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Herding by corporates in the US and the Eurozone through different market conditions

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ABSTRACT

In this study, we test the herding towards a market consensus in the main financial industries of the United States and the Eurozone equity markets. We find that herding is more likely to be present in high quantiles that reflects turbulent market conditions. This herding appears to be more pronounced during financial crisis periods and in cases of asymmetric conditions of volatility, credit deterioration, and illiquid funding. Furthermore, we provide evidence that the cross-sectional dispersion of returns throughout the domestic equity market can be partly explained by the corresponding dispersions of the financial industries. In our analysis we cover the last two main global financial crises and identify new evidence of "spurious" and "intentional" herding by corporates. Further, our results are robust when considering short-selling bans.

1. Introduction

The Global Financial Crisis (GFC) and the Eurozone Crisis (EZC) emphasized the idea that stock market prices may deviate from their fundamentals due to waves of irrational market sentiment. This sentiment may become herding that could undermine financial stability and could pose unhedgeable systemic risk to market participants and financial institutions. Studies commonly describe herding as a behavioral tendency in which investors suppress their own beliefs and mimic collective actions in the market that leads to a convergence or a correlated pattern of actions (see Nofsinger and Sias, 1999; Welch, 2000; Hwang and Salmon, 2004). In a single market set-up herding has been thoroughly discussed for investors' trades at the security level (Lakonishok et al., 1992; Sias, 2004; Barber et al., 2009). More recent studies observed that herding also emerges at the industry level. This means that, after taking into account the characteristics of the securities, institutional investors' demands for securities for a specific industry in consecutive periods are positively correlated (Choi and Sias, 2009).

The Federal Reserve System (FED) and the European Central Bank (ECB) are two of many central banks that monitor cyclical and structural developments in the banking industry as well as other financial industries. Both the FED and the ECB require the corporates in these industries to identify possible sources of risk and vulnerability to financial stability so that they can assess the identified risks in order to develop more stringent measures aimed at improving financial stability and regulation.

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The GFC caused a strong fall in the European financial sector, mainly in banks, from which it has still barely recovered from compared to the strong recovery in the financial sector in the US equity market. This study uses the S&P 500 and the S&P 350 Europe as benchmarking indices for each side of the Atlantic, respectively; both have performed quite differently since the GFC. After this crisis and until the end of December 2017, the S&P 500 had risen by 156%, while the S&P 350 Europe had only gained 76%. This gap is similar when comparing financial industries (141% in the US compared with 71% in the Eurozone). European shares have not managed to keep up with US shares. With GDP growth in the euro area at 21% while it has been 35% in the US, the underlying economic fundamentals are probably the main factor behind this gap between the two stock markets. Furthermore, the impact of these regions' respective monetary policies is important. In the US, the FED acted more quickly and more aggressively than the ECB, which benefited US equities. Moreover, the Eurozone has had to tackle significant local episodes of risk aversion, such as the EZC and, more recently, Brexit. Additionally, financial systems are shaped by the use of different types of financial instruments and by how those instruments are used and in what proportion; for example, bank loans represent a significant share of funding sources for borrowers in the Eurozone, and capital market instruments prevail in the US.

In this study, we test for herding towards a market consensus for the US and the Eurozone equity markets and their financial sectors. As in Straetmans and Chaudhry (2015), we use both US and Eurozone data to facilitate a cross-Atlantic comparison of the financial systems' riskiness and stability. Moreover, we argue that such a study of herding in the Eurozone at the aggregate level, rather than considering ''stand-alone countries'', makes sense. As empirically demonstrated by Kim et al. (2005), the macroeconomic convergence associated with the introduction of the Economic and Monetary Union (EMU) of the European Union increased the regional and global stock market integration of the Eurozone. Schmitz and Von Hagen (2011) show that with the introduction of a common currency, the elasticity with respect to per-capita incomes of net capital flows within the Eurozone has increased for its members. Samarina et al. (2017) find that the effect of the euro's introduction increases the coherence of business credit cycles in the EMU. There is therefore increasing financial integration in the Eurozone in which herding threatens the financial stability of this area as a whole. Therefore, in case of market tail conditions, all the markets within the Eurozone could experience extreme tail conditions that could call for intervention by the ECB.

Along with a cross-Atlantic comparison, we find little evidence of herding based on the standard OLS technique but we also apply the more insightful quantile regression method. Using this method, we find that herding is more likely to be present in the high quantiles in both markets. Herding appears more pronounced during the financial crises, and our results support the presence of herding in cases of asymmetric conditions of volatility, credit deterioration, and illiquid funding. By investigating the presence of herding for corporates due to fundamental or non-fundamental information, we extend this analysis to the last two main global financial crises. Here, we consider the short-selling bans introduced by the market authorities and highlight new evidence of ''spurious'' and ''intentional'' herding that indicates different crises may affect herding in different ways and that these two economies react differently to information spread in the market. For instance, while the banking industry may herd due to fundamental information in the US, the same result does not occur in the Eurozone during the GFC.

Policymakers and supervisory authorities have an interest in identifying correlated patterns of trades that may worsen the volatility in returns that then erodes financial stability (Demirer et al., 2010). The literature identifies several reasons why investors herd. Avery and Zemsky (1998) point out that in turbulent states of the economy, market participants herd because they think that other investors may have more accurate information. This herding may also lead to information cascades as showed by Zhou and Lai (2009). Likewise, Devenow and Welch (1996) argue that investors may have an intrinsic preference for conformity with the market consensus. Money managers may imitate collective actions because of the incentives provided by the compensation scheme and terms of employment, as discussed in Bikhchandani and Sharma (2000), with an increasing trend to herd as their careers progress (Boyson, 2010). Bernile and Jarrell (2009) and Carow et al. (2009) suggest another possible cause and argue that particularly after the arrival of public information, there are systematic patterns in institutional activities that may destabilize market prices that causes herding by private investors.

Hott (2009) develop a model for herding formation without assuming any speculative motivations. This model shows how herding generates a price bubble. In the corporate bond market, institutional investors' herding is higher than the reported level observed in equities, and its effect is highly asymmetric (Cai et al., 2019). However, Bernile et al. (2015) find that the anticipated trades by institutional investors ahead of other firms is more likely to reflect their superior ability to process publicly available information, rather than their access to private information.

A large body of research covers herding effects in several stock markets (see, e.g.; Christie and Huang, 1995; Chang et al., 2000; Gleason et al., 2004; Demirer and Kutan, 2006; Tan et al., 2008; Chiang et al., 2010; Chiang and Zheng, 2010; Economou et al., 2011; Philippas et al., 2013; Zhou and Anderson, 2013; Mobarek et al., 2014). Overall, their findings show that herding is more prevalent within emerging markets and in economic downturns. Galariotis et al. (2015) report evidence of herding for US investors when fundamental macroeconomic announcements are released and spillover herding from the US to the UK markets. Moreover, since herding leads also to important informational inefficiencies in the market that contribute to, on average, 4% of the asset's expected value (Cipriani and Guarino, 2014), they examine the presence of ''spurious'' and ''intentional'' herding in these two markets. In a follow up study, Galariotis et al. (2016) provide new evidence on the relation between herding and the liquidity in the G5 equity markets, namely the US, France, Germany, the UK, and Japan.

In our study, we focus on corporates' herding during the GFC and EZC for the US and Eurozone equity markets by zooming in on the financial sector. Moreover, in our analysis of the US equity market, we consider all the companies included in the S&P500 that capture approximately 80% of the available US market capitalization. As a robustness check, we also consider the short-selling bans imposed in the US during the GFC and in the Eurozone during both crises. This robustness analysis[1] is fundamental because, as argued Diamond and Verrecchia (1987), the short-selling bans moderate the trading of informed traders that prevents bad news from being rapidly impounded into stock prices in the belief that such bad news is "unwarranted" in the sense that it represents a negative bubble or herding rather than fundamental information. To the best of our knowledge, there are no studies on herding that have conducted this type of analysis. Therefore, our study represents an important novel contribution. In particular, we show that not taking into account the short-selling bans actually jeopardizes the results.

Our study enriches the literature by examining the existence of herding in the US and Eurozone equity markets. It contributes by providing new evidence on herding in the financial sector,[2] namely banks, diversified financials, insurance, and real estate, for a sample period that fully captures the aforementioned international financial events. This approach facilitates our investigation into different investing behaviors related to the subperiods in our sample. In particular, despite the literature that offers a comprehensive analysis of herding during the GFC (see, e.g.; Chiang and Zheng, 2010; Galariotis et al., 2015; Mobarek et al., 2014), the investigation of herding during times of turbulence in the primary market is limited. We fill this gap by extending the empirical analysis to both the EZC and the US.

Our study extends the investigation on herding under asymmetric conditions in the market. In particular, we use the implied market volatility as a measure of investors' sentiment as per Baker and Wurgler (2006). Further, we build on Norden and Weber (2009) who report that positive stock returns are associated with negative changes in the CDS spread and use credit default indexes (CDX and iTraxx) as proxies for the credit conditions in the market. Moreover, we consider that firms facing a severe liquidity constraint may have to sell a large part of their assets to avoid bankruptcy. This sell-off causes a fire sale that could affect the entire industry by leading to correlated patterns of actions (Oh, 2018). We also use the TED spread to study herding under tighter funding liquidity. Our study provides evidence that herding is more pronounced in cases of high volatility, credit deterioration, and illiquid funding. This evidence enriches the cases of market asymmetries used to investigate herding that in the literature are mainly related to negative and positive market returns, high or low trading volume, and return volatility (see, e.g.; Chiang and Zheng, 2010; Zhou and Anderson, 2013; Mobarek et al., 2014).

The study also provides new insights into how the spillover of herding in the financial sector migrates to the domestic equity market. It concludes by continuing the analysis of Galariotis et al. (2015) on the presence of "spurious" and "intentional" herding in the US and Eurozone equity markets and their financial sectors during the entire sample period and the last two main crises. As an important, novel contribution, this study considers the short-selling bans that the market authorities imposed in the US and Eurozone during the last two main crises.

The remainder of this study is organized as follows: In 2, we describe the framework of our study and present our method. Section 3 has a summary of the characteristics of the data used in this study. In Section 4, we discuss the empirical results. And Section 5 provides concluding remarks.

2. Methodology

2.1. Quantile regression analysis

Studies by Chiang et al. (2010),Zhou and Anderson (2013), Bekiros et al. (2017) and Pochea et al. (2017) have already examined herding with quantile regressions. However, the findings are confined to Chinese markets, the US REIT, and some US and central and eastern European (CEE) equity markets, respectively. We use quantile regressions on the herding in the US and Eurozone equity markets, financial sectors, and industries.

In this section, we offer a brief description of the quantile regression method.[3] Koenker and Bassett (1978) and Koenker (2005) argue that classical linear regression methods can only provide inference on the conditional mean functions. In this case, information about the tails of the distribution is lost. To address this issue, Koenker and Bassett (1978) developed a quantile regression in order to estimate models for the conditional median function and for the full range of all the other conditional quantile functions.

In financial markets, extreme outliers can significantly affect the tail values of a distribution, and in turn, these values can affect and distort the estimated herding coefficients. Unlike the classical linear regression methods, a quantile regression can alleviate some of the statistical issues due to outliers, especially for fat-tailed distributions[4] (Härdle and Song, 2010). Therefore, we use quantile regressions to test whether the herding is sensitive to different quantiles of the returns' dispersion.

[1] A more detailed description of the robustness test is described in the Supplement Appendix A.

[2] Considering the Global Industry Classification Standard (GICS) framework, the financial sector is composed of the banking, insurance and diversified financial industries. We also add the real estate industry because, before the 31 August, 2016, the GICS considered this industry as part of the financial sector. However, because of the increase in size and importance of the real estate industry, the GICS moved this industry from the financial sector to an independent real estate sector. For a detailed description of the GICS methodology, readers can refer to: "Global Industry Classification Standard (GICS) Methodology", Standard & Poor's, 2009; or, https://www.msci.com/gics.

[3] For a detailed description of the quantile regression method, readers can refer to Koenker and Bassett (1978) and Koenker (2005).

[4] For symmetric conditional distributions, the quantile curve coincides with the mean regression, that is, the quantile estimate with τ = 0.5 (median) coincides with the nonparametric mean regression estimate.

In the simplest terms, a quantile regression facilitates the estimation of a collection of conditional quantile equations that can be generically written as:

$$y_i = \alpha_\tau + \beta_\tau x_i' + \varepsilon_{\tau,i} \tag{1}$$

where y_i is the dependent variable, x_i' is a vector of predictors, α_τ is the constant, β_τ is the vector of the estimated coefficients, and ε_τ is the error term. The subscript $\tau \in (0,1)$ represents the quantile. We write the τ^{th} conditional quantile function as $Q_\tau(y|x) = \beta_\tau x'$.

The estimator $\hat{\beta}_\tau$ is computed by minimizing the weighted sum of the absolute errors, where the weights are dependent on the quantile values:

$$\hat{\beta}_\tau = argmin\left(\sum_{i=y_i>x_i'\beta_\tau} \tau|y_i - x_i\beta_\tau| \quad + \sum_{i=y_i<x_i'\beta_\tau} (1-\tau)|y_i - x_i\beta_\tau| \right) \tag{2}$$

As previously explained, the quantile regression focuses on estimating the interrelation between the dependent variables and their predictors at the median level (τ = 0.5 = 50*th*) and at any other specific quantile. In our study, we consider estimates at the 10*th*, 25*th*, 50*th*, 75*th*, 95*th* and 99*th* quantiles. In the literature, low quantiles (e.g., up to the 50*th*) are considered tranquil periods in the market; while high quantiles (e.g., above the 75*th*) represent distress in the market (see, e.g.; Adrian and Brunnermeier, 2016).

2.2. Detecting herding behavior

In the literature, there are two main measures of herding at this moment in time: the first is based on cross-sectional data from stock returns (Christie and Huang, 1995; Chang et al., 2000; Hwang and Salmon, 2004), and the second is constructed with transaction data (Lakonishok et al., 1992; Wermers, 1999; Welch, 2000).

Our study continues and enriches the line of research that focuses on the cross-sectional dispersion of stock returns in distressed market conditions. The main studies of Christie and Huang (1995) and Chang et al. (2000) introduce measures to detect how herding affects the cross-sectional standard deviation (CSSD) and the cross-sectional absolute deviation (CSAD), respectively. These herding measures rely on the fact that investors tend to ignore their prior heterogeneous beliefs and information in order to follow the market consensus.

Christie and Huang (1995) were the first to point out that herding is more likely to appear in periods of market distress. They argue that when individual returns cluster around the market consensus, return dispersions should be relatively low. By contrast, rational asset pricing models predict an increase in return dispersions in periods of market distress because individual returns differ in their sensitivity to the market returns (Hwang and Salmon, 2004). However, one criticism of the model developed by Christie and Huang (1995) is that it can only be used to analyze herding during periods of market distress,[5] and it does not model herding during tranquil periods of the market (Hwang and Salmon, 2004). Therefore, we use the more robust CSAD herding measure introduced by Chang et al. (2000) as:

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

where $R_{i,t}$ is the company *i* return at time *t*, and $R_{m,t}$ is the cross-sectional average return of the N companies considered in the universe at time *t*. The testing focuses on the nonlinear relation between the return dispersions and the market return as follows:

$$CSAD_t = \alpha + \gamma_1|R_{m,t}| + \gamma_2 R_{m,t}^2 + e_t \tag{4}$$

where $R_{m,t}$ is the cross-sectional average of the N returns in the aggregate market portfolio at time *t*. The nonlinear term ($R_{m,t}^2$) is introduced to capture the herding effect. We use the West and Newey (1987) estimator to obtain the heteroskedastic and autocorrelation consistent (HAC) co-variances for all the OLSs. Further, we use regression model (4) for each market (and financial industry) to test whether or not there is herding within the US and Eurozone equity markets (and their financial sectors) for the entire sample period. Hence, in the presence of herding γ_2 should be negative and statistically significant.

2.2.1. Financial crises and herding behavior

We examine whether or not herding was more pronounced during the GFC and the EZC. To this end, we add a dummy variable, D^{Crisis}, to model (4) that equals one during a crisis and zero otherwise:

$$CSAD_t = \alpha + \gamma_1 D^{Crisis}|R_{m,t}| + \gamma_2(1 - D^{Crisis})|R_{m,t}| + \gamma_3 D^{Crisis} R_{m,t}^2 + \gamma_4(1 - D^{Crisis})R_{m,t}^2 + e_t \tag{5}$$

In model (5), herding exists if γ_3 is negative and significant.

[5] Christie and Huang (1995) developed the following regression to test for herding: $CSSD_t = \alpha + \beta^L D_t^L + \beta^U D_t^U + e_t$; where $CSSD_t = \sqrt{\frac{\sum_{i=1}^{N}(R_{i,t} - R_{m,t})^2}{N-1}}$, and D_t^L (D_t^U) is a dummy variable that equals one if the market return at time *t* lies in the extreme lower (upper) tail of the distribution, and zero otherwise.

In order to determine the length of a crisis, we follow (Forbes and Rigobon, 2002) and consider that the GFC covered the period from August 9, 2007, to the March 31, 2009. August 2007 saw BNP Paribas freeze three funds because of subprime mortgage sector problems that started the crisis. The year 2009 saw declining volatilities and recovering asset prices that followed more determined policy action that gave markets more optimism and managed to halt the financial crisis.[6] The EZC covers the period from the May 2, 2010, to December 31, 2012. May 2 is considered the beginning of the crisis because of the first bailout package of the International Monetary Fund (IMF) for Greece. December of 2012 represents the end of the crisis because the Greek government bought back €21 billion of their bonds.[7] Moreover, this event precedes the ECB announcement of free unlimited support for all the Eurozone countries through the Outright Monetary Transactions and the establishment of the European Stability Mechanism, which took place in September 2013.

2.2.2. Asymmetry and herding behavior

When distressful conditions affect many firms simultaneously, stock prices will react negatively to divestments (Finlay et al., 2018). Avramov et al. (2006) argued that financial stress and bearish markets more generally may have caused herding in a direct and indirect manner through changes in market volatility. Thus, herding could be prevalent in periods of market distress when high values of volatility, credit deterioration, and illiquid funding exist. Thus, we use three sub-cases to capture these conditions.[8] Similar to Chiang and Zheng (2010), the asymmetric behavior of the returns' dispersion is estimated as follows:

$$CSAD_t = \alpha + \gamma_1 D^{High}|R_{m,t}| + \gamma_2(1 - D^{High})|R_{m,t}| + \gamma_3 D^{High} R_{m,t}^2 + \gamma_4(1 - D^{High}) R_{m,t}^2 + e_t \quad (6)$$

where $R_{m,t}$ is the cross-sectional average of the N returns in the aggregate market portfolio at time t, and D^{High} is a dummy variable that equals one if the variable used to measure the market asymmetry on day t is greater than the previous 22-trading-day (1 trading month) moving average and zero otherwise. Therefore, the cross-sectional dispersion of stock returns should lessen during days with high volatility, credit deterioration, and illiquid funding. More formally, herding is present if γ_3 (γ_4) is negative and statistically significant. If $\gamma_3 < \gamma_4$ and these values are significant, then herding is more pronounced during the periods of market distress.

2.2.3. Financial cross-industry analysis of herding behavior

The GFC, and then the EZC, emphasize the importance of the financial sector and the industries within it. Bekaert et al. (2014) analyze the contagion of the GFC from the US to 415 country-industry equity portfolios due to global and domestic factors. While they find small effects of contagion from the US and the global financial sector, their main findings indicate that there was a substantial domestic contagion phenomenon. Baur (2012) shows that the GFC led to an increased co-movement of returns and thus contagion between the financial sector and the domestic market, while Brunnermeier (2009) argues that fire sales amplified the initial negative shocks that then spread across the system. Others, like Allen and Gale (2000), argue that financial crises or shocks initially affect only a few financial institutions and then spread to the rest of the financial sector that then infects other sectors and the whole domestic market later on. Furthermore, studies often advocate that in periods of financial distress, herding can pose a threat to financial stability because the initial negative shocks to the financial sector, or to one of its industries, may be amplified by a pro-cyclical market mechanism that affects other sectors and ultimately the whole domestic market. For this reason, we are motivated to analyze the existence of a spillover of herding. This analysis is of pivotal relevance to policymakers and supervisory authorities, because the presence of spillover herding may lead to a systemic crisis. The following models underpin our analysis for the US and Eurozone, respectively:

$$CSAD_{US,m,t} = \alpha + \gamma_1|R_{US,m,t}| + \gamma_2 R_{US,m,t}^2 + \delta_1 CSAD_{US,j,t} + \delta_2 R_{US,j,t}^2 + e_t \quad (7)$$

$$CSAD_{EZ,m,t} = \alpha + \gamma_1|R_{EZ,m,t}| + \gamma_2 R_{EZ,m,t}^2 + \delta_1 CSAD_{EZ,j,t} + \delta_2 R_{EZ,j,t}^2 + e_t \quad (8)$$

where $CSAD_{US,m,t}$ ($CSAD_{EZ,m,t}$) is the CSAD that refers to the N stock in the aggregate market portfolio at time t; $R_{US,m,t}$ ($R_{EZ,m,t}$) is the cross-sectional average of the corresponding N returns at time t[9]; $CSAD_{US,j,t}$ ($CSAD_{EZ,j,t}$) is the CSAD that refers to the n stock in the financial sector portfolio, or financial industry portfolio, at time t; and $R_{US,j,t}^2$ ($R_{EZ,j,t}^2$) is the squared cross-sectional average of the corresponding n returns at time t. In the US, the presence of herding between the market "m" and the financial sector, or one of its industry, "j", is highlighted by δ_2 that is negative and statistically significant in model (7) (model (8) for the Eurozone).

[6] Major explanations for the usage of this period as a proxy for the GFC time frame can be found on the 79*th* Annual Report of the Bank for International Settlements, (Bank for International Settlements, 2009).

[7] We identify the beginning of the EZC as in Mobarek et al. (2014); however, their sample period ends in February. Our sample period permits a more appropriate identification of the EZC.

[8] Other studies (see, e.g.; Chiang and Zheng, 2010; Zhou and Anderson, 2013; Mobarek et al., 2014) examine and find herding around market asymmetries, such as negative and positive market returns, high or low trading volume, or return volatility.

[9] We computed the aggregate market portfolio after excluding all the companies included within the financial sector, or financial industry, in order to avoid a spurious correlation between the variables involved in models (7) and (8). Keeping these companies within the aggregate market portfolio means that herding that affecting affects the financial sector, or the financial industry, would mechanically impact affect the equity market even in the absence of spillover effects between the two variables.

In order to obtain a more comprehensive analysis, as an additional test, we also use the Granger causality test to study the information available on the past values of $R^2_{US,j,t}$ ($R^2_{EZ,j,t}$) that do not have a statistical effect on the present and values of $CSAD_{US,m,t}$ ($CSAD_{EZ,m,t}$). Further, the Granger causality test is based on the concept of predictability, or a time-based succession, and assumes the stationarity of the time series in the long term. Moreover, it does not mean that one variable is the effect of the other; more precisely, it indicates that one variable contains information about the other.

2.2.4. Herding behavior on fundamental information

Bikhchandani and Sharma (2000) argue that investors' herding may be either "spurious" in the sense of deviations due to changes in fundamental information (fundamental driven), or "intentional" in the sense of deviations due to other reasons (non-fundamental driven). Building on this argument, Galariotis et al. (2015) investigate the herding driven by fundamental or non-fundamental information. Choi and Skiba (2015) present empirical evidence that herding is more likely to be driven by fundamental information. In order to explore this issue, we decompose the CSAD measure into deviations due to fundamental information and deviations due to non-fundamental information. The reasoning behind this decomposition of the CSAD is that the return factors such as the one Fama and French (1995, 1996) and Carhart (1997) adequately capture the important fundamental information that may affect investors' decisions on a market level. Thus, the CSAD due to non-fundamental information is estimated as the residuals of the following regression model:

$$CSAD_t = \alpha + \beta_1(R_{m,t} - Rf_t) + \beta_2 HML_t + \beta_3 SMB_t + \beta_4 MOM_t + \varepsilon_t \tag{9}$$

where $(R_{m,t} - Rf_t)$ is the market risk premium, and the HML_t is the high-minus-low return factor that refers to the outperformance of value stocks over growth stocks. It is estimated as the equally weighted average of the returns for two high book-to-market (BM) equity portfolios for a region minus the average of the returns for two low BM portfolios. SMB_t is the small-minus-big return factor that refers to the excess return of smaller market capitalization stocks versus larger stocks. It is estimated as the equally weighted average of the returns on the three small stock portfolios for the region minus the average of the returns on the three big stock portfolios. Finally, the MOM_t is the momentum factor that is the tendency for the stock price to continue rising if it is going up (positive momentum) or continue declining if it is going down (negative momentum). It is the equally weighted average of the returns for two positive momentum portfolios for a region minus the average of the returns for two negative momentum portfolios.

The residuals of model (9) represent the measure of clustering due to investors responding to non-fundamental information:

$$CSAD_{NONFUND,t} = \varepsilon_t \tag{10}$$

It follows that the difference between the total $CSAD_t$ and the $CSAD_{NONFUND,t}$ represents the measure of clustering due to investors responding to fundamental information:

$$CSAD_{FUND,t} = CSAD_t - CSAD_{NONFUND,t} \tag{11}$$

Once $CSAD_{NONFUND,t}$ and $CSAD_{FUND,t}$ are estimated, the spurious and intentional herding can be separated by estimating the two regressions:

$$CSAD_{NONFUND,t} = \alpha + \gamma_1|R_{m,t}| + \gamma_2 R^2_{m,t} + e_t \tag{12}$$

$$CSAD_{FUND,t} = \alpha + \gamma_1|R_{m,t}| + \gamma_2 R^2_{m,t} + e_t \tag{13}$$

In models (12) and (13), herding is driven by, respectively, non-fundamental and fundamental information and is associated with a negative and statistically significant γ_2.

Moreover, we investigate the herding effects due to non-fundamental and fundamental information during the GFC and the EZC. This analysis facilitates an investigation into whether local corporates have better outcomes than foreign ones because of informational advantages as demonstrated by (Agudelo et al., 2019). We estimate the coefficients of the following two regressions that are similar to model (5):

$$CSAD_{NONFUND,t} = \alpha + \gamma_1 D^{Crisis}|R_{m,t}| + \gamma_2(1 - D^{Crisis})|R_{m,t}| + \gamma_3 D^{Crisis} R^2_{m,t} + \gamma_4(1 - D^{Crisis})R^2_{m,t} + e_t \tag{14}$$

$$CSAD_{FUND,t} = \alpha + \gamma_1 D^{Crisis}|R_{m,t}| + \gamma_2(1 - D^{Crisis})|R_{m,t}| + \gamma_3 D^{Crisis} R^2_{m,t} + \gamma_4(1 - D^{Crisis})R^2_{m,t} + e_t \tag{15}$$

where D^{Crisis} is a dummy variable that equals one during the crisis and zero otherwise. In the presence of the herding driven by non-fundamental and fundamental information during the crisis period, γ_3 is negative and statistically significant in models (14) and (15), respectively.[10]

[10] As a robustness check, we also test models (14) and (15) that consider a sub-sample with only observations from the crisis period analyzed. In particular, we test the following two regressions: $CSAD_{NONFUND,t} = \alpha + \gamma_1|R_{m,t}| + \gamma_2 R^2_{m,t} + e_t$, and $CSAD_{FUND,t} = \alpha + \gamma_1|R_{m,t}| + \gamma_2 R^2_{m,t} + e_t$. The results are both quantitatively and qualitatively similar to those disclosed in Section 4.5 and are available on request.

3. Data

For the empirical analysis we collect daily equity prices from all the constituent stocks of the S&P500 and the S&P Europe 350 for the US and Eurozone equity markets, respectively. The S&P500 index comprises the 500 leading companies and captures approximately 80% of the available market capitalization; while the S&P Europe 350 index is designed to reflect the Eurozone market and accounts for around 70% of the region's market capitalization.

In order to examine the herding that is related to the US (Eurozone) financial industries, namely banks, diversified financials, insurance, and real estate, we collect data on the daily equity prices from all the constituent stocks of the S&P 500 Banks Industry Group GICS Level 2 (S&P Europe 350 Banks Industry Group GICS Level 2), S&P 500 Diversified Financials Industry Group GICS Level 2 (S&P Europe 350 Diversified Financials Industry Group GICS Level 2), S&P 500 Insurance Industry Group GICS Level 2 (S&P Europe 350 Insurance Industry Group GICS Level 2), and the S&P 500 Real Estate Industry Group GICS Level 2 (S&P Europe 350 Real Estate Industry Group GICS Level 2). We are strongly motivated to consider the GICS framework[2] because it has become widely recognized by market participants worldwide and enables meaningful comparisons of sectors and industries across countries, regions, and the globe. Moreover, MSCI and Standard & Poor's review the entire framework annually to ensure an accurate representation of the marketplace.

The S&P Europe 350 is very similar to the STOXX Europe 600 index regarding its methodology, with similar total returns and volatility over the short and long term and with the correlation between the two indices equal to 100% and the tracking error less than 1% (Srivastava and Orzano, 2014).

The sample covers the period from January 3, 2005, to December 29, 2017. We calculate the daily returns as $R_{i,t} = ln(P_{i,t}/P_{i,t-1}) \times 100$. Following the literature, we construct the market portfolio return $R_{m,t}$ as the equally weighted average of the N returns in the aggregate market portfolio at time t.[11] The calculation of $R_{m,t}$ is required to estimate the CSAD as in model (3). The sample consists of 3,271 daily return observations for the US market, and 3,327 observations for the Eurozone. The equity prices are obtained from Bloomberg.

The economic and financial variables we consider in order to detect the herding due to market asymmetries in the US (Eurozone) market are the VIX (VSTOXX) index, the CDX (iTraxx) index, and the US (EU) TED spread. Their values are all taken from Bloomberg on a daily frequency. The daily returns of the SMB, HML, and MOM factors have been downloaded from Kenneth French's online data library.[12]

Table 1 presents the summary statistics of the US (Panel A) and Eurozone (Panel B) equity markets and the corresponding financial sector. The statistics show that the means and standard deviations of CSAD and R_m are similar across the US and Eurozone markets and sectors. However, the t-tests point to a significant difference in means only for the CSAD that excludes the equity markets. The US equity market and the financial sector reach maximum and minimum values, for CSAD and R_m, respectively. They are consistently higher and lower than the Eurozone. These values give the impression that given asymmetric market conditions, herding might exist in the US market.

4. Empirical evidence

4.1. Estimates of herding behavior

We investigate the existence of herding effects in the US and Eurozone equity markets and financial industries, based on model (4). Table 2 presents the estimated results from using daily data for the period from January 2005 to December 2017 for the US and the Eurozone, respectively. As stated earlier, a significantly negative value for the coefficient of $R^2_{m,t}$ (γ_2) is consistent with herding. The OLS results indicate a positive and significant coefficient for the linear term $|R_{m,t}|$ in all cases in both equity markets. This result confirms that the CSAD increases with the magnitude of market returns; this is a feature in line with standard asset pricing models. We find a positive and significant coefficient for the squared market returns ($R^2_{m,t}$) as well. Thus, our analysis based on the OLS estimates does not find any evidence of herding in the US and Eurozone equity markets and financial sectors. For the US, these results are consistent with the finding in the literature on herding (Christie and Huang, 1995; Chang et al., 2000; Gleason et al., 2004). However, the evidence regarding the presence of herding in the Eurozone is mixed in the literature. It mainly finds some evidence of herding in Portugal, Italy, and Greece (Economou et al., 2011) while more recent evidence highlight herding behaviour for CEE countries such as Bulgaria, Croatia, Czech Republic, Estonia, Hungary, Latvia, Lithuania and Slovenia but not for Poland and Romania (see Pochea et al., 2017).

After analyzing the quantile regression estimates, we do not find evidence for differences in the linear term. However, there is evidence that indicates the significance and the sign of the nonlinear term (γ_2) changes across different quantiles. In the US, apart from the insurance industry, this coefficient has a negative and significant value for high quantiles for all the cases analyzed. More specifically, γ_2 is positive and significant up to the 75*th* quantile and then switches to negative in the higher quantiles. In the Eurozone, we find the same result for the equity market and the insurance industry. There

[11] For robustness purposes, we have alternatively used a value-weighted market portfolio returns to test all the employed models in this study. Results are both quantitative and qualitative similar and are available upon request.

[12] Due to the increased synchronization of business cycles and co-movements of equity markets among European (including Eurozone) countries, we consider the SMB, HML, and MOM factors as computed for Europe.

Table 1
Descriptive statistics of CSAD and R_m for the US and Eurozone equity markets, financial sectors and industries.

	All US Equities		All Financial Industries		Banks		Diversified Financials		Insurance		Real Estate	
Panel A: US equity market												
	CSAD	R_m	CSAD	R_m	CSAD	R_m	CSAD	R_m	CSAD	R_m	CSAD	R_m
Mean	1.0764	0.0344	1.0031	0.0213	0.8206	−0.0002	0.9873	0.0300	0.8369	0.0198	0.8477	0.0267
Median	0.9387	0.0819	0.7760	0.0850	0.5458	0.0246	0.7907	0.0840	0.6050	0.0740	0.6756	0.0777
Maximum	5.3164	10.6113	8.3621	16.2744	11.4353	19.8522	8.3038	14.6941	11.9944	14.5828	7.9450	20.7379
Minimum	0.3723	−10.9360	0.2800	−17.9567	0.1324	−22.8871	0.2321	−16.4871	0.1095	−14.6277	0.2112	−20.6799
Std. deviation	0.5175	1.3229	0.7780	1.8666	0.9111	2.4463	0.7058	1.8844	0.8812	1.7686	0.6412	2.0250
N	3271		3271		3271		3271		3271		3271	
Panel B: Eurozone equity market												
	All Eurozone Equities		All Financial Industries		Banks		Diversified Financials		Insurance		Real Estate	
	CSAD	R_m	CSAD	R_m	CSAD	R_m	CSAD	R_m	CSAD	R_m	CSAD	R_m
Mean	1.0778	0.0227	1.0695	0.0005	1.1369	−0.0191	0.9304	0.0249	0.8715	0.0123	0.7861	0.0018
Median	0.9533	0.0749	0.8984	0.0376	0.9435	0.0158	0.7936	0.0894	0.6856	0.0649	0.6193	0.0389
Maximum	4.6379	8.5677	7.5325	12.6799	14.2199	15.4843	5.7161	14.9928	8.2454	13.3316	7.1109	9.8592
Minimum	0.4032	−8.0514	0.3644	−12.3752	0.2332	−15.8685	0.2067	−12.0040	0.1911	−13.9029	0.0000	−11.2021
Std. deviation	0.4551	1.2131	0.6358	1.6453	0.7608	1.9354	0.5343	1.5462	0.6732	1.6769	0.6232	1.5455
N	3327		3327		3327		3327		3327		3327	
	All Market Equities		All Financial Equities		Banks		Diversified Financials		Insurance		Real Estate	
H_0: CSAD	0.368		3.914***		15.499***		−3.458***		1.968**		−3.809***	
$H_0 : R_m$	−0.400		−0.391		−0.189		−0.126		−0.130		−0.555	

Notes: The table provides the descriptive statistics of daily cross-sectional absolute deviations (CSAD) and daily market returns (R_m) for the US and Eurozone equity markets (All US – Eurozone Equities), the corresponding financial sector (All Financial Industries) and industries (Banks, Diversified Financials, Insurance, and Real Estate), for the period from January 2005 to December 2017. The last two rows report the t-statistic of the t-tests, which investigate the equality (H_0: US = Eurozone) of the mean of the CSAD and R_m between the US and the Eurozone. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

Table 2
Estimates of herding for the US and Eurozone equity markets and financial industries, during the period from January 2005 to December 2017.

	Panel A: United States				Panel B: Eurozone			
	γ_1	γ_2	α	Adj. R^2	γ_1	γ_2	α	Adj. R^2
<u>All Market Equities</u>								
OLS	0.261***	1.568***	0.008***	46.98%	0.209***	2.765***	0.009***	41.52%
Quantile Regression								
τ = 10th	0.106***	1.936***	0.006***	12.57%	0.079***	3.088***	0.007***	13.42%
τ = 25th	0.112***	2.639***	0.007***	14.96%	0.092***	3.677***	0.007***	16.00%
τ = 50th	0.139***	3.729***	0.008***	20.40%	0.127***	4.212***	0.008***	19.97%
τ = 75th	0.214***	4.382***	0.009***	27.15%	0.211***	3.894***	0.009***	25.22%
τ = 95th	0.646***	−1.964**	0.012***	39.38%	0.581***	−1.229	0.012***	30.29%
τ = 99th	0.517***	−1.621*	0.021***	36.07%	0.685***	−4.308**	0.020***	31.02%
<u>Banks</u>								
OLS	0.278***	0.466*	0.004***	53.64%	0.220***	1.774*	0.008***	44.74%
Quantile Regression								
τ = 10th	0.077*	0.913	0.002***	14.31%	0.138***	1.011***	0.004***	15.54%
τ = 25th	0.114***	0.947***	0.003***	19.36%	0.164***	1.315***	0.005***	18.34%
τ = 50th	0.178***	0.993***	0.004***	26.04%	0.189***	1.797**	0.007***	21.93%
τ = 75th	0.301***	0.775***	0.005***	32.86%	0.182***	3.155***	0.010***	26.23%
τ = 95th	0.632***	0.039	0.009***	46.46%	0.328***	4.088***	0.015***	32.82%
τ = 99th	1.091***	−2.887***	0.016***	47.56%	0.465***	2.602***	0.025***	33.15%
<u>Diversified Financials</u>								
OLS	0.281***	0.576	0.006***	47.93%	0.198***	1.111***	0.007***	32.53%
Quantile Regression								
τ = 10th	0.132***	0.585***	0.004***	13.08%	0.067***	1.634***	0.004***	9.03%
τ = 25th	0.128***	1.716***	0.005***	16.37%	0.100***	1.390***	0.005***	10.54%
τ = 50th	0.180***	1.768***	0.006***	21.94%	0.141***	1.817***	0.006***	13.56%
τ = 75th	0.283***	1.186***	0.008***	29.52%	0.225***	1.343***	0.008***	17.93%
τ = 95th	0.540***	−0.293	0.012***	37.38%	0.466***	0.080	0.012***	26.10%
τ = 99th	0.991***	−3.839***	0.020***	38.54%	0.318	3.649	0.022***	25.54%
<u>Insurance</u>								
OLS	0.306***	2.001***	0.005***	60.21%	0.223***	1.969***	0.006***	46.32%
Quantile Regression								
τ = 10th	0.047	3.045*	0.003***	13.96%	0.073***	2.023***	0.004***	13.52%
τ = 25th	0.087***	3.349***	0.004***	19.63%	0.073***	3.113***	0.004***	16.95%
τ = 50th	0.143***	3.325***	0.005***	26.69%	0.121***	3.116***	0.005***	21.77%
τ = 75th	0.267***	3.502***	0.006***	35.47%	0.215***	2.599**	0.007***	27.15%
τ = 95th	0.809***	−0.483	0.008***	51.48%	0.725***	−1.440**	0.010***	37.49%
τ = 99th	1.175***	−3.346	0.016***	52.39%	0.992***	−3.847***	0.019***	36.35%
<u>Real Estate</u>								
OLS	0.274***	0.251	0.005***	58.90%	0.131***	2.708***	0.006***	25.92%
Quantile Regression								
τ = 10th	0.105***	0.701***	0.004***	15.47%	0.023	2.298*	0.003***	5.46%
τ = 25th	0.128***	1.050*	0.004***	19.49%	0.046***	2.698***	0.004***	8.25%
τ = 50th	0.174***	1.169	0.005***	26.10%	0.069***	3.466***	0.005***	10.78%
τ = 75th	0.206***	1.683*	0.007***	35.22%	0.141***	3.637***	0.007***	14.96%
τ = 95th	0.482***	−0.144	0.009***	49.70%	0.457***	1.714	0.012***	21.57%
τ = 99th	0.967***	−3.128***	0.013***	48.45%	0.603	0.996	0.022***	21.07%

Notes: The table reports the estimated coefficients for the benchmark model (4): $CSAD_t = \alpha + \gamma_1|R_{m,t}| + \gamma_2 R^2_{m,t} + e_t$, where $CSAD_t$ is the cross-sectional absolute deviation and $R_{m,t}$ is the market return. West and Newey (1987) correction is applied to estimate standard errors. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

is no evidence of herding effects in the other Eurozone financial industries, even for the high quantiles. Fig. 1 displays a more detailed picture of the quantile-varying features of γ_2.

Combining the information on quantile estimates from Table 2 with that in Fig. 1 (Panel A), we deduce that for the US equity market and its financial sector, the returns' dispersion increases in the lower range of quantiles but decreases in the upper quantile range. These results show that herding is more pronounced when the market experiences distressed conditions, and they can be interpreted as the investors changing their previous beliefs and becoming more likely to herd during these periods. Moreover, analyzing the estimates of γ_2 from Fig. 1 (Panel A), we can see that herding becomes more pronounced when the market becomes more turbulent as described by the increasing quantile. The results related to the US point to the presence of herding in the equity market and its financial industries except for the insurance industry in which the coefficient is negative but not statistically significant. In the Eurozone, the same conclusion is valid only for the equity market and the insurance industry. For the entire equity market, 1 (Panel B) also shows that due to the change in sign from positive to negative, the negative slope of the herding coefficient is much more pronounced in the Eurozone than in the US.

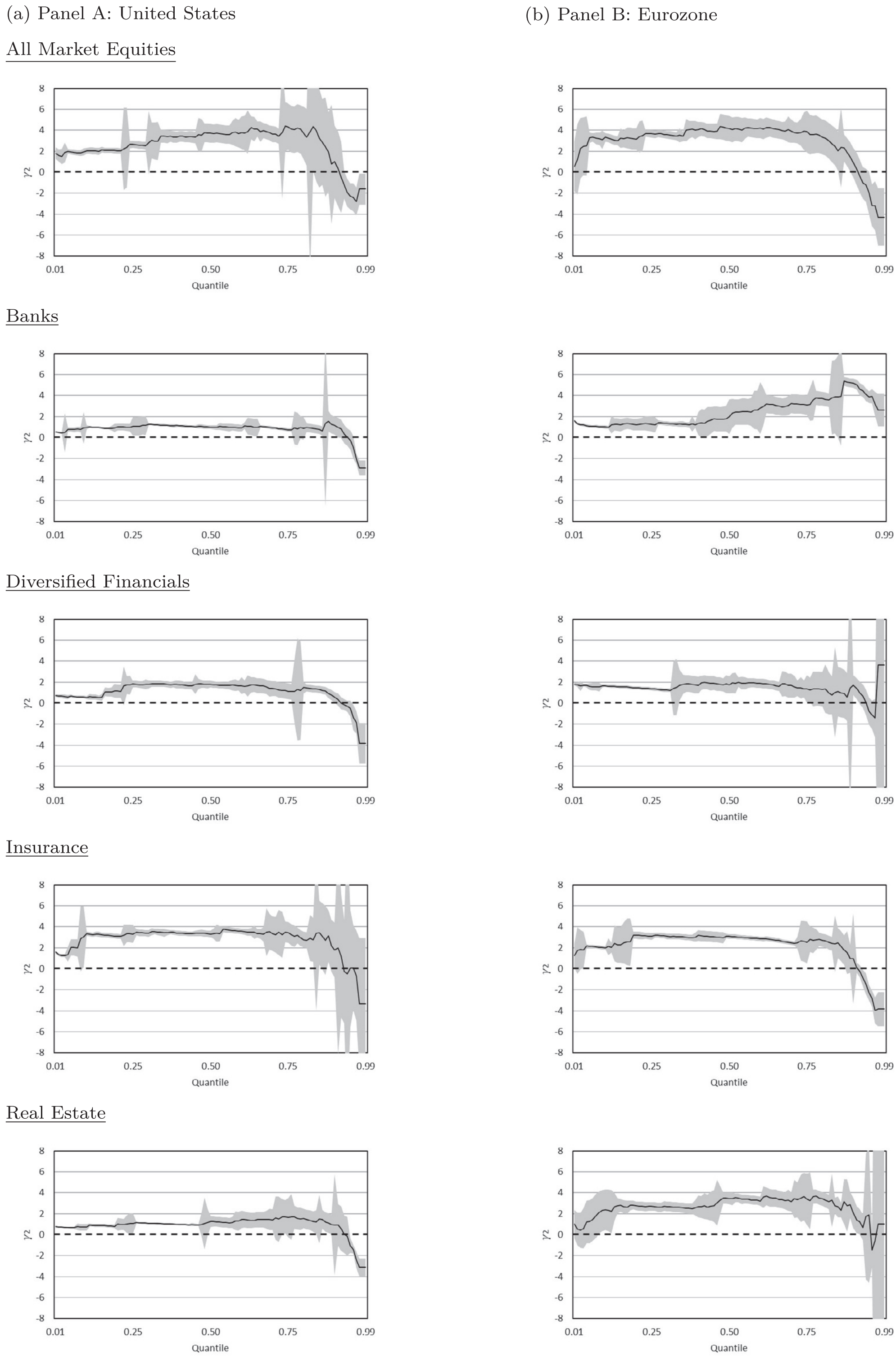

Fig. 1. Quantile regression estimates of herding for the US and Eurozone equity markets and financial industries, during the period from January 2005 to December 2017. *Notes:* The graphs show the quantile herding coefficient (γ_2) for the US (a) and Eurozone (b) equity markets and financial industries. The herding coefficient (γ_2) has been estimated from model (4): $CSAD_t = \alpha + \gamma_1|R_{m,t}| + \gamma_2 R^2_{m,t} + e_t$, where $CSAD_t$ is the cross-sectional absolute deviation and $R_{m,t}$ is the market return. The solid line represents the point estimates of γ_2, and the dashed lines bound the 95% confidence intervals..

For the financial industries, herding is more relevant for the US that is in contrast to a positive return dispersion for banks, diversified financials, and real estate for the entire range of quantiles in the Eurozone.

The results analyzed in this subsection illustrate the advantages of the quantile regression that can offer a more detailed analysis in order to detect herding.

4.2. Herding behavior during crises

The results in Section 4.1 motivate us to inspect whether the reduction in the returns' dispersion was more pronounced during the last two main financial crises. We use model (5) in order to test how the GFC, first, and then the EZC affect herding.

Table 3 presents the estimated coefficients. The OLS estimates for the herding coefficient γ_3 are significant and negative for both the US and the Eurozone equity markets and diversified financials. In the US, we find the same result the real estate industry. These findings support the hypothesis that herding was more pronounced during the GFC. Moreover, the quantile regression estimates demonstrate that the returns' dispersion strongly decreased during this period and that herding increased when the market became more turbulent across all the financial industries. In the Eurozone, the herding coefficient for banks decreases in the upper quantiles. However, the estimates are not statistically significant.

Fig. 2 plots the herding coefficient (γ_3) for the entire range of quantiles during the GFC. It shows the presence of herding during this period that strengthens the hypothesis that herding is more pronounced for the high range of quantiles. Starting from the median, γ_3 is negative and significant that provides evidence of herding during tranquil states of the market, and it decreases in the upper tail of the quantiles that confirms herding is more pronounced during distressed states of the market. The results for the US market in Table 3 and Fig. 2 (Panel A) show that during the GFC, investors also herded in the quantiles lower than the 75*th*. Moreover, Fig. 2 clearly shows that the slope of the herding coefficient is much steeper for US industries than for the Eurozone in the higher quantiles. This slope means that investors changed their beliefs when markets suffered extremely distressed conditions, with the Eurozone being impacted by the GFC more than the US in high quantiles. Based on the combined results for the Eurozone in Table 3 and Fig. 2 (Panel B), we conclude that herding is present and more pronounced mainly for high quantiles.

Table 4 presents the herding estimates for the US and Eurozone equity markets and financial sectors during the EZC. Contrary to the GFC, the results do not show the presence of herding in both equity markets. The OLS and quantile estimates indicate a positive value for the nonlinear term (γ_3). Analyzing the financial sector, we find that the herding coefficient is negative and significant for the middle range of quantiles for banks in both the US and Eurozone. The OLS estimate provides evidence of herding in the insurance industry for the US up to the 95*th* quantile, while in the Eurozone, it shows that the real estate industry has herding during this period in the lower quantiles. Fig. 3 plots the herding coefficient (γ_3) estimated during the EZC for the entire range of quantiles. For the γ_3, rather than being negative and significant only when the market is in extremely distressed conditions like during the GFC, it is negative for almost all the quantiles for banks and not necessarily in the high quantiles for the other financial industries. These findings mean that during the EZC, herding was pronounced during tranquil market states and mainly involved the banking industries in both the Eurozone and the US. This crisis affects the other industries to a lesser extent, with the results pointing to herding in the diversified financials in the US and the insurance and real estate industries in the Eurozone.

These results provide new insights into the US and Eurozone equity markets and financial sectors. They indicate that during crises, the mutual imitation that leads to a convergence of actions may start even without extremely distressed conditions.

4.3. Herding behavior under asymmetric market conditions

We focus on three sub-cases to investigate the herding under asymmetric market conditions that are captured by model (6). Tables 5–7 present the results related to any significant herding effects during asymmetric market conditions.

4.3.1. Asymmetric equity market volatility

We present the first set of our results in Table 5. The implied market volatility is used as a measure of investors' sentiment (see, e.g.; Baker and Wurgler, 2006). The OLS estimates show that there is no evidence of herding during higher and lower volatility conditions in both markets and the industries. However, the quantile regression analysis shows evidence of herding during higher volatility conditions for the US equity market and its financial sector except for the insurance industry. The herding exists for the high quantiles that indicates it is more likely during cases of higher volatility.

Overall, for the US market, we find evidence that herding is likely to occur more in higher (γ_3) than in lower (γ_4) conditions of market volatility, which is indicative of the asymmetry of herding. Analyzing the quantile regression coefficients, we observe that γ_3 is negative and significant over a wider distribution range of quantiles compared to γ_4. This range means that herding is more pronounced during distressed markets due to conditions of high volatility. In cases where we find herding for both conditions of the market, we conduct an equality test for the two herding coefficients ($\gamma_3 = \gamma_4$) to confirm that herding asymmetry is more apparent during conditions of higher volatility.

Table 3
Estimates of herding for the US and Eurozone equity markets and financial industries, during the GFC.

	Panel A: United States						Panel B: Eurozone					
	γ_1	γ_2	γ_3	γ_4	α	Adj. R^2	γ_1	γ_2	γ_3	γ_4	α	Adj. R^2
<u>All Market Equities</u>												
OLS	0.528***	0.019	−1.842***	3.430***	0.009***	62.85%	0.529***	−0.007	−2.270**	5.947***	0.009***	57.65%
Quantile Regression												
τ = 10th	0.283***	0.081***	0.256	1.678***	0.006***	18.54%	0.259***	0.070***	1.006***	2.379**	0.007***	18.03%
τ = 25th	0.390***	0.076***	−0.509**	1.817***	0.007***	23.26%	0.336***	0.064***	0.500	3.099***	0.008***	22.51%
τ = 50th	0.502***	0.063***	−1.519***	2.764***	0.008***	31.27%	0.494***	0.053***	−1.568***	4.243***	0.009***	29.83%
τ = 75th	0.687***	0.038	−3.429***	3.947**	0.010***	42.05%	0.748***	0.023	−5.150***	6.492***	0.010***	38.92%
τ = 95th	0.942***	−0.229	−5.730***	12.889*	0.014***	55.23%	1.229***	−0.118	−10.883***	11.481***	0.013***	50.48%
τ = 99th	0.814***	−1.161**	−5.229**	48.094*	0.022***	52.07%	1.691**	−0.291	−16.271**	14.930	0.017***	51.39%
<u>Banks</u>												
OLS	0.413***	0.024	−0.439	1.961***	0.005***	61.79%	0.382***	0.139***	0.528	1.697***	0.008***	49.44%
Quantile Regression												
τ = 10th	0.203***	0.040***	−0.049	1.274***	0.003***	18.09%	0.194***	0.108***	0.598***	1.222***	0.005***	16.59%
τ = 25th	0.270***	0.052***	−0.131	1.478***	0.003***	24.72%	0.271***	0.127***	0.366	1.699***	0.006***	19.86%
τ = 50th	0.397***	0.085***	−0.545**	1.217***	0.004***	33.52%	0.344***	0.180***	0.419	1.308***	0.007***	23.67%
τ = 75th	0.566***	0.098*	−0.900***	1.267	0.006***	42.29%	0.508***	0.164***	−0.352	2.343***	0.009***	29.46%
τ = 95th	0.947***	−0.023	−2.162***	4.218**	0.011***	57.36%	0.892***	−0.027	−0.609	5.673	0.016***	42.33%
τ = 99th	1.613**	−0.491	−5.235*	13.071	0.019***	61.04%	1.440**	−0.585	−4.351	19.712	0.026***	47.75%
<u>Diversified Financials</u>												
OLS	0.474***	0.031	−1.169***	2.440**	0.008***	59.56%	0.360***	0.000	−0.721*	3.974***	0.008***	40.96%
Quantile Regression												
τ = 10th	0.300***	0.074***	−0.570***	0.914***	0.004***	19.47%	0.176***	0.026	0.339	2.301***	0.004***	11.25%
τ = 25th	0.376***	0.085***	−0.944***	1.191**	0.005***	23.86%	0.252***	0.030	−0.423	2.294***	0.005***	13.97%
τ = 50th	0.462***	0.046***	−1.516***	2.773***	0.007***	30.52%	0.340***	0.008	−0.547	3.950***	0.007***	18.79%
τ = 75th	0.597***	0.058**	−1.664***	3.255***	0.008***	38.41%	0.472***	0.035	−1.252***	3.585***	0.009***	25.31%
τ = 95th	1.158***	−0.111	−5.077***	8.165*	0.013***	51.84%	0.822***	−0.115	−3.793***	11.780	0.013***	36.05%
τ = 99th	1.349***	−0.496	−6.340***	19.642	0.019***	56.64%	0.640***	−1.030***	−3.043***	42.265***	0.024***	36.24%
<u>Insurance</u>												
OLS	0.525***	0.081**	−0.046	2.066**	0.006***	67.89%	0.451***	0.026	−0.337	3.428***	0.006***	56.46%
Quantile Regression												
τ = 10th	0.172***	0.053***	2.305***	1.588***	0.003***	18.42%	0.182***	0.054***	1.201***	1.878***	0.004***	16.93%
τ = 25th	0.242***	0.061***	1.887***	1.872***	0.004***	24.17%	0.205***	0.046**	1.868***	2.637***	0.005***	20.32%
τ = 50th	0.427***	0.092***	0.794**	2.163***	0.005***	32.39%	0.341***	0.051***	0.760**	3.313***	0.006***	26.72%
τ = 75th	0.648***	0.095***	−0.338	2.834**	0.006***	43.52%	0.661***	0.091***	−2.048**	3.061***	0.007***	35.17%
τ = 95th	1.357***	0.131**	−4.790***	3.068**	0.010***	61.18%	1.282***	0.007	−5.524***	5.434	0.011***	53.84%
τ = 99th	2.510***	−0.392	−13.061***	21.010	0.018***	65.84%	2.067	−0.387	−11.466	21.104	0.017	54.30%
<u>Real Estate</u>												
OLS	0.372***	0.041*	−0.545***	1.549***	0.006***	67.63%	0.412***	−0.095***	−1.429	4.988***	0.007***	38.10%
Quantile Regression												
τ = 10th	0.212***	0.049***	0.116***	1.218***	0.004***	21.59%	0.186*	0.050*	−0.402	0.159	0.003***	8.32%
τ = 25th	0.260***	0.069***	−0.132**	0.927***	0.005***	26.32%	0.277***	0.006	−1.020	2.430**	0.004***	12.05%
τ = 50th	0.321***	0.077***	−0.101	0.979	0.006***	33.6%	0.388***	−0.048***	−1.481*	4.554***	0.006***	17.33%
τ = 75th	0.452***	0.054	−0.919***	2.110*	0.007***	43.73%	0.667***	−0.016	−3.871***	4.136***	0.007***	25.00%
τ = 95th	0.848***	−0.078	−2.490***	5.875	0.011***	59.72%	1.078***	−0.431***	−6.525***	17.920***	0.014***	37.91%
τ = 99th	1.251	−0.209	−4.551	7.675	0.016***	62.33%	1.279***	−1.050	−9.171***	35.464	0.024***	40.59%

Notes: The table reports the estimated coefficients for the augmented model (5): $CSAD_t = \alpha + \gamma_1 D^{Crisis}|R_{m,t}| + \gamma_2(1 - D^{Crisis})|R_{m,t}| + \gamma_3 D^{Crisis} R^2_{m,t} + \gamma_4(1 - D^{Crisis})R^2_{m,t} + e_t$, where $CSAD_t$ is the cross-sectional absolute deviation, $R_{m,t}$ is the market return and D^{Crisis} is a dummy variable that equals one during the GFC and zero otherwise. West and Newey (1987) correction is applied to estimate standard errors. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

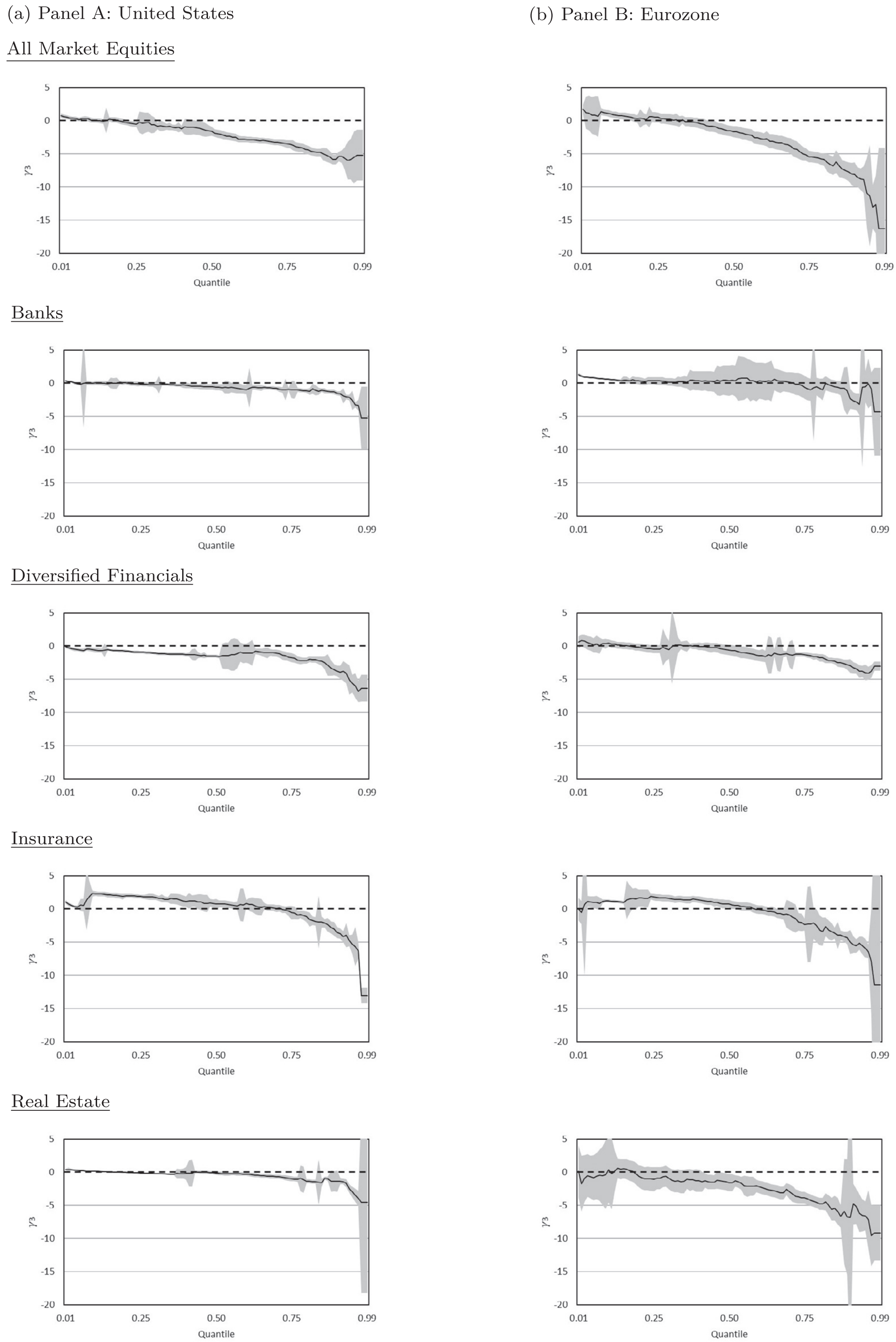

Fig. 2. Quantile regression estimates of herding for the US and Eurozone equity markets and financial industries, during the GFC. *Notes:* The graphs show the quantile herding coefficient (γ_3) for the U.S. (a) and Eurozone (b) equity markets and financial industries during the GFC. The herding coefficient (γ_3) has been estimated from model (5): $CSAD_t = \alpha + \gamma_1 D^{Crisis}|R_{m,t}| + \gamma_2(1 - D^{Crisis})|R_{m,t}| + \gamma_3 D^{Crisis} R^2_{m,t} + \gamma_4(1 - D^{Crisis})R^2_{m,t} + e_t$, where $CSAD_t$ is the cross-sectional absolute deviation, $R_{m,t}$ is the market return and D^{Crisis} is a dummy variable that equals one during the GFC and zero otherwise. The solid line represents the point estimates of γ_3, and the dashed lines bound the 95% confidence intervals..

Table 4
Estimates of herding for the US and Eurozone equity markets and financial industries, during the EZC.

	Panel A: United States						Panel B: Eurozone					
	γ_1	γ_2	γ_3	γ_4	α	Adj. R^2	γ_1	γ_2	γ_3	γ_4	α	Adj. R^2
<u>All Market Equities</u>												
OLS	0.138***	0.332***	0.969***	0.925*	0.008***	50.76%	0.195***	0.241***	0.895	2.619***	0.009***	42.66%
Quantile Regression												
τ = 10th	0.134***	0.123***	0.945***	1.878***	0.006***	13.00%	0.147***	0.065***	1.251	3.426***	0.007***	14.01%
τ = 25th	0.127***	0.136***	0.992***	3.267***	0.007***	16.22%	0.159***	0.093***	1.173*	3.713***	0.007***	16.42%
τ = 50th	0.130***	0.184***	0.783***	3.263***	0.008***	22.43%	0.196***	0.121***	0.481	4.766***	0.008***	20.52%
τ = 75th	0.106***	0.307***	2.011**	2.803*	0.009***	30.13%	0.249***	0.257***	−0.011	3.935***	0.009***	26.08%
τ = 95th	−0.040	0.739***	6.653*	−3.646***	0.012***	44.16%	0.169**	0.735***	3.219	−3.470***	0.012***	33.92%
τ = 99th	−0.657***	0.527***	18.721**	−1.736*	0.021***	40.97%	−0.326***	0.895***	12.468***	−7.223***	0.019***	35.98%
<u>Banks</u>												
OLS	0.260***	0.317***	−1.234	0.257	0.004***	54.92%	0.297***	0.213***	−0.380*	2.074**	0.008***	45.53%
Quantile Regression												
τ = 10th	0.178***	0.059***	−0.796*	1.092***	0.002***	15.90%	0.192***	0.100***	0.581***	1.643***	0.005***	16.51%
τ = 25th	0.212***	0.082***	−1.442**	1.395***	0.003***	20.71%	0.280***	0.130***	−0.600	1.681***	0.006***	19.83%
τ = 50th	0.283***	0.168***	−2.266***	1.199***	0.004***	27.13%	0.311***	0.127**	−0.406**	3.383*	0.007***	23.46%
τ = 75th	0.306***	0.337***	−1.862	0.620***	0.005***	33.92%	0.356***	0.124*	−0.862***	4.525**	0.009***	27.52%
τ = 95th	0.275***	0.668***	−0.819**	−0.228	0.009***	48.51%	0.344***	0.389***	−0.632	3.658***	0.015***	34.34%
τ = 99th	0.090	1.133***	0.185	−3.100***	0.017***	51.29%	−0.225	0.664***	7.276	1.180	0.025***	37.83%
<u>Diversified Financials</u>												
OLS	0.176***	0.339***	−0.123	0.171	0.006***	50.71%	0.174***	0.220***	0.241	0.931**	0.007***	33.05%
Quantile Regression												
τ = 10th	0.184***	0.141***	−0.868	0.603***	0.004***	13.32%	0.080***	0.062***	1.450***	1.686***	0.004***	9.06%
τ = 25th	0.162***	0.157***	−0.094	1.735***	0.005***	17.49%	0.115***	0.104***	0.895*	1.363***	0.005***	10.56%
τ = 50th	0.159***	0.214***	−0.098	1.566***	0.006***	23.45%	0.173***	0.149***	−0.118	1.784***	0.006***	13.72%
τ = 75th	0.151***	0.343***	0.897	0.655***	0.008***	31.60%	0.238***	0.256***	−0.849	1.334	0.008***	18.38%
τ = 95th	0.034	0.645***	3.262	−1.035*	0.012***	40.74%	0.328***	0.564***	−2.146*	−0.937	0.012***	27.45%
τ = 99th	−0.348*	1.089***	9.949*	−4.521***	0.020***	44.07%	−0.630**	0.518	25.668***	−0.013	0.022***	29.34%
<u>Insurance</u>												
OLS	0.258***	0.384***	−1.070**	1.421**	0.004***	62.64%	0.167***	0.275***	1.096	1.611***	0.006***	47.98%
Quantile Regression												
τ = 10th	0.133***	0.049***	−0.088	3.411***	0.003***	15.78%	0.121***	0.070***	0.471	2.175***	0.004***	13.78%
τ = 25th	0.176***	0.098***	0.101	3.417***	0.004***	20.98%	0.135***	0.084***	0.702	3.123***	0.004***	17.59%
τ = 50th	0.205***	0.164***	−0.272	3.643***	0.005***	27.73%	0.173***	0.136***	0.816	3.012***	0.005***	22.31%
τ = 75th	0.252***	0.370***	−0.927***	2.516***	0.006***	37.29%	0.226***	0.248***	0.336	2.701***	0.007***	27.83%
τ = 95th	0.341***	0.917***	−2.252***	−1.259	0.008***	54.14%	0.217***	0.883***	1.247***	−2.586***	0.010***	41.91%
τ = 99th	−0.172	1.273***	7.537	−4.541***	0.017***	56.27%	−0.326	1.192***	11.793*	−5.216***	0.017***	42.03%
<u>Real Estate</u>												
OLS	0.167***	0.309***	−0.346	0.023	0.005***	61.17%	0.131***	0.171***	−0.988*	2.400***	0.006***	27.62%
Quantile Regression												
τ = 10th	0.108***	0.113***	0.374	0.852***	0.004***	15.89%	0.098***	0.008	−1.300*	3.006***	0.003***	6.76%
τ = 25th	0.107***	0.142***	0.419*	1.046***	0.004***	20.52%	0.148***	0.058***	−1.865***	2.710***	0.003***	9.09%
τ = 50th	0.148***	0.208***	−0.081	0.945***	0.005***	27.55%	0.145***	0.094***	−1.452	3.306***	0.005***	11.59%
τ = 75th	0.154***	0.281***	−0.178	0.944	0.006***	37.16%	0.141***	0.182***	−0.233	3.450***	0.007***	15.84%
τ = 95th	0.146***	0.578***	−0.459	−1.162***	0.009***	52.29%	0.181	0.626***	−0.816	−1.065	0.011***	23.53%
τ = 99th	0.028	1.054***	0.994	−3.555***	0.014***	51.89%	−0.335	0.770	14.242	−2.943	0.022***	24.51%

Notes: The table reports the estimated coefficients for the augmented model (5): $CSAD_t = \alpha + \gamma_1 D^{Crisis}|R_{m,t}| + \gamma_2(1 - D^{Crisis})|R_{m,t}| + \gamma_3 D^{Crisis} R^2_{m,t} + \gamma_4(1 - D^{Crisis})R^2_{m,t} + e_t$, where $CSAD_t$ is the cross-sectional absolute deviation, $R_{m,t}$ is the market return and D^{Crisis} is a dummy variable that equals one during the EZC and zero otherwise. West and Newey (1987) correction is applied to estimate standard errors. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

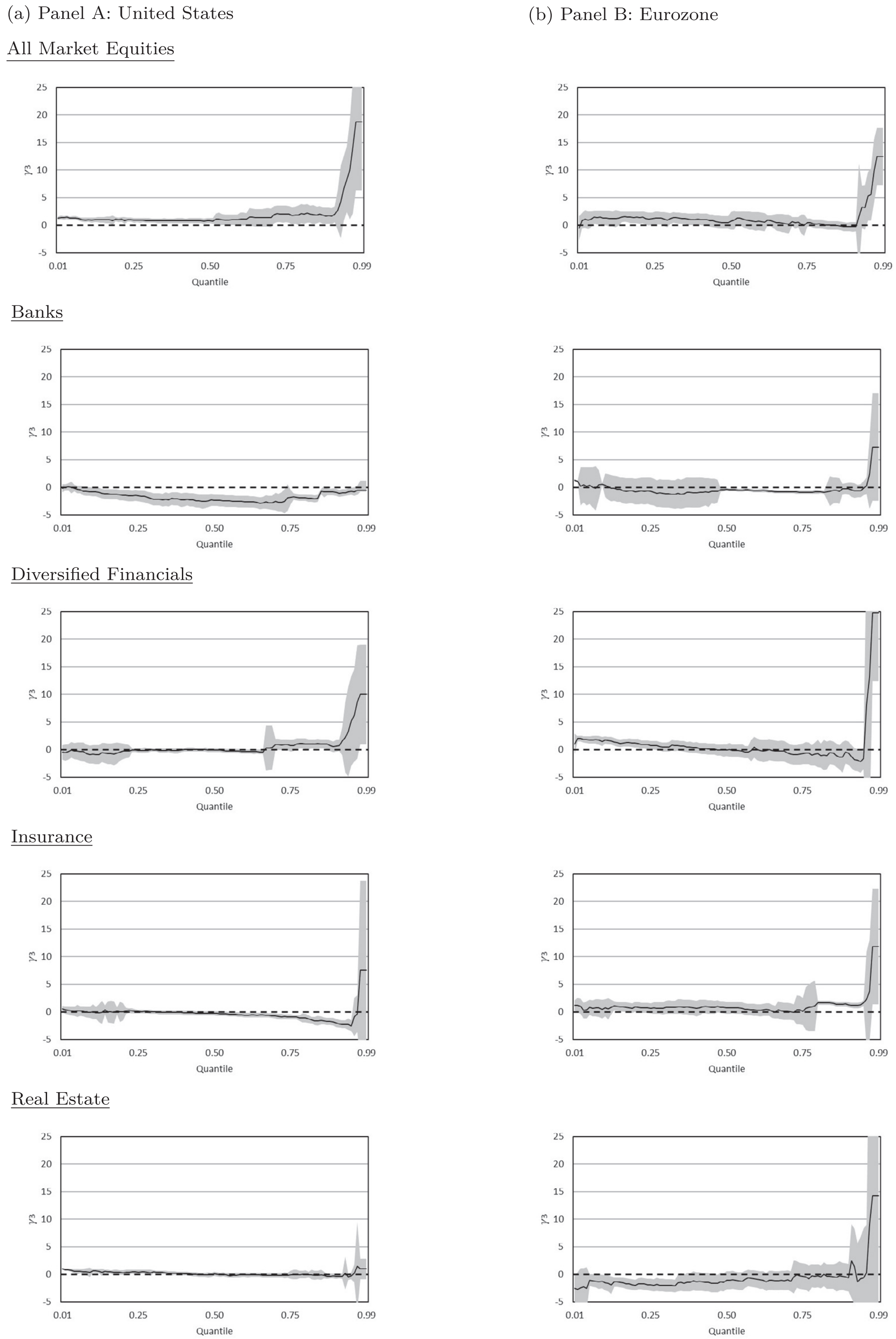

Fig. 3. Quantile regression estimates of herding for the US and Eurozone equity markets and financial industries, during the EZC. *Notes:* The graphs show the quantile herding coefficient (γ_3) for the U.S. (a) and Eurozone (b) equity markets and financial industries during the EZC. The herding coefficient (γ_3) has been estimated from model (5): $CSAD_t = \alpha + \gamma_1 D^{Crisis}|R_{m,t}| + \gamma_2(1 - D^{Crisis})|R_{m,t}| + \gamma_3 D^{Crisis} R^2_{m,t} + \gamma_4(1 - D^{Crisis})R^2_{m,t} + e_t$, where $CSAD_t$ is the cross-sectional absolute deviation, $R_{m,t}$ is the market return and D^{Crisis} is a dummy variable that equals one during the EZC and zero otherwise. The solid line represents the point estimates of γ_3, and the dashed lines bound the 95% confidence intervals..

Table 5
Estimates of herding for the US and Eurozone equity markets and financial industries, during days of high and low volatility.

	Panel A: United States							Panel B: Eurozone						
	γ_1	γ_2	γ_3	γ_4	α	Adj. R^2	$\gamma_3 = \gamma_4$	γ_1	γ_2	γ_3	γ_4	α	Adj. R^2	$\gamma_3 = \gamma_4$
All Market Equities														
OLS	0.236***	0.248***	1.532***	3.018***	0.008***	47.77%	−1.486	0.183***	0.244***	3.038***	2.731**	0.009***	41.88%	0.307
Quantile Regression														
τ = 10th	0.075***	0.089***	2.168***	3.358**	0.006***	13.46%	−1.190	0.062***	0.097***	3.418***	3.730***	0.007***	14.11%	−0.312
τ = 25th	0.102***	0.119***	2.139***	3.523***	0.007***	15.73%	−1.385***	0.086***	0.118***	3.346***	4.032***	0.007***	16.52%	−0.686
τ = 50th	0.125***	0.140***	3.393***	4.544***	0.008***	20.81%	−1.151**	0.114***	0.136***	3.996***	5.012***	0.008***	20.15%	−1.016
τ = 75th	0.192***	0.202***	3.519***	6.476***	0.009***	27.83%	−2.957*	0.201***	0.263***	3.827***	3.481***	0.009***	25.46%	0.346
τ = 95th	0.543**	0.674***	−0.653	−2.300***	0.012***	39.51%	1.647	0.517***	0.724***	−0.312	−5.321***	0.012***	30.50%	5.009***
τ = 99th	0.533***	0.442***	−2.430***	−0.767	0.021***	36.26%	−1.663*	0.704***	0.558***	−4.660***	−4.459***	0.020***	31.43%	−0.201
Banks														
OLS	0.259***	0.305***	0.635**	0.204	0.004***	53.73%	0.431	0.193***	0.259***	1.996**	1.384*	0.008***	44.91%	0.612
Quantile Regression														
τ = 10th	0.075***	0.093***	0.735***	0.923***	0.002***	14.79%	−0.188	0.120***	0.152***	1.078***	1.187***	0.005***	16.17%	−0.108
τ = 25th	0.086***	0.137***	1.293**	0.691***	0.003***	19.81%	0.602	0.143***	0.188***	1.491***	1.518***	0.005***	18.77%	−0.027
τ = 50th	0.146***	0.202***	1.156***	0.713***	0.004***	26.32%	0.443**	0.166***	0.191***	1.991**	2.285***	0.007***	22.04%	−0.294
τ = 75th	0.265***	0.351***	1.055	0.087	0.005***	33.07%	0.968	0.127***	0.228***	4.162***	2.440***	0.010***	26.51%	1.721**
τ = 95th	0.610***	0.617***	0.183	0.444	0.009***	46.45%	−0.261	0.237***	0.536***	4.758***	0.237	0.015***	33.46%	4.521
τ = 99th	1.287***	0.877***	−3.751***	−2.059	0.016***	48.32%	−1.692	0.478***	0.799***	2.531**	−3.852***	0.025***	33.34%	6.382***
Diversified Financials														
OLS	0.277***	0.295***	0.692	0.255	0.006***	47.98%	0.438	0.176***	0.204***	1.063***	1.915***	0.007***	33.30%	−0.852
Quantile Regression														
τ = 10th	0.131***	0.157***	0.597***	0.281**	0.004***	13.26%	0.316**	0.058***	0.064***	1.608***	2.485***	0.004***	9.58%	−0.877***
τ = 25th	0.121***	0.139***	1.787**	1.732***	0.005***	16.52%	0.055	0.088***	0.116***	1.401***	2.114***	0.005***	11.22%	−0.713*
τ = 50th	0.160***	0.211***	1.930***	1.159***	0.006***	22.19%	0.770***	0.123	0.131***	1.505	2.848**	0.007***	13.80%	−1.343
τ = 75th	0.266***	0.296***	1.338***	0.988	0.008***	29.62%	0.350	0.201***	0.216***	1.422***	3.125***	0.008***	18.30%	−1.704***
τ = 95th	0.598***	0.568***	−0.693	−1.351	0.012***	37.52%	0.658	0.456***	0.542***	−0.953*	−0.478	0.012***	26.44%	−0.475
τ = 99th	1.193***	0.571***	−5.282***	−2.063**	0.020***	40.28%	−3.220*	0.245	0.617	3.405	−0.030	0.021***	26.45%	3.435
Insurance														
OLS	0.312***	0.291***	1.843**	2.383***	0.005***	60.25%	−0.539	0.200***	0.265***	2.217***	1.475**	0.006***	46.50%	0.742
Quantile Regression														
τ = 10th	0.072***	0.058***	1.965***	3.354***	0.003***	14.82%	−1.389***	0.059***	0.088***	2.127***	2.091***	0.004***	13.96%	0.036
τ = 25th	0.081***	0.110***	3.238***	3.280***	0.004***	19.88%	−0.043	0.063***	0.096***	3.192***	2.995***	0.004***	17.27%	0.197
τ = 50th	0.135***	0.142***	3.301***	3.784***	0.005***	26.94%	−0.483***	0.097***	0.153***	3.290***	2.588***	0.005***	22.05%	0.702**
τ = 75th	0.241***	0.288***	3.758***	3.035***	0.006***	35.53%	0.723	0.193***	0.237***	2.890**	2.628	0.007***	27.23%	0.262
τ = 95th	0.847***	0.773***	0.025	−0.713	0.008***	51.70%	0.737	0.618***	0.918***	1.043	−4.554***	0.009***	38.05%	5.597
τ = 99th	1.266**	1.054	−4.434	0.434	0.017***	52.47%	−4.868	1.007***	1.125***	−3.932***	−7.061***	0.018***	36.62%	3.129*
Real Estate														
OLS	0.263***	0.288***	0.205	0.274	0.005***	59.16%	−0.069	0.089***	0.197***	3.409***	1.621**	0.006***	26.64%	1.788*
Quantile Regression														
τ = 10th	0.100***	0.123***	0.665***	0.810***	0.004***	16.51%	−0.146	0.027	0.050	2.159	2.051*	0.003***	5.93%	0.108
τ = 25th	0.116***	0.144***	0.830***	1.055***	0.004***	20.17%	−0.225	0.034**	0.058***	2.892***	2.700***	0.004***	8.53%	0.192
τ = 50th	0.170***	0.188***	0.848***	1.152***	0.005***	26.47%	−0.304	0.048***	0.098***	3.755***	3.135***	0.005***	11.04%	0.620
τ = 75th	0.207***	0.250***	1.304**	1.248	0.006***	35.50%	0.055	0.104***	0.223***	4.216***	2.482**	0.007***	15.44%	1.734
τ = 95th	0.523***	0.506***	−0.509	−0.805***	0.009***	49.82%	0.296	0.362***	0.537***	2.109	0.237	0.012***	21.87%	1.872
τ = 99th	0.984***	1.076***	−3.839***	−3.654***	0.013***	48.62%	−0.185	0.280	0.696*	10.62	−1.097	0.022***	21.63%	11.717

Notes: The table reports the estimated coefficients for the augmented model (6): $CSAD_t = \alpha + \gamma_1 D^{High}|R_{m,t}| + \gamma_2(1 - D^{High})|R_{m,t}| + \gamma_3 D^{High} R^2_{m,t} + \gamma_4(1 - D^{High})R^2_{m,t} + e_t$, where $CSAD_t$ is the cross-sectional absolute deviation, $R_{m,t}$ is the market return and D^{High} is a dummy variable that equals one in case of high volatility market conditions and zero otherwise. The last column of Panel A and B reports the result for the hypothesis test $\gamma_3 = \gamma_4$. West and Newey (1987) correction is applied to estimate standard errors. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

Table 6
Estimates of herding for the US and Eurozone equity markets and financial industries, during days of high and low credit deterioration.

	Panel A: United States							Panel B: Eurozone						
	γ_1	γ_2	γ_3	γ_4	α	Adj. R^2	$\gamma_3 = \gamma_4$	γ_1	γ_2	γ_3	γ_4	α	Adj. R^2	$\gamma_3 = \gamma_4$
<u>All Market Equities</u>														
OLS	0.262***	0.263***	1.307**	2.047**	0.008***	47.16%	−0.740	0.19***	0.179***	2.825***	5.361***	0.009***	41.98%	−2.536*
Quantile Regression														
τ = 10th	0.104***	0.135***	1.902***	1.913***	0.006***	13.04%	−0.011	0.063***	0.060	3.378***	5.146**	0.007***	13.76%	−1.768
τ = 25th	0.114***	0.120***	1.978***	3.512***	0.007***	15.35%	−1.534**	0.073***	0.062***	3.867***	6.673***	0.008***	16.50%	−2.806**
τ = 50th	0.146***	0.130***	3.135***	4.658***	0.008***	20.59%	−1.523**	0.121***	0.113***	3.875***	6.073***	0.008***	20.37%	−2.198**
τ = 75th	0.245***	0.192***	2.773***	5.316***	0.009***	27.46%	−2.543	0.201***	0.149*	3.677***	10.049*	0.010***	25.61%	−6.372
τ = 95th	0.734***	0.575***	−3.557***	−1.093	0.012***	39.62%	−2.464***	0.547***	0.557***	−0.744	−0.049	0.012***	30.22%	−0.695
τ = 99th	0.559***	0.342***	−2.773***	0.390	0.021***	36.52%	−3.163***	0.678***	0.461	−4.411**	−1.771	0.021***	31.63%	−2.640
<u>Banks</u>														
OLS	0.256***	0.298***	0.714***	0.285	0.004***	53.72%	0.429	0.222***	0.158***	1.082***	4.027***	0.008***	47.31%	−2.945***
Quantile Regression														
τ = 10th	0.060***	0.092***	1.203***	0.705***	0.002***	14.70%	0.498*	0.128***	0.117***	1.030***	2.218***	0.005***	16.33%	−1.188***
τ = 25th	0.089***	0.125***	1.375***	0.744***	0.003***	19.72%	0.631***	0.156***	0.160***	1.148***	2.375***	0.005***	18.98%	−1.227*
τ = 50th	0.159***	0.192***	1.036***	1.059***	0.004***	26.26%	−0.023	0.195***	0.153***	1.252***	3.636***	0.007***	22.42%	−2.384***
τ = 75th	0.258***	0.324***	1.256	0.674***	0.005***	32.94%	0.582	0.161***	0.129***	3.084***	5.710***	0.010***	26.66%	−2.626***
τ = 95th	0.633***	0.630***	0.031	−0.098	0.009***	46.42%	0.129	0.254*	0.386***	5.269**	3.680***	0.015***	32.91%	1.589
τ = 99th	1.338***	0.874***	−4.702***	−1.941***	0.016***	49.19%	−2.761***	0.755***	0.447	−2.723	2.732	0.025***	33.46%	−5.455
<u>Diversified Financials</u>														
OLS	0.272***	0.288***	0.772	0.384	0.006***	47.98%	0.388	0.18***	0.166***	1.063***	2.989***	0.007***	33.31%	−1.926**
Quantile Regression														
τ = 10th	0.112*	0.147***	1.075	0.496***	0.004***	13.34%	0.579	0.061***	0.080***	1.582***	1.776***	0.004***	9.25%	−0.194
τ = 25th	0.119***	0.151	1.939***	1.084	0.005***	16.50%	0.855	0.085***	0.085**	1.482***	3.410*	0.005***	10.89%	−1.928
τ = 50th	0.180***	0.193***	1.613***	1.710***	0.006***	22.03%	−0.097	0.116***	0.118***	1.951***	3.484***	0.007***	14.07%	−1.533**
τ = 75th	0.296***	0.255***	1.065**	1.436	0.008***	29.67%	−0.371	0.2***	0.179***	1.427***	3.504***	0.008***	18.40%	−2.077***
τ = 95th	0.637***	0.494***	−0.972	−0.172	0.012***	37.61%	−0.800	0.523***	0.373***	−1.524***	6.054	0.012***	26.35%	−7.578
τ = 99th	1.165***	0.656***	−5.056***	−1.997**	0.020***	39.63%	−3.059**	0.272	0.002	2.095	15.007	0.023***	26.39%	−12.912
<u>Insurance</u>														
OLS	0.277***	0.367***	2.303***	1.359	0.004***	60.43%	0.944	0.216***	0.233***	2.021***	1.967*	0.006***	46.30%	0.054
Quantile Regression														
τ = 10th	0.040***	0.092***	3.390***	1.168***	0.003***	14.29%	2.222***	0.07***	0.071***	2.045***	2.162***	0.004***	13.62%	−0.117
τ = 25th	0.075***	0.117***	3.590***	2.814***	0.004***	19.95%	0.776***	0.072***	0.080***	3.119***	2.993***	0.004***	17.01%	0.126
τ = 50th	0.130***	0.147***	3.415***	3.939***	0.005***	26.94%	−0.524	0.104***	0.128***	3.096***	3.479***	0.005***	22.03%	−0.383
τ = 75th	0.275***	0.296***	2.822***	3.751***	0.006***	35.79%	−0.929	0.204***	0.201***	2.450***	3.844***	0.007***	27.42%	−1.394*
τ = 95th	0.805***	0.712***	−0.943*	3.268*	0.008***	51.87%	−4.211**	0.755***	0.794***	−1.650**	−3.336**	0.009***	37.54%	1.686
τ = 99th	1.194***	0.811	−4.023***	7.414	0.017***	52.70%	−11.437	1.234***	1.077***	−5.484***	−7.471***	0.017***	36.55%	1.987
<u>Real Estate</u>														
OLS	0.259***	0.290***	0.428	0.114	0.005***	59.01%	0.314	0.107***	0.179***	3.305***	1.652**	0.006***	26.36%	1.653*
Quantile Regression														
τ = 10th	0.084***	0.123***	1.084***	0.555***	0.004***	15.76%	0.529***	0.024	0.031*	2.256*	2.744***	0.003***	5.93%	−0.488
τ = 25th	0.119***	0.140***	1.023***	1.074***	0.004***	19.73%	−0.051	0.035	0.062***	2.880***	2.493***	0.004***	8.53%	0.387
τ = 50th	0.161***	0.198***	1.369***	0.773***	0.005***	26.34%	0.596**	0.066***	0.104***	3.507***	2.729**	0.005***	10.98%	0.778
τ = 75th	0.200***	0.243***	1.749**	1.121	0.006***	35.37%	0.628	0.128***	0.171***	3.828***	2.766*	0.007***	15.06%	1.062
τ = 95th	0.593***	0.426***	−1.335**	0.561	0.009***	50.03%	−1.896	0.426**	0.476***	2.682	1.327	0.012***	21.57%	1.355
τ = 99th	1.028***	0.870***	−4.615***	−2.663**	0.014***	48.95%	−1.952*	0.026	0.648***	14.748**	−5.332***	0.023***	21.97%	20.080***

Notes: The table reports the estimated coefficients for the augmented model (6): $CSAD_t = \alpha + \gamma_1 D^{High}|R_{m,t}| + \gamma_2(1 - D^{High})|R_{m,t}| + \gamma_3 D^{High} R^2_{m,t} + \gamma_4(1 - D^{High}) R^2_{m,t} + e_t$, where $CSAD_t$ is the cross-sectional absolute deviation, $R_{m,t}$ is the market return and D^{High} is a dummy variable that equals one in case of high credit instability conditions and zero otherwise. The last column of Panel A and B reports the result for the hypothesis test $\gamma_3 = \gamma_4$. West and Newey (1987) correction is applied to estimate standard errors. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

Table 7
Estimates of herding for the US and Eurozone equity markets and financial industries, during days of high and low funding illiquidity.

	Panel A: United States							Panel B: Eurozone						
	γ_1	γ_2	γ_3	γ_4	α	Adj. R^2	$\gamma_3 = \gamma_4$	γ_1	γ_2	γ_3	γ_4	α	Adj. R^2	$\gamma_3 = \gamma_4$
All Market Equities														
OLS	0.215***	0.302***	1.649***	1.698*	0.008***	48.24%	−0.049	0.172***	0.242***	3.062***	2.548***	0.009***	41.97%	0.515
Quantile Regression														
τ = 10th	0.092***	0.114	2.005***	2.443	0.006***	12.96%	−0.438	0.075***	0.083***	3.214***	3.020***	0.007***	13.45%	0.194
τ = 25th	0.101***	0.117***	2.149***	3.546***	0.007***	15.85%	−1.398***	0.102***	0.093***	3.087***	3.880***	0.007***	16.04%	−0.793
τ = 50th	0.119***	0.159***	3.365***	4.205***	0.008***	21.13%	−0.840	0.126***	0.137***	3.817***	4.757***	0.008***	20.11%	−0.940
τ = 75th	0.161***	0.299***	3.503**	3.135*	0.009***	28.22%	0.368	0.197***	0.276***	3.411***	3.363***	0.009***	25.59%	0.048
τ = 95th	0.407**	0.729***	2.487	−2.939***	0.012***	40.04%	5.426	0.373***	0.768***	1.765	−4.538***	0.012***	31.53%	6.304***
τ = 99th	0.542***	0.517***	−2.584***	−1.621*	0.021***	36.10%	−0.963	0.496***	0.737***	−1.609	−5.480***	0.020***	31.39%	3.870*
Banks														
OLS	0.222***	0.331***	0.793**	0.157	0.004***	54.35%	0.637	0.202***	0.186***	1.196***	3.169**	0.008***	46.70%	−1.973
Quantile Regression														
τ = 10th	0.073***	0.098***	0.746***	0.896***	0.002***	15.14%	−0.150	0.128***	0.132***	1.025***	1.366***	0.005***	15.76%	−0.341
τ = 25th	0.086***	0.140***	1.136***	0.761***	0.003***	20.05%	0.374	0.151***	0.162***	1.265***	1.976**	0.005***	18.66%	−0.711
τ = 50th	0.132***	0.206***	1.539***	0.819***	0.004***	26.54%	0.720***	0.195***	0.178***	1.211***	2.896**	0.007***	22.26%	−1.685
τ = 75th	0.235***	0.393***	1.082***	−0.076	0.005***	33.73%	1.157***	0.168***	0.232***	2.996***	3.454***	0.009***	26.80%	−0.458
τ = 95th	0.471***	0.690***	1.118**	−0.142	0.009***	47.02%	1.260	0.034	0.396***	7.958***	3.581***	0.015***	34.04%	4.377**
τ = 99th	0.875***	1.186***	−1.942***	−3.579	0.016***	48.08%	1.637	0.089	0.607***	9.865	1.562	0.026***	33.93%	8.303
Diversified Financials														
OLS	0.261***	0.298***	0.584	0.625	0.006***	48.19%	−0.041	0.170***	0.216***	1.185***	1.163**	0.007***	32.88%	0.022
Quantile Regression														
τ = 10th	0.123***	0.131***	0.638***	1.277***	0.004***	13.53%	−0.638**	0.058***	0.086***	1.713***	1.341***	0.004***	9.20%	0.372*
τ = 25th	0.136***	0.153***	1.060***	1.633***	0.005***	16.96%	−0.572*	0.082***	0.107***	1.504***	1.851***	0.005***	10.73%	−0.346
τ = 50th	0.152***	0.191***	1.740***	1.949***	0.006***	22.29%	−0.209	0.112***	0.153***	2.001***	1.760***	0.007***	13.72%	0.241
τ = 75th	0.244***	0.302	1.441	1.401	0.008***	29.78%	0.039	0.194***	0.241***	1.487***	1.760	0.008***	18.21%	−0.273
τ = 95th	0.489***	0.545***	−0.153	−0.340	0.012***	37.40%	0.187	0.393***	0.546***	−0.358	−0.746	0.012***	26.51%	0.388
τ = 99th	1.228***	1.003***	−5.823**	−3.907***	0.019***	38.71%	−1.916	−0.036	0.335	16.410	3.337	0.022***	26.16%	13.073
Insurance														
OLS	0.251***	0.363***	2.369***	1.584***	0.005***	60.69%	0.785	0.186***	0.259***	2.137***	1.814***	0.006***	46.79%	0.322
Quantile Regression														
τ = 10th	0.084***	0.074***	1.261***	3.390***	0.003***	16.13%	−2.130***	0.061***	0.085***	2.114***	2.004***	0.004***	13.81%	0.110
τ = 25th	0.074***	0.128***	3.111***	3.182***	0.004***	20.63%	−0.071	0.069**	0.078***	3.012***	3.170***	0.004***	17.05%	−0.158
τ = 50th	0.100***	0.184***	3.535***	3.030***	0.005***	27.27%	0.505**	0.110***	0.143***	2.767***	3.026***	0.005***	22.09%	−0.260
τ = 75th	0.185***	0.374***	4.309***	2.033**	0.006***	36.13%	2.276**	0.173***	0.274***	3.135**	2.111	0.007***	27.60%	1.024
τ = 95th	0.643***	0.915***	2.697	−2.446***	0.008***	51.95%	5.143	0.447*	0.860***	1.447	−2.431***	0.010***	38.59%	3.877
τ = 99th	1.069***	0.784	−2.276	7.739	0.018***	52.76%	−10.015	1.127***	1.215***	−6.401***	−5.357***	0.017***	36.45%	−1.044
Real Estate														
OLS	0.238***	0.310***	0.319	0.103	0.005***	59.72%	0.216	0.071***	0.198***	3.620***	1.653**	0.006***	26.88%	1.967**
Quantile Regression														
τ = 10th	0.101***	0.117***	0.658***	1.095***	0.004***	16.52%	−0.436*	0.031	0.026*	1.511	2.965***	0.003***	6.14%	−1.454
τ = 25th	0.122***	0.141***	0.542***	1.065***	0.004***	20.32%	−0.523***	0.042**	0.062***	2.507***	2.659***	0.004***	8.58%	−0.151
τ = 50th	0.142***	0.206***	1.502	0.978***	0.005***	26.71%	0.524	0.043***	0.113***	3.797***	2.769***	0.005***	11.17%	1.028
τ = 75th	0.173***	0.302***	1.652***	0.729	0.006***	36.35%	0.924	0.098***	0.220***	4.252***	2.052***	0.007***	15.39%	2.199***
τ = 95th	0.206***	0.565***	3.433***	−1.100***	0.010***	50.64%	4.533***	0.295*	0.710***	5.175	−4.189*	0.012***	22.35%	9.364*
τ = 99th	0.856***	1.132***	−3.215***	−3.921***	0.013***	49.42%	0.706	−0.304	0.689*	20.989***	−3.467	0.024***	23.17%	24.455**

Notes: The table reports the estimated coefficients for the augmented model (6): $CSAD_t = \alpha + \gamma_1 D^{High}|R_{m,t}| + \gamma_2(1 - D^{High})|R_{m,t}| + \gamma_3 D^{High} R^2_{m,t} + \gamma_4(1 - D^{High})R^2_{m,t} + e_t$, where $CSAD_t$ is the cross-sectional absolute deviation, $R_{m,t}$ is the market return and D^{High} is a dummy variable that equals one in case of high funding illiquidity conditions and zero otherwise. The last column of Panel A and B reports the result for the hypothesis test $\gamma_3 = \gamma_4$. West and Newey (1987) correction is applied to estimate standard errors. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

In the Eurozone, we find the same pattern for the equity market. However, we find evidence of herding only in the higher quantiles of the diversified financials and insurance industries when there is high volatility. We find no evidence of herding for the real estate industry; while, for the banking and insurance industries, herding is more likely when there is lower volatility. In particular, for the insurance industry, we find that the difference between the two herding coefficients ($\gamma_3 = \gamma_4$) at the 99*th* quantile is statistically significant. Thus, for the banking and insurance industries of the Eurozone, herding is more likely during other distressed market conditions than high volatility.

4.3.2. Asymmetric credit quality

Norden and Weber (2009) report that positive stock returns are associated with negative changes in the CDS spread. Furthermore, Friewald et al. (2014) advocate that firms' CDS forward curves are strongly related to equity excess returns, and Zhang et al. (2009) argue that the equity volatility alone predicts 48% of the variation in CDS spreads. Given this background and using the CDX and iTraxx indexes as proxies for the credit condition of the market, we investigate herding during higher and lower credit deteriorations of the market.

Table 6 presents the results. The OLS coefficients do not indicate any herding, neither for the lower nor for the higher credit deterioration for both equity markets and the respective financial sectors. Analyzing the quantile estimates, the US equity market and all its financial industries herd more in the high quantiles when the credit deterioration is higher (γ_3) than when it is lower (γ_4). The herding coefficient related to high credit deterioration (γ_3) is negative and statistically significant over a wider range of quantiles compared to γ_4. In the case where both estimates are negative and significant, the difference between the two herding coefficients ($\gamma_3 = \gamma_4$) is statistically significant that means herding is more likely during distressed market states due to high credit deterioration. In the Eurozone equity market, the diversified financials and the insurance industry herd in more (in the sense of absolute value) in the case of higher credit deterioration. There is no evidence of herding for the banks, while the real estate industry herds when there is lower credit deterioration in the high quantiles.

4.3.3. Asymmetric funding liquidity

The literature indicates that high values of the TED spread lead to tighter funding liquidity. By construction, a widening of this spread indicates a destabilizing spiral between the liquidity of the equity market and the margin loan market (Brunnermeier and Pedersen, 2008). Therefore, the TED spread provides a useful basis for gauging the severity of a liquidity crisis, and it can be used as a proxy for funding liquidity. Moreover, Oh (2018) argues that firms that facing a severe liquidity constraint may be forced to sell a large part of their assets to avoid bankruptcy that causes a fire sale effect that could lead to correlated patterns of actions that then affect the entire industry. Analyzing the GFC, Cornett et al. (2011) find that the time variation in the TED tracked the severity of the GFC very closely. Thus, analyzing herding during periods of higher and lower illiquid funding is relevant.

The results in Table 7 indicate that in both the US and the Eurozone, there is no evidence of herding from the OLS analysis. On the other hand, the quantile regression estimates offer a richer perspective, and the evidence points to a change across the two markets.

In the US, except for the insurance industry that herds when there is lower illiquid funding, we find evidence of herding when there is higher illiquid funding in the equity market and the other financial industries for the upper quantiles. This finding indicates that in the US, herding is more likely during periods of strict illiquid funding. The results related to the Eurozone are different, we could not find any evidence of herding by banks but the real estate industry and the equity market herd during lower illiquid funding. And, there is evidence that the insurance industry herds during low and high illiquid funding when the strict illiquid funding (γ_3) is greater in absolute value than its relative γ_4 in the highest quantile (99*th*).

4.4. The role of the financial sector and industries

In addition to an investigation on herding under asymmetric market conditions, we are also interested in examining how the financial sector affects herding, given its role in the equity market.[9] As discussed in Section 2.2, the initial negative shocks may be exacerbated and amplified by procyclical market mechanisms in other sectors, and this in turn may lead to a crisis in the whole domestic market. Therefore, we test whether various sources of herding synchronize across the domestic equity market and the financial sector.

The results in Table 8 show the estimates of models (7) and (8). The domestic equity market should potentially be subject to the spillover of herding from the financial sector to bilateral trade and payoffs. For both equity markets, the cross-sectional dispersion in the domestic equity market is strongly affected by the measure of dispersion and the returns of the financial sector. This is demonstrated by the adjusted-R^2 reported in Table 8 that in all the cases, has a value that is almost double that of the respective one estimated with model (4) (without the CSAD and the return of the financial sector or industry) in Table 2. The positive and highly significant CSAD coefficient δ_1 across all the cases indicates a dominant influence of the financial sector on the domestic equity market.

For the US equity market, we do not find evidence of herding around the financial sector δ_2. The results change when we consider individual financial industries. First, there is no evidence of spillovers from the real estate industry. However, we find that the US equity market herds around the banks for the lowest quantiles (we report $\tau = 10th$) and the other industries during distressed states of the market ($\tau = 99th$). The results for the insurance industry are very interesting. We find evi-

Table 8
Estimates of herding between the US and Eurozone equity markets and the related financial sectors and industries.

	Panel A: United States						Panel B: Eurozone					
	γ_1	γ_2	δ_1	δ_2	α	Adj. R^2	γ_1	γ_2	δ_1	δ_2	α	Adj. R^2
j = Financial Sector												
OLS	0.062***	−0.083	0.560***	0.113	0.005***	88.78%	0.089***	0.794	0.602***	−0.530*	0.004***	85.83%
τ = 10th	0.056***	0.414	0.471***	−0.023	0.004***	45.19%	0.074***	1.473**	0.498***	−0.931***	0.003***	44.78%
τ = 25th	0.051***	0.103	0.500***	0.272***	0.004***	50.11%	0.050***	1.640***	0.523***	−0.482	0.004***	49.47%
τ = 50th	0.049***	0.171	0.578***	0.070	0.004***	56.82%	0.061***	1.254*	0.581***	−0.411	0.004***	56.02%
τ = 75th	0.058***	−0.029	0.622***	0.071	0.005***	65.69%	0.074***	1.168***	0.671***	−0.488***	0.004***	64.11%
τ = 95th	0.061**	−0.406	0.785***	−0.043	0.005***	78.14%	0.154***	−1.515*	0.807***	−0.070	0.004***	74.96%
τ = 99th	0.028	0.432	0.894***	−0.431	0.006***	81.08%	0.223***	−3.771***	0.918***	0.261	0.004***	77.21%
j = Banks												
OLS	0.137***	0.999***	0.338***	−0.026	0.007***	71.98%	0.112***	1.936**	0.410***	−0.398	0.005***	73.75%
Quantile Regression												
τ = 10th	0.094***	1.240***	0.238***	−0.082**	0.005***	27.34%	0.080***	1.466*	0.272***	−0.010	0.005***	29.03%
τ = 25th	0.091***	1.041***	0.255***	0.191	0.006***	30.87%	0.071***	1.547***	0.297***	0.097	0.005***	34.55%
τ = 50th	0.097***	1.473***	0.334***	0.123***	0.007***	38.23%	0.071***	2.120***	0.387***	−0.064	0.005***	42.27%
τ = 75th	0.124***	0.916**	0.426***	0.048	0.007***	48.95%	0.089***	2.446**	0.505***	−0.330*	0.005***	51.86%
τ = 95th	0.083	2.047**	0.761***	−0.107	0.008***	64.46%	0.170***	0.823*	0.674***	−0.578***	0.006***	66.06%
τ = 99th	0.032	1.285	0.986***	0.717	0.010***	67.31%	0.331***	−2.146**	0.746***	−0.474	0.006***	67.75%
j = Diversified Financials												
OLS	0.078***	0.530	0.549***	0.014	0.005***	81.05%	0.127***	1.227	0.536***	−0.084	0.005***	71.45%
Quantile Regression												
τ = 10th	0.052***	1.009*	0.371***	0.067	0.004***	34.01%	0.085***	2.163**	0.282***	−0.197	0.005***	25.25%
τ = 25th	0.061***	0.001	0.442***	0.521***	0.004***	39.76%	0.078***	2.475***	0.353***	−0.237**	0.005***	30.44%
τ = 50th	0.058***	−0.418	0.534***	0.666**	0.005***	47.92%	0.092***	1.451	0.492***	0.310	0.005***	38.96%
τ = 75th	0.066***	−0.200	0.617***	0.589***	0.005***	57.78%	0.116***	−0.022	0.625***	1.217**	0.005***	50.24%
τ = 95th	0.058	0.723	0.825***	−0.044	0.006***	73.00%	0.136***	−2.296*	0.825***	2.352**	0.006***	65.39%
τ = 99th	−0.020	1.820***	1.003***	−0.428***	0.007***	75.94%	0.173***	−2.256**	1.068***	1.230*	0.006***	69.06%
j = Insurance												
OLS	0.107***	1.744***	0.450***	−0.956***	0.006***	75.81%	0.136***	−0.186	0.498***	−0.114	0.005***	77.29%
Quantile Regression												
τ = 10th	0.055***	2.095***	0.315***	−0.687***	0.005***	30.22%	0.083***	1.360***	0.339***	−0.262**	0.005***	30.79%
τ = 25th	0.070***	1.976***	0.395***	−0.902**	0.005***	34.94%	0.088***	0.681***	0.410***	0.012	0.005***	36.26%
τ = 50th	0.073***	1.738***	0.492***	−0.903***	0.006***	42.64%	0.108***	−0.121	0.485***	0.094	0.005***	44.08%
τ = 75th	0.108***	1.166	0.578***	−0.831	0.006***	52.65%	0.109***	−0.366	0.589***	0.495	0.006***	53.98%
τ = 95th	0.147***	0.881	0.838***	−1.121***	0.007***	68.09%	0.185***	−1.527	0.746***	0.166	0.006***	67.74%
τ = 99th	0.128	0.794	1.155***	−1.045	0.007***	70.04%	0.237***	−2.110	0.854***	−0.482	0.007***	68.94%
j = Real Estate												
OLS	0.114***	0.010	0.623***	−0.096	0.005***	81.69%	0.147***	1.473***	0.366***	0.342	0.006***	63.84%
Quantile Regression												
τ = 10th	0.092***	−0.193	0.462***	0.137*	0.004***	35.50%	0.075***	2.564***	0.170***	0.169	0.006***	21.10%
τ = 25th	0.080***	0.543	0.530***	−0.093	0.004***	40.45%	0.080***	2.286***	0.213***	0.713***	0.006***	25.24%
τ = 50th	0.091***	0.381	0.620***	−0.047	0.004***	48.03%	0.109***	1.913***	0.309***	0.773*	0.007***	32.58%
τ = 75th	0.118***	−0.331	0.703***	0.126	0.005***	57.81%	0.153***	1.146***	0.446***	0.918***	0.007***	42.59%
τ = 95th	0.114***	−0.378	0.917***	0.078	0.006***	72.10%	0.191***	1.441**	0.741***	0.725	0.008***	57.87%
τ = 99th	0.105	1.246	1.241***	−0.537	0.006***	72.60%	0.274***	−0.192	0.997***	1.916	0.008***	62.34%

Notes: The table reports the estimated coefficients for the augmented models (7) and (8). West and Newey (1987) correction is applied to estimate standard errors. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

Table 9
Granger causality test between the US and Eurozone financial sectors and industries and the related equity markets.

	Panel A: United States				
Lag of R_j^2	j = Financial sector	j = Banks	j = Diversified Financials	j = Insurance	j =Real Estate
$t-1$	92.640***	108.293***	92.473***	21.111**	61.668***
$t-2$	24.786***	24.105***	36.971***	16.636***	17.635***
$t-3$	9.220***	10.038***	14.938***	12.319**	9.701***
$t-4$	7.446***	7.908***	15.254***	12.245***	9.233***
$t-5$	5.329***	6.878***	7.982***	11.666***	9.856***
$t-6$	3.912***	6.185***	6.036***	11.997***	8.002***
$t-7$	4.717***	9.138***	5.626***	11.564***	7.375***
$t-8$	5.126***	9.050***	6.801***	10.226***	7.469***
$t-9$	5.285***	9.801***	7.391***	8.978***	6.682***
$t-10$	5.374***	9.947***	7.264***	8.859***	6.423***
$t-11$	5.157***	9.044***	6.790***	8.299***	6.245***
$t-12$	5.029***	8.559***	6.381***	7.515***	6.221***
$t-13$	4.686***	8.080***	5.901***	7.029***	5.989***
$t-14$	5.025***	8.677***	5.834***	6.823***	5.909***
$t-15$	4.472***	8.199***	5.161***	6.104***	5.469***
$t-16$	4.629***	7.482***	5.549***	5.806***	5.448***
$t-17$	4.349***	7.058***	5.206***	5.556***	5.106***
$t-18$	4.131***	6.783***	4.988***	5.448***	4.836***
$t-19$	3.940***	6.568***	4.946***	5.141***	4.749***
$t-20$	3.687***	6.490***	4.648***	4.896***	4.519***
	Panel B: Eurozone				
Lag of R_j^2	j = Financial sector	j = Banks	j = Diversified Financials	j = Insurance	j =Real Estate
$t-1$	180.460***	215.383***	52.594***	100.868***	27.609***
$t-2$	58.009***	66.244***	14.240***	37.689***	6.786***
$t-3$	24.261***	29.104***	5.645***	16.386***	2.212*
$t-4$	16.253***	18.141***	4.158***	12.477***	5.133***
$t-5$	11.832***	11.796***	4.213***	9.978***	6.149***
$t-6$	9.317***	9.347***	3.627***	7.786***	4.729***
$t-7$	7.591***	7.919***	3.947***	6.564***	4.352***
$t-8$	6.762***	7.509***	3.356***	5.879***	3.782***
$t-9$	5.574***	6.272***	3.383***	5.763***	2.797***
$t-10$	4.773***	5.530***	3.586***	5.559***	2.729***
$t-11$	4.724***	5.310***	3.962***	5.141***	2.723***
$t-12$	4.652***	5.179***	4.198***	4.759***	2.725***
$t-13$	4.492***	4.979***	3.913***	4.406***	2.583***
$t-14$	4.447***	4.688***	4.818***	4.150***	2.883***
$t-15$	4.105***	4.391***	5.073***	3.859***	2.778***
$t-16$	3.834***	4.074***	4.726***	3.601***	2.871***
$t-17$	3.707***	3.844***	4.534***	3.809***	2.710***
$t-18$	3.600***	3.770***	4.354***	3.709***	2.626***
$t-19$	3.459***	3.538***	4.495***	3.597***	2.438***
$t-20$	3.358***	3.334***	4.986***	3.426***	2.391***

Notes: The table reports the F-Statistics from the Granger causality test between the $R^2_{US,j,t}$ ($R^2_{EZ,j,t}$) and the $CSAD_{US,m,t}$ ($CSAD_{EZ,m,t}$), for the entire financial sector and each industry included in this study. The null hypothesis states that each variable "does not Granger Cause" the other. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

dence of herding in both the OLS and the quantile analyses. The OLS has a negative and significant δ_2. The quantile regression estimates of δ_2 show that this value decreases when the quantiles increase. This increase indicates that the herding in the US equity market around the insurance industry intensifies when the market becomes more distressed. This result underlines the relevance of the insurance industry to the US economy.

The OLS shows that the Eurozone equity market herds around the financial sector. The different quantile estimations show that the spillover herding decreases when the quantile increases. This increase indicates that the herding around the financial sector is more intense when the market is in a tranquil state. Almost the same result appears for the insurance industry. No spillover herding is detected in the real estate industry. Contrary to what we found for the other financial industries, Table 8 shows that the Eurozone equity market herds around banks when the market becomes more distressed, that is, in the high quantiles. These results mark the importance of the banking industry as a major systemic risk source in the Eurozone, which is in line with Black et al. (2016) who argue that the systemic contribution of this industry significantly increased during the EZC.

Table 10
Estimates of herding due to non-fundamentals and fundamentals for the US and Eurozone equity markets and financial industries.

	Panel A: United States				Panel B: Eurozone			
	$CSAD_{NONFUND,t}$		$CSAD_{FUND,t}$		$CSAD_{NONFUND,t}$		$CSAD_{FUND,t}$	
	γ_1	γ_2	γ_1	γ_2	γ_1	γ_2	γ_1	γ_2
<u>All Market Equities</u>								
OLS	0.253***	1.693***	0.008**	−0.133	0.184***	2.751***	0.019***	0.071
Quantile Regression								
τ = 10th	0.108***	1.737***	−0.014***	−0.204***	0.056**	2.840***	−0.009	0.024
τ = 25th	0.120***	2.472	−0.013*	−0.007	0.084***	2.908***	−0.001	−0.024
τ = 50th	0.147***	3.261***	0.001	0.014	0.120***	3.821***	0.017***	0.039
τ = 75th	0.211***	4.011*	0.017***	0.018	0.229***	3.032***	0.028***	0.374***
τ = 95th	0.608***	−1.797***	0.028*	0.082	0.546***	−1.115	0.070***	0.101
τ = 99th	0.473***	−1.380**	0.027	0.330	0.661***	−4.362***	0.099***	−0.127
<u>Banks</u>								
OLS	0.274***	0.451*	0.005**	0.006	0.204***	1.767*	0.010***	0.034
Quantile Regression								
τ = 10th	0.077***	0.814	−0.027***	0.107***	0.107***	1.259***	−0.003	−0.043
τ = 25th	0.110***	0.998***	−0.011***	0.066***	0.148***	1.372***	−0.006*	0.139***
τ = 50th	0.176***	0.996***	0.003	0.029	0.174***	1.981**	0.006	0.082
τ = 75th	0.297***	0.763***	0.024***	−0.074***	0.165***	3.226***	0.020***	0.003
τ = 95th	0.640***	−0.229	0.047***	−0.120**	0.324***	4.039***	0.033	0.210
τ = 99th	1.156***	−3.210***	0.055***	−0.167	0.466***	2.447***	0.064***	−0.120
<u>Diversified Financials</u>								
OLS	0.272***	0.634	0.005**	−0.040	0.176***	1.154***	0.016***	−0.001
Quantile Regression								
τ = 10th	0.124***	0.631***	−0.011***	−0.062***	0.038***	1.801***	−0.008	0.050
τ = 25th	0.124***	1.726***	−0.007***	−0.013	0.079***	1.480***	−0.003	0.073***
τ = 50th	0.175***	1.715***	0.003*	−0.021	0.138***	1.257***	0.012**	0.005
τ = 75th	0.259***	1.598**	0.013***	0.010	0.192***	1.541***	0.021***	0.205**
τ = 95th	0.501***	0.036	0.027***	−0.063	0.429***	0.569	0.057***	−0.146**
τ = 99th	0.902***	−3.165***	0.036***	−0.100	0.331	2.925	0.072	0.154
<u>Insurance</u>								
OLS	0.301***	2.034***	0.005**	−0.037	0.204***	1.995***	0.014***	0.010
Quantile Regression								
τ = 10th	0.051	2.832**	−0.026***	0.106***	0.050***	1.987***	−0.008*	0.044
τ = 25th	0.082***	3.452***	−0.014***	0.062	0.053***	3.024***	0.000	0.035
τ = 50th	0.139***	3.324***	0.002	0.016	0.098***	3.070***	0.010**	0.079
τ = 75th	0.270***	3.203***	0.019***	−0.075**	0.201***	2.922**	0.023***	0.027
τ = 95th	0.790***	−0.373	0.033***	−0.070***	0.730***	−1.440***	0.050***	0.033
τ = 99th	1.201***	−3.791***	0.037***	−0.070	0.971***	−3.639***	0.100***	−0.514***
<u>Real Estate</u>								
OLS	0.274***	0.240	0.002	−0.004	0.113***	2.783***	0.011***	−0.003
Quantile Regression								
τ = 10th	0.116***	0.594***	−0.012***	−0.031	0.028	1.839	−0.004	−0.072
τ = 25th	0.125***	1.112***	−0.010***	0.061***	0.029*	2.711***	−0.001	0.032
τ = 50th	0.172***	1.213**	0.001	0.005	0.058***	3.479***	0.003	0.075
τ = 75th	0.204***	1.899***	0.010***	−0.026***	0.123**	3.609*	0.016*	0.065
τ = 95th	0.466***	0.020	0.018***	0.050	0.428***	1.187	0.045***	−0.042
τ = 99th	0.989***	−3.249***	0.025*	0.002	0.359	4.824	0.059	0.203

Notes: The table reports the estimated coefficients for the augmented models (12) and (13): $CSAD_{NONFUND,t} = \alpha + \gamma_1|R_{m,t}| + \gamma_2 R^2_{m,t} + e_t$, and $CSAD_{FUND,t} = \alpha + \gamma_1|R_{m,t}| + \gamma_2 R^2_{m,t} + e_t; CSAD_{NONFUND,t} = \varepsilon_t$, form regression (9): $CSAD_t = \alpha + \beta_1(R_{m,t} - R_f) + \beta_2 HML_t + \beta_3 SMB_t + \beta_4 MOM_t + \varepsilon_t$; $CSAD_{FUND,t} = CSAD_t$ - $CSAD_{NONFUND,t}$. West and Newey (1987) correction is applied to estimate standard errors. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

Our results are also robust to the Granger causality test[13] as reported in Table 9. The null hypothesis states that $R^2_{US,j,t}$ ($R^2_{EZ,j,t}$) "does not cause" $CSAD_{US,m,t}$ ($CSAD_{EZ,m,t}$). The results indicate that there is strong Granger causality between the two variables used in this test, with the banking industry having a greater influence in both panels.

Our results highlight the fact that any shockwave in the financial sector, except in real estate, affects the domestic equity market depending on the state of the economy. Recognizing this effect could help policymakers and supervisory authorities to more efficiently observe that the insurance industry in the US and the banks in the Eurozone are more affected by herding in the equity market during distressed states of the economy.

[13] The augmented Dickey-Fuller test (ADF) and KPSS test indicate that the $R^2_{US,j,t}$ ($R^2_{EZ,j,t}$) and the $CSAD_{US,m,t}$ ($CSAD_{EZ,m,t}$) are stationary.

Table 11
Estimates of herding due to non-fundamentals and fundamentals for the US and Eurozone equity markets and financial industries, during the GFC.

	Panel A: United States				Panel B: Eurozone			
	$CSAD_{NONFUND,t}$		$CSAD_{FUND,t}$		$CSAD_{NONFUND,t}$		$CSAD_{FUND,t}$	
	γ_3	γ_4	γ_3	γ_4	γ_3	γ_4	γ_3	γ_4
All Market Equities								
OLS	0.112	−0.279	−1.920***	3.948***	0.214	−0.106	−2.195**	6.258***
Quantile Regression								
τ = 10th	−0.025	0.915***	−0.355	1.804***	0.213**	0.812***	1.072**	2.261**
τ = 25th	0.873**	−4.349**	−0.875***	1.638***	2.297***	−0.580	−0.474	3.141***
τ = 50th	0.054	−0.214**	−2.907***	2.669***	0.256	0.152	−2.415***	4.627***
τ = 75th	−0.679***	0.359	−3.077***	6.059***	−1.080***	0.115	−3.873***	7.437***
τ = 95th	−0.309***	0.723**	−4.108***	14.283	−0.486***	0.671	−8.018***	12.167***
τ = 99th	−0.125***	1.498***	−3.547**	35.024	−0.256***	0.908***	−13.163	21.573
Banks								
OLS	0.019	−1.540***	−0.411	3.543***	0.136	−0.641***	0.628	2.475***
Quantile Regression								
τ = 10th	−0.116**	−0.901**	−0.390	1.308***	−0.172***	−0.377	0.501***	1.384***
τ = 25th	0.099	−8.574***	−0.545**	1.716***	0.405**	−4.870***	−0.030	2.146***
τ = 50th	0.160*	−0.529***	−1.004***	2.702***	0.717**	−0.246***	−0.042	3.678***
τ = 75th	−0.393***	−0.362***	−0.357**	7.808***	−0.734***	−0.099	1.056	4.632***
τ = 95th	−0.141***	0.938*	−1.699***	5.524***	−0.320***	0.388	0.403	6.916**
τ = 99th	−0.081***	1.347***	−3.892	7.208	−0.146***	0.486***	−2.912	20.662
Diversified Financials								
OLS	0.011	−0.245	−1.122**	2.896**	−0.012	−0.152	−0.565	4.211***
Quantile Regression								
τ = 10th	−0.119*	0.583***	−0.650***	0.996***	0.062***	−0.249	0.213	2.238***
τ = 25th	0.366***	−2.799**	−1.052***	1.449**	0.483***	−2.196***	−0.366	2.577***
τ = 50th	−0.031	−0.143*	−1.600***	3.316***	0.000	0.138	−0.690	3.871***
τ = 75th	−0.437***	−0.073	−0.901	5.762***	−0.528***	0.157	−1.051***	3.907***
τ = 95th	−0.181***	1.058**	−3.720***	6.406	−0.219***	0.770	−3.255***	13.634
τ = 99th	−0.090***	1.200***	−6.098***	15.312	−0.090*	0.951**	−2.655***	44.341***
Insurance								
OLS	0.109	−1.810***	−0.144	4.011***	0.177	−0.351	−0.402	3.845***
Quantile Regression								
τ = 10th	0.153**	1.130***	0.188	1.885***	0.006	0.615***	1.246***	1.662***
τ = 25th	0.525***	−12.33***	0.180	2.039***	0.676***	−4.572***	0.249	2.225***
τ = 50th	−0.202	−0.730***	−0.665	3.311***	0.012	−0.204	−0.371	3.338***
τ = 75th	−0.706***	−0.347**	0.887**	10.704***	−0.880***	−0.296**	−0.116	4.247***
τ = 95th	−0.306***	1.501*	−3.810***	5.921***	−0.229***	0.616	−5.071***	3.778***
τ = 99th	−0.122***	1.367***	−11.699***	13.412	−0.097***	1.144**	−7.570	30.943
Real Estate								
OLS	0.122	0.032	−0.676***	1.549**	0.334	−0.115	−1.522	5.404***
Quantile Regression								
τ = 10th	0.047	0.577	−0.122	0.966***	−0.400	−0.072	−0.773	0.832
τ = 25th	1.057***	−0.554	−0.513***	0.941***	1.560***	−0.678***	−0.936	2.241
τ = 50th	−0.069	0.207	−0.830***	0.758***	0.695***	−0.012	−2.518***	4.702***
τ = 75th	−0.287***	0.067	−0.841***	1.320	−0.689***	0.042	−3.903***	5.085***
τ = 95th	−0.118***	1.186*	−1.754*	5.387	−0.192***	0.656	−4.854***	19.322***
τ = 99th	−0.075***	1.370***	−3.687***	6.958	−0.061*	0.720**	−9.476***	30.770

Notes: The table reports the estimated coefficients for the augmented models (14) and (15): $CSAD_{NONFUND,t} = \alpha + \gamma_1 D^{Crisis}|R_{m,t}| + \gamma_2(1-D^{Crisis})|R_{m,t}| + \gamma_3 D^{Crisis} R^2_{m,t} + \gamma_4(1-D^{Crisis})R^2_{m,t} + e_t$, and $CSAD_{FUND,t} = \alpha + \gamma_1 D^{Crisis}|R_{m,t}| + \gamma_2(1-D^{Crisis})|R_{m,t}| + \gamma_3 D^{Crisis} R^2_{m,t} + \gamma_4(1-D^{Crisis})R^2_{m,t} + e_t$; $CSAD_{NONFUND,t} = \varepsilon_t$, form regression (9): $CSAD_t = \alpha + \beta_1(R_{m,t} - R_f) + \beta_2 HML_t + \beta_3 SMB_t + \beta_4 MOM_t + \varepsilon_t$; $CSAD_{FUND,t} = CSAD_t$ - $CSAD_{NONFUND,t}$. D^{Crisis} is a dummy variable that equals one during the GFC and zero otherwise. West and Newey (1987) correction is applied to estimate standard errors. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

4.5. Herding on fundamental information

The results in Table 10 are from the estimates of models (12) and (13) for the CSAD ($CSAD_{NONFUND,t}$) driven by non-fundamental information and the CSAD ($CSAD_{FUND,t}$) driven by fundamental information, respectively. The OLS shows that for the US and the Eurozone equity markets and financial sectors, we have no evidence of herding due to either non-fundamental or fundamental information.

However, the quantile estimates indicate that in the US, herding due to fundamental information occurs in the lower range of quantiles (with $\tau = 10th$, the γ_2 estimates are also statistically significant) for the equity market and diversified financials. Banks and insurance industries are characterized by fundamental information in the upper range of quantiles, while the real estate industry has only a negative and significant γ_2 up to the 75*th* quantile but is not statistically significant

Table 12
Estimates of herding due to non-fundamentals and fundamentals for the US and Eurozone equity markets and financial industries, during the EZC.

	Panel A: United States				Panel B: Eurozone			
	$CSAD_{NONFUND,t}$		$CSAD_{FUND,t}$		$CSAD_{NONFUND,t}$		$CSAD_{FUND,t}$	
	γ_3	γ_4	γ_3	γ_4	γ_3	γ_4	γ_3	γ_4
<u>All Market Equities</u>								
OLS	−2.582***	0.294	3.614***	0.481	−2.642***	0.467*	4.171***	2.128***
Quantile Regression								
τ = 10th	−11.692***	0.317***	1.633***	1.856***	−10.794***	0.405***	3.324***	3.521***
τ = 25th	−7.162***	0.744***	1.395***	2.608***	−3.84***	2.088***	3.219***	3.473***
τ = 50th	−1.689***	0.225***	2.391**	1.088*	−1.691***	0.266***	3.133***	3.399***
τ = 75th	−1.235***	0.448	7.868***	−0.078	−1.197***	0.653**	6.027***	1.615***
τ = 95th	0.516*	−0.262***	15.636***	−2.797***	0.522	−0.401***	10.012***	−3.043***
τ = 99th	1.133***	−0.097**	23.071***	−2.149**	1.092***	−0.158	14.016***	−5.206***
<u>Banks</u>								
OLS	−2.836***	−0.003	1.825***	0.241	−1.582***	−0.027	1.555**	2.205**
Quantile Regression								
τ = 10th	−11.878***	0.102	0.828***	0.841***	−7.895***	0.198**	1.311***	1.371***
τ = 25th	−10.947***	−0.023	0.703*	1.085***	−7.662***	0.035	0.887***	1.598***
τ = 50th	−2.198***	0.152***	0.514	0.548***	−1.312***	0.107	3.553***	3.898***
τ = 75th	−1.905***	0.048	6.657***	0.834***	−0.886***	0.231*	3.198***	4.082***
τ = 95th	0.507	−0.157***	6.341*	−0.563	0.294	−0.221***	1.382**	4.140***
τ = 99th	1.477***	−0.052***	4.719**	−2.823***	0.878***	−0.026	8.730	0.655
<u>Diversified Financials</u>								
OLS	−1.866***	0.134	1.915***	0.008	−1.791***	0.098	2.675***	0.836***
Quantile Regression								
τ = 10th	−9.349***	0.188***	0.763***	0.576***	−5.951***	0.082***	2.938***	1.502***
τ = 25th	−5.251***	0.373***	0.376	1.374***	−4.165***	0.391***	2.508***	1.228***
τ = 50th	−1.559***	0.178***	0.940	0.781**	−1.548***	0.078	2.641**	1.475**
τ = 75th	−1.122***	0.215	4.877***	0.418	−1.046***	0.239**	2.881**	0.997***
τ = 95th	0.574	−0.167***	10.485**	−1.005*	0.450	−0.207***	3.957	−0.318
τ = 99th	1.172***	−0.068***	13.766***	−4.084***	1.378***	−0.046	28.149***	0.095
<u>Insurance</u>								
OLS	−4.289***	0.145	3.198***	1.181**	−2.305***	0.335	3.697***	1.246**
Quantile Regression								
τ = 10th	−16.957***	0.208**	2.188***	3.096***	−11.19***	0.301***	2.213***	1.880***
τ = 25th	−16.93***	0.490***	1.911***	2.903***	−9.338***	0.645***	3.111***	2.436***
τ = 50th	−3.241***	0.234	2.049**	1.427***	−2.046***	0.250***	3.674***	1.591***
τ = 75th	−2.786***	−0.012	10.351***	2.158***	−1.597***	0.141	5.172**	1.642***
τ = 95th	0.680*	−0.290***	8.616	−1.217	0.407	−0.170***	7.343	−2.184***
τ = 99th	1.783***	−0.080**	19.801*	−5.169***	1.103***	−0.086***	14.364**	−4.878***
<u>Real Estate</u>								
OLS	−2.373***	0.202	1.957***	−0.251	−2.684***	0.460***	2.424*	1.922***
Quantile Regression								
τ = 10th	−13.934***	0.145***	1.189***	0.568***	−9.116***	0.277***	−0.079	2.818***
τ = 25th	−7.637**	0.731***	0.940***	0.084	−2.513***	1.609***	−0.006	1.975***
τ = 50th	−1.879***	0.235***	0.915***	−0.118	−2.060***	0.373***	1.831*	1.976
τ = 75th	−1.695***	−0.083	6.218***	−0.122	−1.331***	0.617***	4.178***	1.732***
τ = 95th	0.328	−0.140***	12.182*	−0.866	0.743**	−0.148**	9.149	−0.810
τ = 99th	1.242***	−0.056***	7.584	−3.103***	1.432***	−0.053	30.259	1.169

Notes: The table reports the estimated coefficients for the augmented models (14) and (15): $CSAD_{NONFUND,t} = \alpha + \gamma_1 D^{Crisis}|R_{m,t}| + \gamma_2(1 - D^{Crisis})|R_{m,t}| + \gamma_3 D^{Crisis} R^2_{m,t} + \gamma_4(1 - D^{Crisis})R^2_{m,t} + e_t$, and $CSAD_{FUND,t} = \alpha + \gamma_1 D^{Crisis}|R_{m,t}| + \gamma_2(1 - D^{Crisis})|R_{m,t}| + \gamma_3 D^{Crisis} R^2_{m,t} + \gamma_4(1 - D^{Crisis})R^2_{m,t} + e_t$; $CSAD_{NONFUND,t} = \varepsilon_t$, form regression (9): $CSAD_t = \alpha + \beta_1(R_{m,t} - R_f) + \beta_2 HML_t + \beta_3 SMB_t + \beta_4 MOM_t + \varepsilon_t$; $CSAD_{FUND,t} = CSAD_t$ - $CSAD_{NONFUND,t}$. D^{Crisis} is a dummy variable that equals one during the EZC and zero otherwise. West and Newey (1987) correction is applied to estimate standard errors. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

in the upper quantiles. Hence, herding due to fundamental information affects the US equity market and diversified financials in tranquil periods. Banks and insurance tend to herd on fundamental information when the market becomes more distressed, and there is slight evidence that the real estate industry does also. On the other hand, we find that the herding that is driven by non-fundamental information occurs in the US equity market and the related financial sector only for the extreme upper quantiles. This finding indicates that the herding due to non-fundamental information is more likely during tail events of the market.

In the Eurozone, we find evidence that the herding driven by fundamental information is present for the diversified financials and the insurance industries, while the herding driven by non-fundamental information occurs in the equity market and the insurance industry. In both cases, we find that the herding coefficients are negative and significant only for the extreme upper distribution of the quantiles that means "intentional" and "spurious" herding are present only during extremely distressed periods of the related market.

Table 13
Summary of the results for the United States (Panel) A.

	Panel A: United States				
	All Market Equities	Banks	Diversified Financials	Insurance	Real Estate
Full sample	Yes - $\tau = 95th$ and $99th$	Yes - $\tau = 99th$	Yes - $\tau = 99th$	No	Yes - $\tau = 99th$
Herding behavior during crises					
Global financial crisis	Yes - OLS and $\tau = 25th$ to $99th$	Yes - $\tau = 50th$ to $99th$	Yes - OLS and $\tau = 10th$ to $99th$	Yes - $\tau = 95th$ and $99th$	Yes - OLS and $\tau = 25th$ to $99th$
Eurozone Crisis	No	Yes - $\tau = 10th$ to $95th$	No	Yes - OLS and $\tau = 75th$ and $95th$	No
Asymmetric market conditions					
Volatility					
High	Yes - $\tau = 99th$	Yes - $\tau = 99th$	Yes - $\tau = 99th$	No	Yes - $\tau = 99th$
Low	Yes - $\tau = 95th$	No	Yes - $\tau = 99th$	No	Yes - $\tau = 95th$ and $99th$
Funding illiquidity					
High	Yes - $\tau = 95th$ and $99th$	Yes - $\tau = 99th$	Yes - $\tau = 99th$	Yes - $\tau = 99th$	Yes - $\tau = 95th$ and $99th$
Low	No	Yes - $\tau = 99th$	Yes - $\tau = 99th$	No	Yes - $\tau = 99th$
Credit deterioration					
High	Yes - $\tau = 99th$	Yes - $\tau = 99th$	Yes - $\tau = 99th$	No	Yes - $\tau = 99th$
Low	Yes - $\tau = 95th$ and $99th$	No	Yes - $\tau = 99th$	Yes - $\tau = 95th$	Yes - $\tau = 95th$ and $99th$
Herding spillovers					
Financial sector	No				
Banks	Yes - $\tau = 10th$				
Diversified Financials	Yes - $\tau = 99th$				
Insurance	Yes - OLS and $\tau = 10th$ to $50th$ and $95th$				
Real Estate	No				
Non-fundamental and fundamental information					
Full sample (Jan. 2005 - Dec. 2017)					
Non-fundamental	Yes - $\tau = 95th$ and $99th$	Yes - $\tau = 99th$	Yes - $\tau = 99th$	Yes - $\tau = 99th$	Yes - $\tau = 99th$
Fundamental	Yes - $\tau = 10th$	Yes - $\tau = 75th$ and $95th$	Yes - $\tau = 10th$	Yes - $\tau = 95th$	Yes - $\tau = 75th$
Global financial crisis					
Non-fundamental	Yes - $\tau = 75th$ to $99th$	Yes - $\tau = 10th$ and $75th$ to $99th$	Yes - $\tau = 10th$ and $75th$ to $99th$	Yes - $\tau = 75th$ to $99th$	Yes - $\tau = 75th$ to $99th$
Fundamental	Yes - OLS and $\tau = 25th$ to $99th$	Yes - $\tau = 25th$ to $95th$	Yes - OLS and $\tau = 10th$ to $99th$	Yes - $\tau = 75th$ and $99th$	Yes - OLS and $\tau = 25th$ to $99th$
Eurozone Crisis					
Non-fundamental	Yes - OLS and $\tau = 10th$ to $75th$	Yes - OLS and $\tau = 10th$ to $75th$	Yes - OLS and $\tau = 10th$ to $75th$	Yes - OLS and $\tau = 10th$ to $75th$	Yes - OLS and $\tau = 10th$ to $75th$
Fundamental	No	No	No	No	No

Notes: The table presents the main results concerning our analyses in the United States. In case herding is detected, we report "Yes", and "No" otherwise. OLS ($\tau = n^{th}$) indicates the presence of herding detected with OLS (quantile) regression (at the n^{th} quantile).

Table 11 illustrates the results of testing based on models (14) and (15) during the GFC for the US and the Eurozone, respectively. We find that the US investors herd due to fundamental information during the GFC. The OLS analysis shows a negative and significant herding coefficient γ_3 for the equity market, diversified financials, and real estate. The results related to the US market become more interesting when analyzing the estimates of the quantile regression. There is evidence that the US equity market and all the financial industries start herding when the market has intermediately distressed conditions ($\tau = 50th$). Overall, our results indicate that the herding detected during the GFC in the US was spurious more than intentional. The above analysis shows that there is herding during the GFC for the US equity market and financial industries. The analysis disclosed in this subsection gives a more comprehensive view compared to the results discussed in Section 4.2, since it shows that herding is based on fundamental information and thus likely due to informational cascades.

Our results are in line with Galariotis et al. (2015) for the US equity market and with Humayun Kabir (2018) for the US financial sector during the GFC. Our analysis is more comprehensive, because it includes the estimates for all the US financial industries and, moreover, considers the quantile regression method that provides a better understanding of herding across different states of the economy.

The GFC affects the herding due to non-fundamental and fundamental information in the Eurozone as well. For the herding driven by fundamental information, the OLS analysis does not show any evidence of herding apart for the equity market, whose coefficient γ_3 is negative and significant. The quantile regression analysis shows evidence of herding in all the financial industries, except for banks that herd due to non-fundamental information. Similar to what we find in the US, the herd-

Table 14
Summary of the results for the Eurozone (Panel B).

	Panel B: Eurozone				
	All Market Equities	Banks	Diversified Financials	Insurance	Real Estate
Full sample	Yes - $\tau = 99th$	No	No	Yes - $\tau = 95th$ and $99th$	No
Herding behavior during crises					
Global financial crisis	Yes - OLS and $\tau = 50th$ to $99th$	No	Yes - OLS and $\tau = 75th$ to $99th$	Yes - $\tau = 75th$ and $95th$	Yes - $\tau = 50th$ to $99th$
Eurozone Crisis	No	Yes - OLS and $\tau = 50th$ and $75th$	$\tau = 95th$	No	Yes - OLS and $\tau = 10th$ and $25th$
Asymmetric market conditions					
Volatility					
High	Yes - $\tau = 99th$	No	Yes - $\tau = 95th$	Yes - $\tau = 99th$	No
Low	Yes - $\tau = 95th$ and $99th$	Yes - $\tau = 99th$	No	Yes - $\tau = 95th$ and $99th$	No
Funding illiquidity					
High	Yes - $\tau = 99th$	No	Yes - $\tau = 95th$	Yes - $\tau = 95th$ and $99th$	No
Low	No	No	No	Yes - $\tau = 95th$ and $99th$	Yes - $\tau = 99th$
Credit deterioration					
High	No	No	No	Yes - $\tau = 99th$	No
Low	Yes - $\tau = 95th$ and $99th$	No	No	Yes - $\tau = 95th$ and $99th$	Yes - $\tau = 95th$ and $99th$
Herding spillovers					
Financial sector	Yes - OLS and $\tau = 10th$ and $75th$				
Banks	Yes - $\tau = 95th$				
Diversified Financials	Yes - $\tau = 25th$				
Insurance	Yes - $\tau = 10th$				
Real Estate	No				
Non-fundamental and fundamental information					
Full sample (Jan. 2005 - Dec. 2017)					
Non-fundamental	Yes - $\tau = 99th$	No	No	Yes - $\tau = 95th$ and $99th$	No
Fundamental	No	Yes - $\tau = 25th$	No	Yes - $\tau = 10th$	No
Global financial crisis					
Non-fundamental	Yes - $\tau = 75th$ to $99th$	Yes - $\tau = 10th$ and $75th$ to $99th$	Yes - $\tau = 75th$ to $99th$	Yes - $\tau = 75th$ to $99th$	Yes - $\tau = 75th$ to $99th$
Fundamental	Yes - OLS and $\tau = 50th$ to $99th$	No	Yes - $\tau = 75th$ to $99th$	Yes - $\tau = 95th$	Yes - $\tau = 50th$ to $99th$
Eurozone Crisis					
Non-fundamental	Yes - OLS and $\tau = 10th$ to $75th$	Yes - OLS and $\tau = 10th$ to $75th$	Yes - OLS and $\tau = 10th$ to $75th$	Yes - OLS and $\tau = 10th$ to $75th$	Yes - OLS and $\tau = 10th$ to $75th$
Fundamental	No	No	No	No	No

Notes: The table presents the main results concerning our analyses in the Eurozone. In case herding is detected, we report "Yes", and "No" otherwise. OLS ($\tau = n^{th}$) indicates the presence of herding detected with OLS (quantile) regression (at the n^{th} quantile).

ing due to fundamental information is more pronounced in the left half of the quantiles and the estimates again indicate that herding was spurious more than intentional during this period.

Table 12 presents the estimates of models (14) and (15) that test the herding due to non-fundamental and fundamental information during the EZC for the US and the Eurozone, respectively. During the EZC, the OLS analysis shows the presence of herding due to non-fundamental information for the US and the Eurozone equity markets and financial sectors.

In the US, the quantile regression analysis in Table 12 provides evidence of "intentional" herding in the equity markets and all the financial industries especially in the lower quantiles that means investors were herding due to non-fundamental information during the EZC. There is no evidence of "spurious" herding. The findings related to the Eurozone are similar to the US case.

Overall, our results indicate that different crises may affect herding differently. During the GFC, investors engaged in "spurious" herding. This result changes during the EZC, because investors show more "intentional" than "spurious" herding.

The findings presented in this subsection represent a new and interesting contribution to describing herding during the GFC and the EZC in US and the Eurozone. The distinction between "spurious" and "intentional" herding explains the main driver of herding during the crises and gives a more specific analysis compared to the usage of the total CSAD, which cannot give a specific reason for herding (see, e.g., the results referred to the GFC in Section 4.2).

5. Summary and conclusions

Herding arises when investors take collective actions in the market. In the short term, herding increases market volatility by reducing the information content in stock prices and, thus, potentially causing an information cascade that is characterized by traders merely copying the actions of others. In the long term, herding could affect economic cycles by generating price bubbles (Hott, 2009). For these reasons, it has important implications for policymakers, supervisory authorities, and academia who are involved in identifying and assessing the sources of risk and the vulnerability of financial stability with the final goal of developing policies that limit the extent of noise trading.

Our study follows the approach based on the CSAD that Chang et al. (2000) propose by using a quantile regression analysis in addition to the common practice of an OLS in order to have a more complete analysis of herding. This approach alleviates some of the statistical issues related to the OLS. The main findings are summarized in Tables 13 and 14.

We find evidence of herding during the GFC with both methods for the US and Eurozone equity markets and financial industries, except for banks in the Eurozone. On the other hand, we do not find significant herding during the EZC in either equity market. However, in the US banks and insurance industries and in the Eurozone, banks, diversified financials, and real estate industries, we find herding during the EZC. The results show that during the GFC, investors tended to herd when the market was moderately distressed, while during the EZC this behavior was limited to specific industries only.

We show that herding in the US is more likely during extremely distressed market states with higher volatility, while in the Eurozone, this trend exists only for the diversified financials. The Eurozone's banks and insurance industries tend to herd more when there is lower volatility. We find that credit deterioration affects herding in the US and Eurozone equity markets and financial industries, except for the banks in the Eurozone. We find similar results when illiquid funding exists in the market.

Furthermore, we inspect the presence of spillover herding from the financial sector and its industries to the domestic equity market. Our results indicate the presence of a spillover effect from the insurance industry to the domestic market in the US and from the banks to the domestic market in the Eurozone.

We find evidence of "intentional" herding in the US equity market and all the financial industries. On the other hand, in the Eurozone, there is herding by the corporates in the equity market and the insurance industry, while we find the presence of "spurious" herding by the diversified financials and, again, for corporates in the insurance industries. Analyzing the GFC, our results indicate that the herding detected during this period was "spurious" more than "intentional". During the EZC, the corporates in the US and the Eurozone equity markets and financial industries tended to herd due to non-fundamental information – "intentional" herding – that highlights that the two recent financial crises affected herding differently.

Following our analysis we can conclude that any shockwave in the financial sector or industries (real estate excluded) will affect the domestic equity market depending on the state of that economy. Herding detected under a high volatility state of the economy is more prevalent in the extreme parts of the CSAD distributions. One possible explanation is that smaller value stocks are subject to more intensive manipulations attracting herding related to these assets. Previous literature suggests that at the institutional level herding may be based on fundamental values that determine a faster prices adjustment. The empirical results contained in our study imply that policy makers may further strengthen the legal framework to decrease the level of speculative activities in the stock markets. Hence, policymakers and supervisory authorities will use this information to observe more efficiently these industries in a country specific manner, that is the insurance companies in the U.S. and the banks in the Eurozone.

The CSAD methodology is largely used in the literature for capturing herding behavior but this is a static model and it can lead to biased results as the parameters are considered constant over the entire period under analysis. Employing the quantile regression to extract inference to substantiate the existence of herding is a methodological step forward in this area of research since the analysis can capture effects in various parts of the distribution of the herding measure, including the tails of the distribution, and not just an average effect. Because herding behavior is a time-varying phenomenon, a dynamic methodology would be preferable although currently not available. At the same, there are still challenges how to deal with quantile regression in the presence of structural breaks and also for panel data. Any new developments in the econometric theory of quantile regression along these directions will improve the depth of the analysis.

Due to the increasing macroeconomic convergence among Eurozone's countries, it suggests that future researches should take into account the effects of the international integration of stock markets. Thus, even though representing variables at the global level may be difficult, investigating herding by adding a layer by considering a global benchmark would provide a deeper insight into the concept of herding. Another further line of research may look at both equity and debt of companies when analyzing herding. Designing a herding measure that will cover both sides of the balance sheet of the company will provide a bridge between the market based herding measures and the more detailed balance sheet driven herding measures.

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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Appendix A. Supplementary material

Supplementary data associated with this article can be found, in the online version, at https://doi.org/10.1016/j.jimonfin.2020.102311.

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