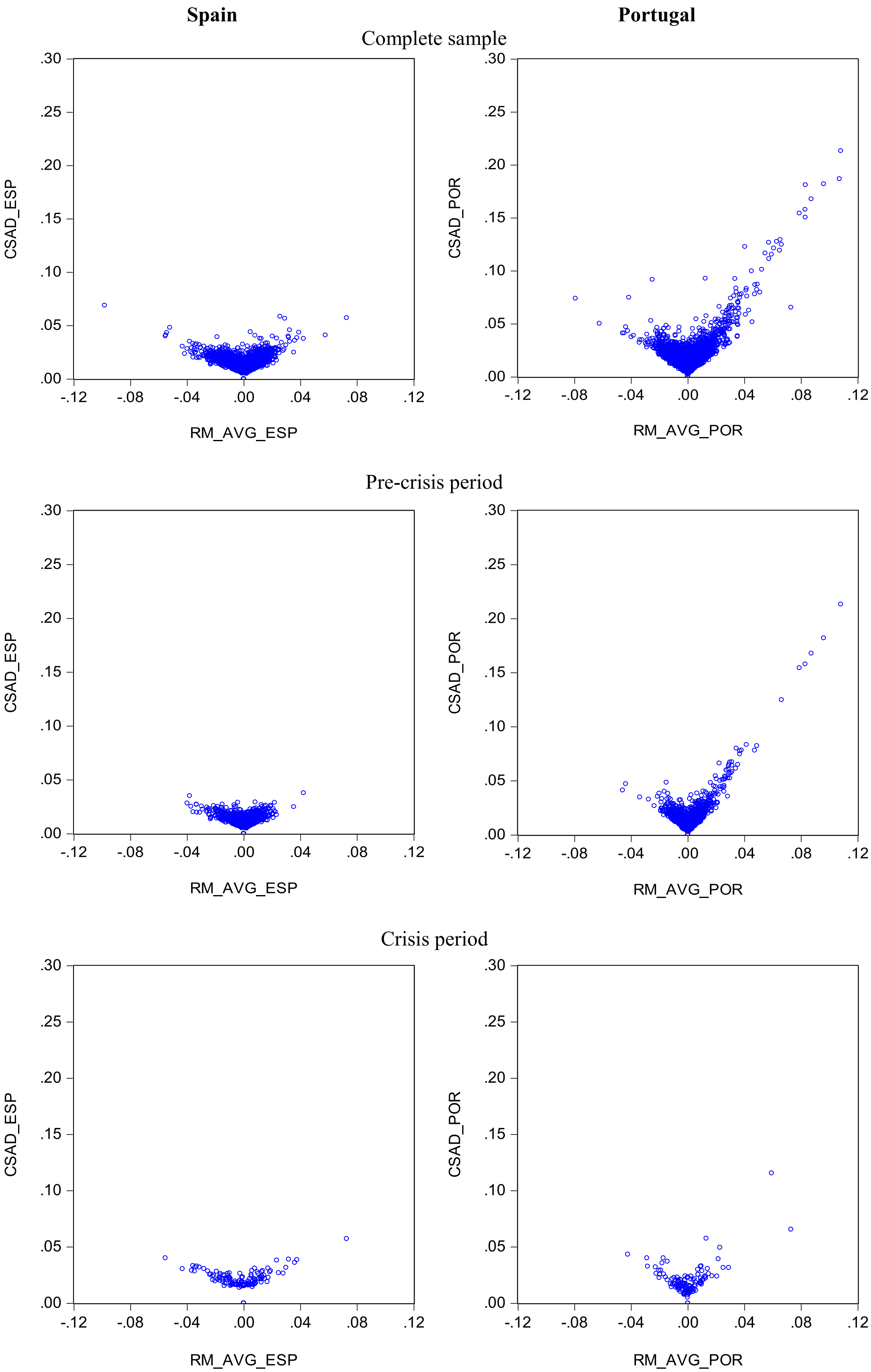

Fig. 2. CSAD-Return.

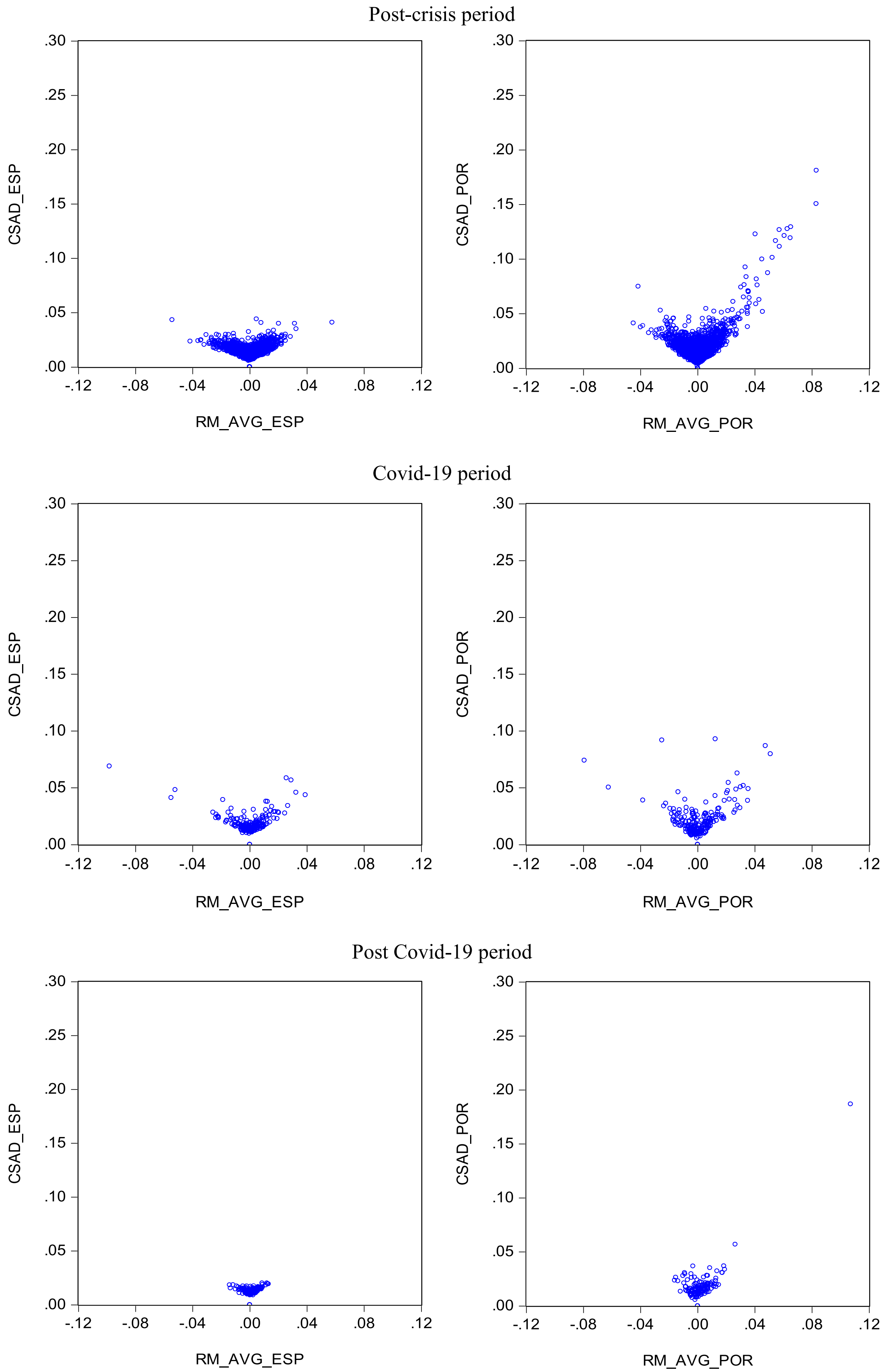

Fig. 2. (*continued*).

Table 3
Estimates of herding behavior 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 estimated coefficients for the benchmark model Eq. (4). The sample periods are January 2000–May 2021, 1st January 2000–30th September 2008, 1st October 2008–1st April 2009, 2nd April 2009–31st January 2020, 20th February 2020–27th November 2021, 18th March 2020–18th May 2020 (only in Spain) and 28th November 2021–31st May 2021. Eq. (4) has been estimated using OLS with White's variance and covariance matrix, due to 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 regard to the pre-crisis, crisis and post-crisis periods, the results are in line with those obtained when the analysis was carried out without distinguishing between positive and negative returns in the market, as herding is only detected before and after the crisis (although only in bearish days for the pre-crisis subsample), while during the crisis there is no evidence of herding on either bullish or bearish days. Also, the coefficient of the pre-crisis period on days with negative average returns indicates a greater intensity of herding than that of the post-crisis subsample. However, analyzing the differences between rising and declining markets noticeably modifies the results obtained for the Covid-19 and short selling restriction periods. The results now point to the existence of mild herding behavior during the market drop due to the pandemic, although with an asymmetric component, as the coefficient for bearish days is much larger in absolute value than that for bullish days. Additionally, a Wald test for the null hypothesis that the herding coefficients (γ_3 and γ_4) are equal on days with rising and falling market prices reliably points towards the rejection of this hypothesis, confirming the described asymmetry (Table 5). However, as in the case where no distinction between bearish and bullish days was made, the period after the pandemic shows the highest levels of herding, especially on bearish days. These results are similar to those obtained by Economou, Kostakis and Philippas (2011) for the Spanish market, as they find strongly significant evidence in favor of herding effects on days with falling market prices, while our results also suggest the existence of this asymmetry when looking at the subsamples. Nevertheless, focusing on the entire period without considering the subsamples might result in this effect going unnoticed, which highlights the importance of separately analyzing herding in 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, crisis and post-crisis subsamples continue to show the same results as in Table 3, with herding being present pre- and post- crisis but not during the crisis. The main novelty is that when distinguishing between up and down markets, it is observed that the imitating behavior has a strong asymmetric character in Portugal, appearing mainly on bearish days for both the complete sample and the subsamples where this collective phenomenon is found to be significant. In bullish situations, evidence contrary to the existence of herding is obtained. Herding was not found in the complete sample when the distinction between rising and falling days in terms of market return was not taken into account, thus it is important to analyze different market situations, as not doing so could hide herding effects if they take place only on bullish or bearish days. In addition, if we look at the results of the Wald test for the null hypothesis that the herding coefficients (γ_3 and γ_4) are equal on days with rising and falling market prices, the hypothesis is rejected, thus indicating that such asymmetry is significant and that Portuguese investors behave differently when the market is trending downwards. These investors

Table 4
Estimates of herding behavior with the CSAD measure in rising and declining 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 for the benchmark model Eq. (5). The sample periods are January 2000–May 2021, 1st January 2000–30th September 2008, 1st October 2008–1st April 2009, 2nd April 2009–31st January 2020, 20th February 2020–27th November 2021, 18th March 2020–18th May 2020 (only in Spain) and 28th November 2021–31st May 2021. Eq. (5) has been estimated using OLS with White's variance and covariance matrix, due to 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 tests for the null hypothesis.
$\gamma_3 - \gamma_4$ in the model estimated in Eq. (5). The sample periods are January 2000–May 2021, 1st January 2000–30th September 2008, 1st October 2008–1st April 2009, 2nd April 2009–31st January 2020, 20th February 2020–27th November 2021, 18th March 2020–18th May 2020 (only in Spain) and 28th November 2021–31st May 2021. Eq. (5) has been estimated using OLS with White's variance and covariance matrix, due to the presence of heteroskedasticity. ***, ** and * represent statistical significance at the 1%, 5%, and 10% levels.

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

3.1.2. Herding behavior under different market conditions: high vs. normal volatility

Authors such as Gleason, Mathur, and Peterson (2004) affirm that investor decision-making is affected by periods of high volatility and oscillations. Specifically, they hypothesize that the tendency to imitate would increase with volatility, since investors in these situations would feel more comfortable following the market consensus, thus making sure they achieve the average return of the market. However, in their study, they do not find any evidence of herding in the period/market analyzed, and other authors (e.g. Economou et al., 2011) only find mixed evidence of this relationship. Nonetheless, this relationship between volatility and herding has been found by authors such as Adem and Eren (2020), or Humayun Kabir and Shakur (2018), who conclude that the level of herding is significantly high 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 affected the said relationship. Given the results obtained in both markets applying the two herding measures indicated above, we decided to adopt only the CCK measure for subsequent analyses.

Shu and Zhang (2006) indicate that the variances estimated with range estimators are quite close to the daily integrated variance. Therefore, we use two measures of historical volatility in the markets based on this kind of estimator, those suggested by Parkinson (1980) and Garman and Klass (1980). Parkinson's measure incorporates the maximum and the minimum daily prices so that it is possible to follow the evolution of extreme price variations that occur intraday which are 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 on day t by the Ibex-35 index for the Spanish market or the PSI-20 for the Portuguese.

Garman and Klass's measure, in addition to including extreme prices, incorporates market opening and closing prices. Historical volatilities are thus 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 on day t by the market indexes, while C_t and O_t are, respectively, the closing and opening prices of Ibex-35 or PSI-20 on day t.

The descriptive statistics of the Parkinson and the Garman and Klass measures in the Spanish and Portuguese markets are shown in Table 6. It can be concluded from the data that both measures show similar values for each country. On average, the Spanish market is characterized by slightly lower volatility, with the Portuguese market showing higher maximums in both measures. Both measures have a distribution characterized by a high number of days in which the volatility shows values close to the mean, as well as by the non-normality of any of the series.

To address this potential source of asymmetric behavior and assess the influence of market volatility on the imitating behavior of investors, the following regression is estimated:

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

where D^{vol} is a dummy variable that takes a value of 1 during the days characterized by high volatility and 0 in any other case. Following Tan, et al. (2008), we assume that the market presents high volatility at a specific moment t if volatility that day 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
St. 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 of the two volatility estimators, Parkinson (1980) and Garman and Klass (1980), for the period 2000–2021.

Table 7
Estimates of herding behavior on days of high volatility 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 restrictions	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 restrictions	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 for the benchmark model Eq. (8). The sample periods are January 2000–May 2021, 1st January 2000–30th September 2008, 1st October 2008–1st April 2009, 2nd April 2009–31st January 2020, 20th February 2020–27th November 2021, 18th March 2020–18th May 2020 (only in Spain) and 28th November 2021–31st May 2021. Eq. (8) has been estimated using OLS with White's variance and covariance matrix, due to the presence of heteroskedasticity. The T-statistics are reported in parentheses. ***, ** and * represent statistical significance at the 1%, 5%, and 10% levels.

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

The results for both volatility measures in the Spanish market are shown in Table 7, Panels A (Parkinson 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 on high volatility days and on the rest, although 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, crisis and post-crisis periods, we find evidence similar to that presented in Tables 3 and 4. In the period prior to the crisis, when the highest herding intensities 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 crisis, the coefficients that would show the existence of imitation are no longer significant, in line with what was previously observed. Herding reappears after the global financial crisis, but it is less intense and appears only on high volatility days.

With regard to the Covid-19 (including the short-selling restrictions period) and post-Covid-19 subsamples, imitation appears only on days of high volatility according to the Parkinson volatility measure. The results remain practically unchanged when replacing this measure with that of Garman and Klass. These results differ from those reported by Economou, Kostakis and Philippas (2011) for the Spanish market, as these authors do not find any difference between high and low volatility days, although their dataset ends soon after the 2008 crisis. On the other hand, Tan et al. (2008) provide evidence suggesting that herding in Chinese equity markets occurs only during periods of high volatility.

Table 7, Panels C and D, report the results for the Portuguese market. Unlike in 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, investor behavior changes in periods of crisis, with herding being detected exclusively on days of high volatility in the period of the global financial crisis (although only for Parkinson's measure) and in the Covid-19 period.

These results reveal the difference between investor behavior in two markets that, a priori, would seem to be similar due to geographic proximity and investor characteristics, and they highlight the impact of volatility on investor behavior, especially during periods of turmoil.

3.2. *Cross-country herding effects*

Finally, herd behavior is worth analyzing from both regulatory and investment perspectives, as different markets could influence each other, amplifying the impact of imitation, a behavior that affects market efficiency. Thus, geographical diversification becomes more difficult. Economou, Kostakis and Philippas (2011) report a strong positive statistically-significant relationship between the CSAD measures across the Spanish and the Portuguese markets. Mobarek, Mollah and Keasey (2014) present overwhelming evidence that the cross-sectional dispersions of returns can be partly explained by the cross-sectional dispersions of other markets, and also find that neighboring countries are more prone to show co-movement with regard to CSAD. This observation motivates us to follow these

Table 8
Wald tests 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 corresponding to the Wald tests for the null hypothesis $\gamma_3 - \gamma_4$ in the model estimated in Eq. (8). The sample periods are January 2000–May 2021, 1st January 2000–30th September 2008, 1st October 2008–1st April 2009, 2nd April 2009–31st January 2020, 20th February 2020–27th November 2021, 18th March 2020–18th May 2020 (only in Spain) and 28th November 2021–31st May 2021. Eq. (8) has been estimated using OLS with White's variance and covariance matrix, due to the presence of heteroskedasticity. ***, ** and * represent statistical significance at the 1%, 5%, and 10% levels.

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

To examine the links of cross-sectional dispersions across these two markets, we estimate the following model for Spain and Portugal:

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

where, $R_{Mi,t}$ is the equally weighted average return of the N stocks listed on market i at time t and $R_{Mj,t}$ is the equally weighted average return of the N stocks listed on 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 dispersion of returns of market j as explanatory variables of CSAD in country i.

The results are shown in Table 9. Panel A reports the coefficients for the Spanish market. Like Economou, Kostakis & Philippas (2011) and Mobarek, Mollah & Keasey (2014), we find a strongly positive significant relationship between the CSADs of Portugal and Spain for the complete period and all the subsamples except the 2008 crisis. According to the coefficients, the relationship becomes stronger in the Covid-19 and short-selling restriction periods. The significant negative coefficient for the squared average return of the Portuguese market indicates that herding formation in the Spanish market is also influenced by market conditions in Portugal in all but the crisis and Covid-19 subsamples. Panel B of Table 9 reports the results for the Portuguese market. In this case, the significant positive relationship between CSADs is found in all the subsamples, whereas the squared average return of the Spanish market impacts the CSAD of the Portuguese market in the subsamples prior to 2020. Even though both countries have shown noticeable differences regarding herding, Portugal's CSAD helps to explain part of the Spanish market's CSAD and vice versa, as Economou, Kostakis and Philippas (2011) already pointed out. As they suggest, this finding shows that international diversification in the south European region may be hard to achieve, as significant positive coefficients also imply a co-varying risk in the two markets. As Chiang and Zheng (2010b) argue, one possible interpretation is that a shock in a similar sector tends to be transmitted or fluctuates in a similar fashion across borders. Also, our results serve to underpin the conclusions obtained in the previous sections about the differences between the 2008 crisis and the period of turbulence caused by the Covid-19 pandemic. It can also be concluded that in analyzing herding activity, one cannot rule out the role of neighboring markets.

Table 9
Influence of the other market's CSAD on the estimates 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 restrictions	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 estimated coefficients for the benchmark model Eq. (9). The sample periods are January 2000–May 2021, 1st January 2000–30th September 2008, 1st October 2008–1st April 2009, 2nd April 2009–31st January 2020, 20th February 2020–27th November 2021, 18th March 2020–18th May 2020 (only in Spain) and 28th November 2021–31st May 2021. Eq. (9) has been estimated using OLS with White's variance and covariance matrix, due to the presence of heteroskedasticity. The T-statistics are reported in parentheses. ***, ** and * represent statistical significance at the 1%, 5%, and 10% levels.

4. Conclusions

This study investigates herding behavior in the South European markets of Spain and Portugal in different market periods, including the extreme events of the 2008 crisis and the recent Covid-19 pandemic. Herding under different market conditions (rising vs. declining markets and high volatility vs. normal volatility days) is also assessed. Finally, we have tested whether common herding forces exist across these two markets in Europe.

Our results show that herding effects are present in both markets, but differences are observed regarding the subsamples analyzed and the market conditions. In both markets, herding is found in the subsamples prior to and subsequent to the 2008 crisis, but not during the crisis itself. The main differences between the two markets arise from the year 2020 onwards, as herding is not generally detected in Spain during the pandemic but appears stronger than ever after it, while in Portugal there is herding during the Covid-19 subsample period but not after it. These results suggest that in times of crisis investors would be negotiating following their own information, and also highlight the differences between investor response to the turmoil caused by the outbreak of a global financial crisis and that initiated by a global pandemic and between the two markets.

Additionally, different market conditions also cause variations in investor behavior. We find that herding effects present significant asymmetries when considering rising and falling markets in Portugal and Spain, with herding appearing to be especially strong during bearish days (pre and post crisis). In the Spanish market, this result is also found for the pre-crisis, Covid-19, short selling restriction and post Covid-19 subsamples, highlighting the importance of analyzing up and down markets separately, as herding had remained unnoticed in the Covid-19 period.

However, when we investigate herding during high volatility days, the differences between two markets that, a priori, could be similar due to their geographical proximity, are notable. In Spain, we find a tendency to herd especially during high volatility days (post-crisis, Covid-19, short selling restriction and post Covid-19 subsamples). Conversely, Portugal shows herding in calm periods only during the "low" volatility days, while herding is detected on high volatility days during periods of turmoil (2008 crisis and Covid-19).

Finally, we studied the degree of co-movement in the cross-sectional returns' dispersion across Portugal and Spain, and found a strongly positive significant relationship 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 contributes to explaining herding in the other, as the squared return of the other country has a significant coefficient, although this relationship becomes weaker or disappears during the crisis and Covid-19 subsamples. We could say that these results, although expected, are worrying due to the contagion effect that the existence of this relationship can imply. In any case, the results confirm the intuition that the periods of the global financial crisis and the pandemic have different characteristics. While the relationship between the CSADs of both countries is not bi-directional during the financial crisis, in the Covid-19 period the relationship holds, perhaps due to the fact that geographical proximity could be indicative that the impact of the disease will be similar, although Portugal was able to control the pandemic in the initial stages much more effectively than Spain, one of the worst affected countries in Europe. Therefore, the results presented in this paper show the different effects that various types of crisis (endogenous vs. exogenous shocks) may have on the behavior of market participants, depending on the origin of the crisis and the various psychological responses that it may provoke in investors, as well as the characteristics of the investors themselves and the situations present in the 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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