On the time varying nature of herding behavior: Evidence from major European indices

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Abstract: The recent financial crisis clearly demonstrated that herding behavior incorporates an unhedgeable systemic risk, exposing investors and financial institutions to market prices and valuations, which cannot be solely explained by fundamentals. We examine the existence of herding behavior of the major European stock market indices employing daily data during a recent period from 15-April-2005 to 31-December-2012. Following the recent events that unfolded in the Eurozone sovereign debt crisis our analysis is further expanded on two subsamples namely north and south European countries. Since the observation of significant herding patterns is very sensitive not only to the selected indices universe, but also to the time frame under consideration, a novel approach of this work is to explore the dynamics of the system with the use of time rolling window of varying size. A snick review of our results indicates significant herding behavior for the countries under examination. Finally, we test whether herding effects became more intense during the recent financial crisis as a function of the conducted rolling window size.

Keywords: Financial time series, Herding behavior, Cross sectional absolute dispersion, International Financial Markets, Rolling window regression.

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1 Introduction

Imitation and mimicry are among our basic instincts (Devenow & Welch, 1996) leading to herd behavior, describing how individuals can form a group acting together. Herding can be identified during several activities including street demonstrations, riots and general strikes (Braha, 2012), sporting events, religious gatherings, decision-making and opinion-forming, as well as stock market bubbles and crashes. Herding requires a coordination mechanism which can be either a widely spread rule to coordinate based on some signal, or based to a direct ability to observe other decision makers.

Literature related to managerial performance indicates that managers are evaluated relative to one another, and benchmark evaluation is more accurate when more managers use the same technology (Zwiebel, 1995), therefore subsequent managers prefer to adopt this technology in order to signal their skills, instead of a possibly superior technology. Principal agents models show that managers, in order to preserve or gain reputation when markets are imperfectly formed, may either prefer to 'hide in the herd' not to be evaluable, or to 'ride the herd' in order to prove quality. As a result, even the better managers may herd instead of the taking the risk of an ex-ante better idea with the fear of turning out to be an ex-post bad decision, or according to Keynes, "it is better for reputation to fail conventionally than to succeed unconventionally".

In the financial realm herding could be universal, yet it is difficult to precisely define herding. In its most general form, herding can be defined as behavior patterns that are correlated across individuals, or correlated information arrival in independently acting investors. Representative definition of rational herding in finance include, a group of investors trading in the same direction over a period of time (Nofsinger & Sias, 1999), and when individuals alter their private beliefs, to correspond more closely with the publicly expressed opinion of others (Cote & Sanders, 1977). Herding may lead to the formation of bubbles, implying that investors may be ignoring their private information driving prices away from their financial values and economic fundamentals, with the result that assets are not appropriately priced. This feature poses a constant threat to financial stability, exposing market participants and financial institutions to an unhedgeable systemic risk. Although widely discussed, herding is anything but clearly defined. Not all instances of simultaneous and similar actions lead to inefficiencies and excess volatility, spurious or unintentional. Herding emerges when investors, independently of each other, react in a similar manner to common news. Such behavior can result in efficient price reactions to news about fundamentals which is something desirable (Gebka & Wohar, 2013). However if knowledge about other investors' affects one's own actions, intentional herding takes place and can result in inefficient outcome. It should be noted that investors are one of the primary roles in a stock market along with hedgers who engage in transactions to offset some other pre-existing risk, arbitrageurs who seek to profit from situations where fungible instruments trade at different prices in different market segments, and speculators who absorb excess risk that other participants do not want, and provide liquidity in the marketplace by buying or selling when no participants from the other categories are available.

Measures of herding could be grouped roughly into two broad categories: those that are constructed using observed stock market returns (Christie and Huang, 1995, Gleason et al., 2004) and measures that rely solely on transactions data (Lakonishok, Shleifer & Vishny, 1992). The latter includes one of the most influential herding statistics employed in many empirical studies in the mutual fund market such as Grinblatt et al. (1995) and Wermers (1999) for US market and in Choe et al. (1999) for South Korean, Kyrolainen and Perttunen (2003) for Finland, Wylie (2005) for the UK, Voronkova and Bohl (2005) for Poland and Walter and Weber (2006) for Germany. Apart from the approach to measure herding from observed transactions, another strand of the literature relies on assets' returns to gauge the existence of herding behavior. Herding measures that relies on asset returns is rooted in the CAPM theory. In the same vein, Hwang and Salmon (2004) have suggested the use of shifts in the cross sectional dispersion of asset betas against market and various style portfolios as a method of detecting and measuring herding while Chevalier and Ellison (1999) have proposed measures of herding relying on relative risk-taking attitude of market participants especially fund managers. The existence of herding or not in the studies in the literature is subjected to the dataset under consideration and the time interval used.

In this work we examine the herding behavior for a set of fifteen major European countries benchmarking indices. The markets under examination are afterwards split into two subsets, the southern Europe which includes, Greece, Italy, Portugal, and Spain, and the rest countries which form the northern Europe. Since the studies in the literature are static with respect to the time frame, the datasets are also examined via overlapping rolling window regression of varying window size, to capture potential time-varying parameters.

2 Market microstructure and herding theories

In order to quantify herding a measure of dispersion is needed. There are two alternative measures of dispersion, the cross-sectional standard deviation (CSSD) used in Christie and Huang (1995),

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

where, $R_{i,t}$ is the return of the i-th asset at time t, and $R_{m,t}$ is the average of the $R_{i,t}$'s. In case $R_{m,t}$ is an exogenous variable, then CSSD should be referred as the root mean square error.

An alternative measure of dispersion is provided by Chang et al. (2000), who define the cross-sectional absolute deviation (CSAD) as,

$$CSAD_t = \frac{1}{N}\sum_{i=1}^{N}\left|R_{i,t} - R_{m,t}\right| \tag{2}$$

since the CSSD definition, calculated by squared return-deviations might be sensitive and considerably affected by the existence of outliers. Both of these dispersion models are used to identify any possible herding behavior. The approach taken by Christie and Huang (1995) is to argue that herding will be more prevalent during periods of market stress. They consider the equation for herding identification using a dummy variable approach,

$$CSSD_t = \alpha + \beta_1 D_t^U + \beta_2 D_t^L + \varepsilon_t \tag{3}$$

where $D_t^U = 1$ ($D_t^L = 1$) if the return on the asset is for the time period t lies in the extreme upper (lower) tail of the returns distribution, and 0 otherwise respectively. On the other hand, Chang et al. (2000) argued that the model in Eq. (3) requires defining what is meant by market stress. Under normal circumstances, the conditional CAPM specifies a linear relationship between CSAD and market returns. Following this assumption, during period of market stress, if herding occurs a nonlinear relationship will also exist. This nonlinear relationship can be modeled as follows,

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

If herding is present, then γ_2 will be significantly negative implying that the deviation of returns declines during periods of market stress. Several authors have proposed models of testing herding behavior in cases where positive and negative market returns are treated in a different manner with the inclusion of appropriate dummy variables or other regressors in the base models as follows:

$$CSAD_t = \alpha + \gamma_1 |R_{m,t}| + \gamma_2 R_{m,t}^2 + \sum_i \beta_i X_{it} + \varepsilon_t \tag{5}$$

where X_{it} are explanatory variables, endogenous or exogenous and β_i the corresponding coefficients. These include, Gleason, et. al. (2004), Hachicha et. al. (2007), Chiang & Zheng (2010), Economou et. al. (2011), Gebka and Wohar (2013).

3 Methodology and data

3.1 The data

The data under examination include fifteen major European countries benchmarking indices, Austria (ATX), Belgium (BFX20), Denmark (OMXC20), Finland (OMX25), France (CAC40), Germany (DAX), Greece (FTSE-ASE20), Holland (AEX), Italy (FTSE-MIB), Norway (OSEAX), Portugal (PSI20), Spain (IBEX35), Sweden (OMX-30), Switzerland (SMI20), and UK (FTSE100) daily returns, from 15-Apr-2005 to 31-Dec-2012 comprising of 2000 entries for each country. The time series under consideration, containing the close values of the indices, obtained from http://finance.yahoo.com/, are shown in Fig. (1) for the time interval examined. The return is the difference of the natural logarithm of the prices, where P_t denotes the value of the index,

$$R_t = [\ln(P_t) - \ln(P_{t-1})] \times 100 \tag{6}$$

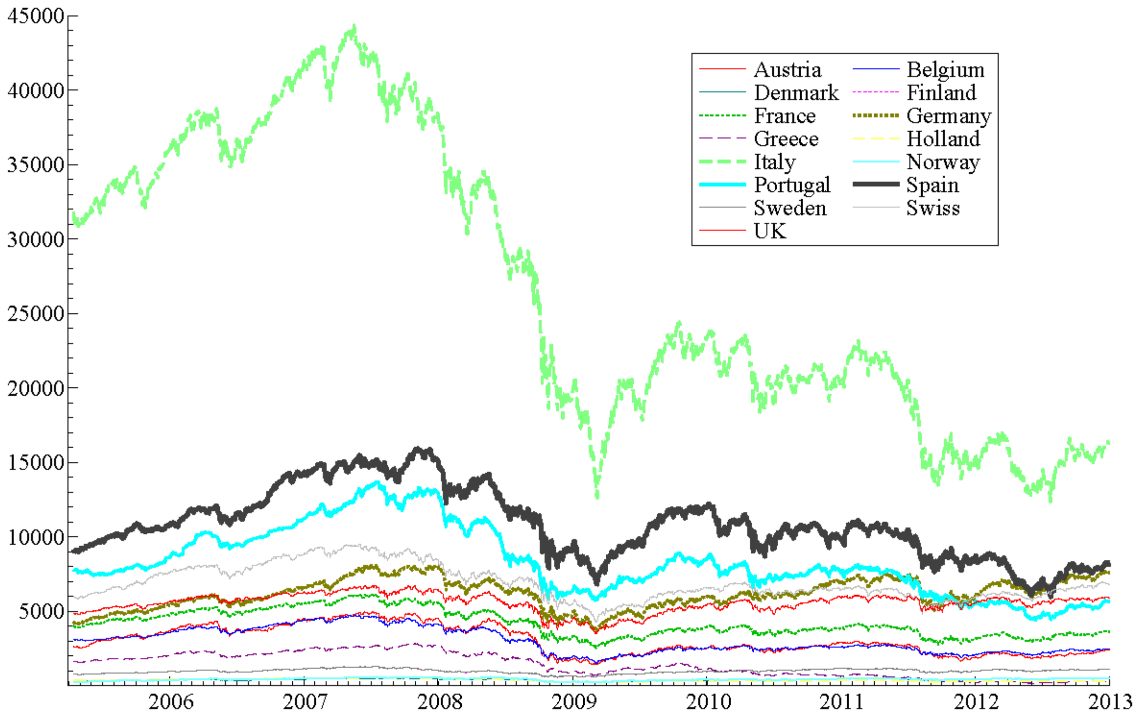

Fig. (1) The market time series indices under consideration

3.2 Methodology

We utilize the most commonly used measure of dispersion of returns in the literature, the CSAD measure,

$$CSAD_t = \frac{1}{N}\sum_{i=1}^{N}\left|R_{i,t} - R_{m,t}\right| \quad (7)$$

where $R_{m,t}$ is the value of an equally weighted average of all indices returns. One can argue that in an integrated global financial market facilitated by high-tech devices and efficient information processing, financial activities are unlikely to be insulated from the rest of the world, and it is reasonable to include major foreign variables in the model to identify the role and significance of the global factor. Nevertheless, our study is mostly focused on the rolling window technique, and the estimated equation proposed by CCK is appropriate for a close system, in that no foreign repercussions are involved. The nonlinear relationship, in case of herding phenomena is described by,

$$CSAD_t = \alpha + \gamma_1\left|R_{m,t}\right| + \gamma_2 R_{m,t}^2 + \varepsilon_t \,. \quad (8)$$

The analysis can be summarized in the following hypothesis,

H1. *In the absence of herding effects we expect in the model* $\gamma_1 > 0$ *and* $\gamma_2 = 0$. *If herding effects are encountered, we expect* $\gamma_2 < 0$.

After examining any herding behavior of the three datasets assuming constant parameters throughout the estimation period, the rolling window regression technique is employed. Rolling window regression is a common technique to assess the stability of a model's parameters providing parameter estimates over a rolling window of a fixed size through the sample. If the parameters are truly constant over the entire sample, then the estimates over the rolling windows should not deviate significantly. However, should the parameters change randomly during the period of analysis, then the rolling estimates should capture this instability. Rolling window regression is a recursive methodology that repeats regressions using dataset subsamples by shifting the start and end points, either by overlapping or non-overlapping window of fixed values at a time. A non-overlapping window of size k -days is splitting the sample to m subsets of k points each, so that $n = k \times m$ is the total number of points, and regressing from $1:k$, $k+1:2k$ ..., while for the overlapping case rolled by 1 day, the regression is $1:k$, $2:k+1$,…, until the end of the sample. The advantage of using this technique is basically to look at any changing property of a series over time. Hence, the rolling window regression captures potential time-varying parameters and it is a more robust procedure, as a statistical methodology, than ordinary regressions. The size of the rolling window is related to the timescales of the system (response times). For systems with fast timescales short windows can be appropriate, whereas systems with slow timescales require longer rolling windows for the metrics to be able to capture changes in the signature of the time series. Short rolling windows may lead to irregular trends in the estimates of the metrics whereas long rolling windows smooth out the trends. Also, the shorter the rolling window is, the less accurate the estimate of the metric becomes. There is no golden rule for the right size of the rolling window and there is a trade-off between having a long enough window to estimate the metrics and short enough to have a sufficient number of windows in order to be able to derive a trend. In this study we consider rolling window regression with a varying window size from 200 days to 700 days, rolled by 1 day. The window sizes were chosen since we would like to investigate two critical intervals in the time frame, the fast market crush around the minimum, and the general market crush.

4 Results and discussion

Using the CCK measure of dispersion, the cross-sectional absolute deviation was calculated for all datasets and the results are shown in Fig. (2). In case herding effects are encountered in days of extreme market movements the cross-sectional dispersion of stock returns is expected to decrease or increase considerably less than proportionally with market return. Dispersion measures indicate that, when herding behavior arises, investors tend to ignore their private information and follow the market consensus. Under these circumstances asset returns have the tendency to cluster around the market portfolio returns, and their cross-sectional dispersion is significantly reduced. By contrast, rational asset pricing models predict an increase in cross sectional dispersion of returns in periods of extreme market movements, because individual assets differ in the sensitivity to the market returns. Herding would be evidenced by a lower or less than proportional increase in the CSAD during periods of market stress (Gleason, 2004). During normal periods, rational asset pricing models predict that the dispersion in cross-sectional returns will increase with the absolute value of the market returns, since individual investors are trading based on their own private information, which is diverse. However, during periods of extreme market movements, individual tend to suppress their own private information, and their investment decisions are likely to mimic collective actions, following the market consensus. Under these conditions individual stock returns tend to cluster around the overall market return (Chiang & Zheng, 2010). From the CSAD figure we can reach the conclusion that

(i) there is a relative increase of the CSAD measure for all three datasets right before the 2009 crash, and also smaller increments at the other local minima too about 300, 1300, 1600, and 1800 data points.

(ii) since CSAD is a measure of dispersion and it's a positive number, one cannot comment directly on its magnitude, but comparing the three graphs we can see a decrease in the main peak strength, relative to the other peaks in the same graph, as we move from North countries, to EU, and to South countries datasets.

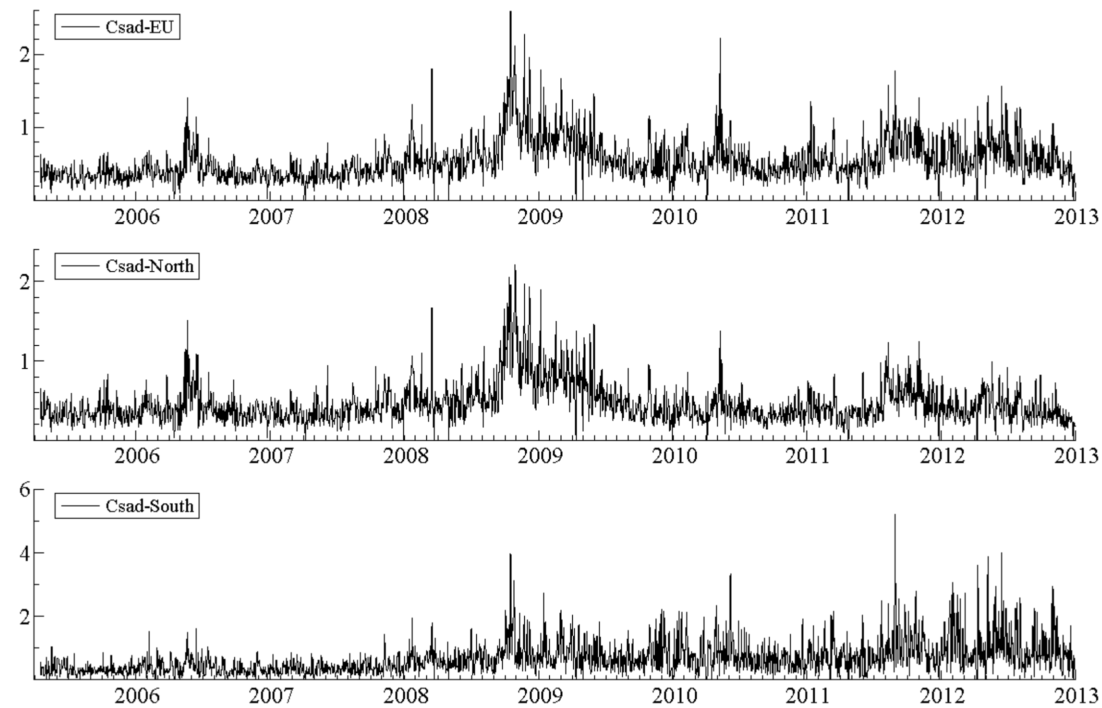

Fig. (2) CSAD measure of dispersion for the EU (top), North (middle) and South (bottom) datasets.

Applying the model of Eq. (8) to the European dataset and the north and south subsets, the results are shown in Table (1). It is evident in agreement with the CSAD figures, that the North dataset alone has a non-significant anti-herding behavior, when we incorporate the South dataset the full EU results in a non-significant herding behavior, and the South dataset indicates significant herding behavior.

	EU			NORTH			SOUTH		
Coeff.	value	t-stat	p-value	value	t-stat	p-value	value	t-stat	p-value
a	0.3942	45.7353	0.0000	0.3320	40.6184	0.0000	0.4090	23.8195	0.0000
γ_1	0.1699	15.5305	0.0000	0.1377	13.3043	0.0000	0.3075	15.7508	0.0000
γ_2	-0.0028	-1.3310	0.1833	0.0007	0.3484	0.7276	-0.0216	-6.2399	0.0000

Table (1). Results of the CCK regression for the EU (left), North countries (middle) and South countries (right).

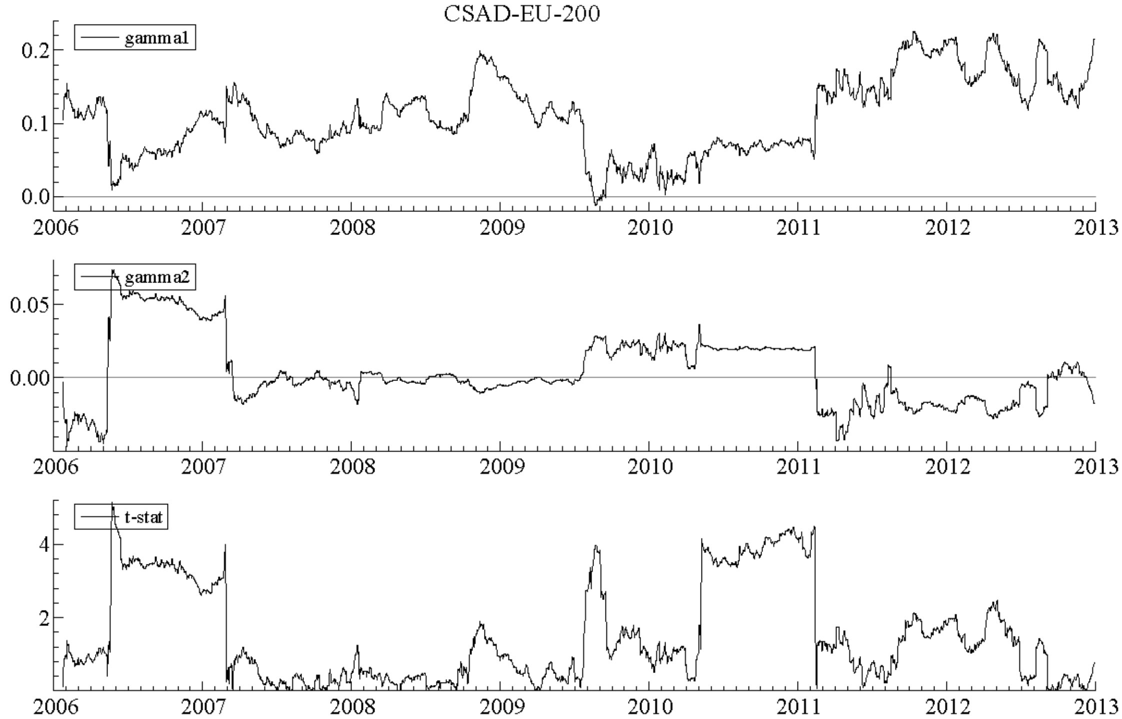

Fig. (3) Results of the rolling window of 200 points size for the EU showing the gamma1 coefficient (top) the gamma2 coefficient (middle), and the t-statistics significance of the gamma2 coefficient (down).

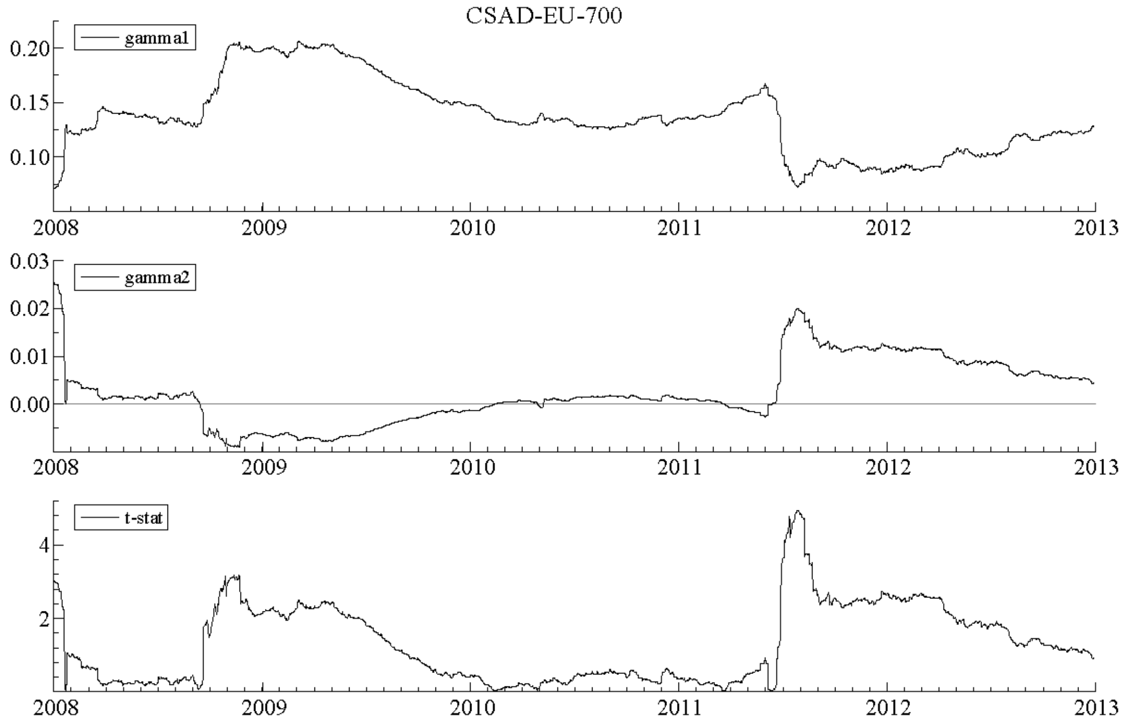

Fig. (4) Results of the rolling window of 700 points size for the EU showing the gamma1 coefficient (top), the gamma2 coefficient (middle), and the t-statistics significance of the gamma2 coefficient (down).

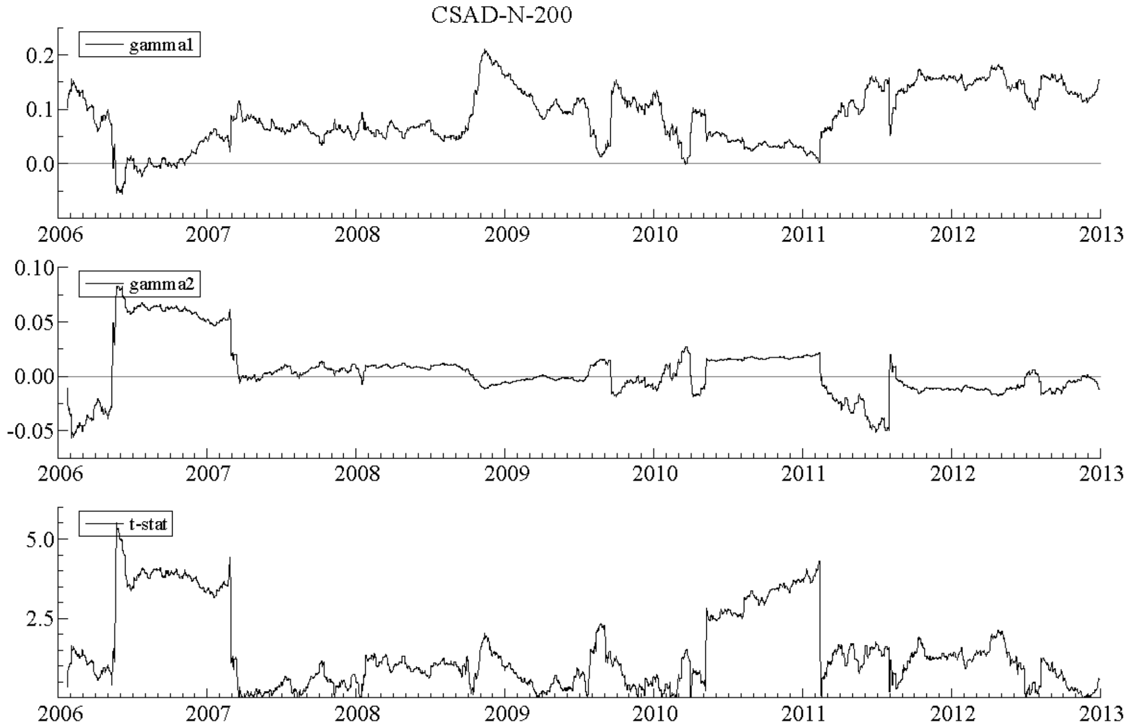

Fig. (5) Results of the rolling window of 200 points size for the North dataset showing the gamma1 coefficient (top), the gamma2 coefficient (middle), and the t-statistics significance of the gamma2 coefficient (down).

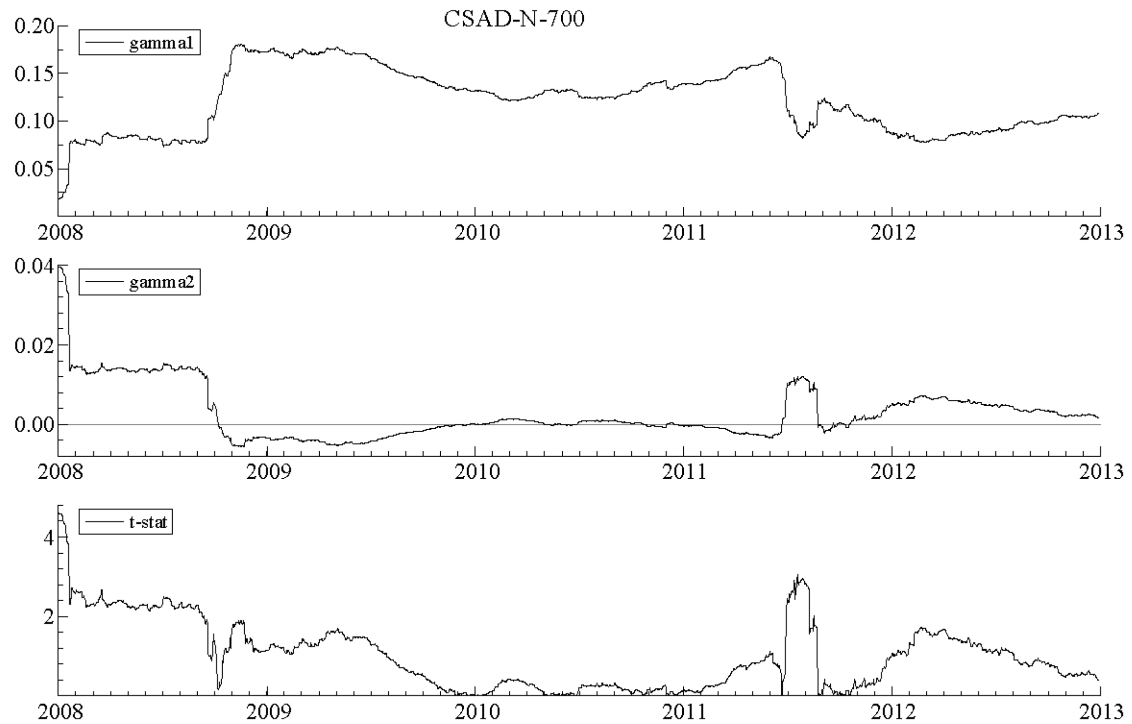

Fig. (6) Results of the rolling window of 700 points size for the North dataset showing the gamma1 coefficient (top), the gamma2 coefficient (middle), and the t-statistics significance of the gamma2 coefficient (down).

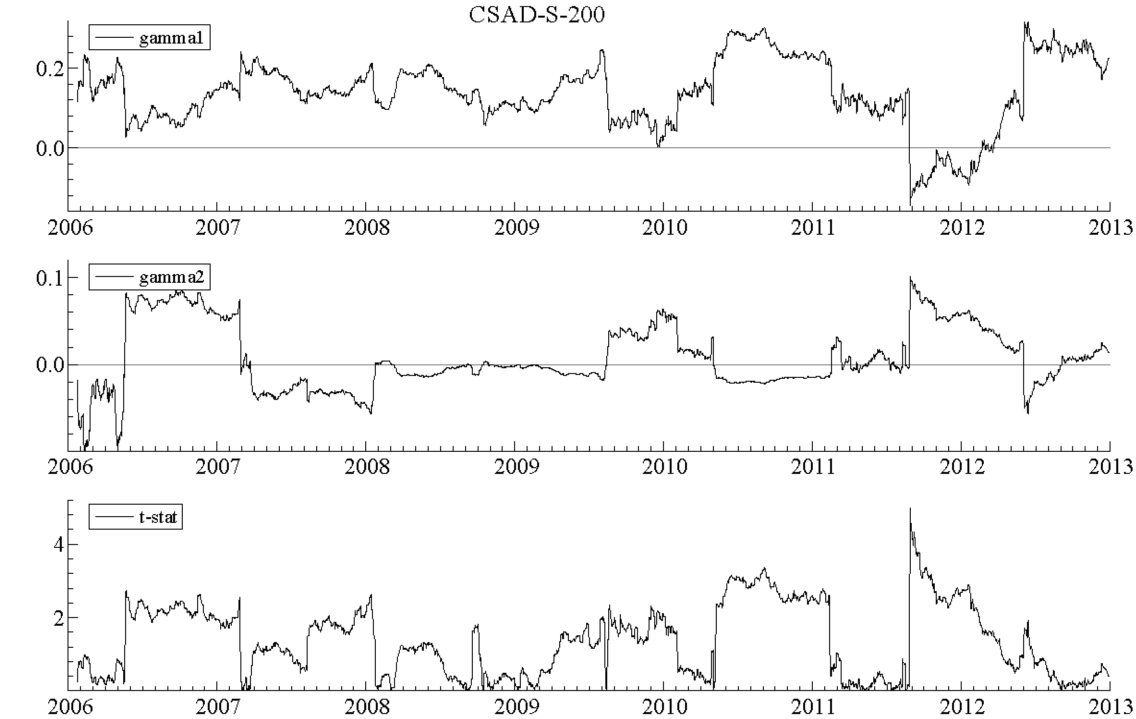

Fig. (7) Results of the rolling window of 200 points size for the South dataset showing the gamma1 coefficient (top), the gamma2 coefficient (middle), and the t-statistics significance of the gamma2 coefficient (down).

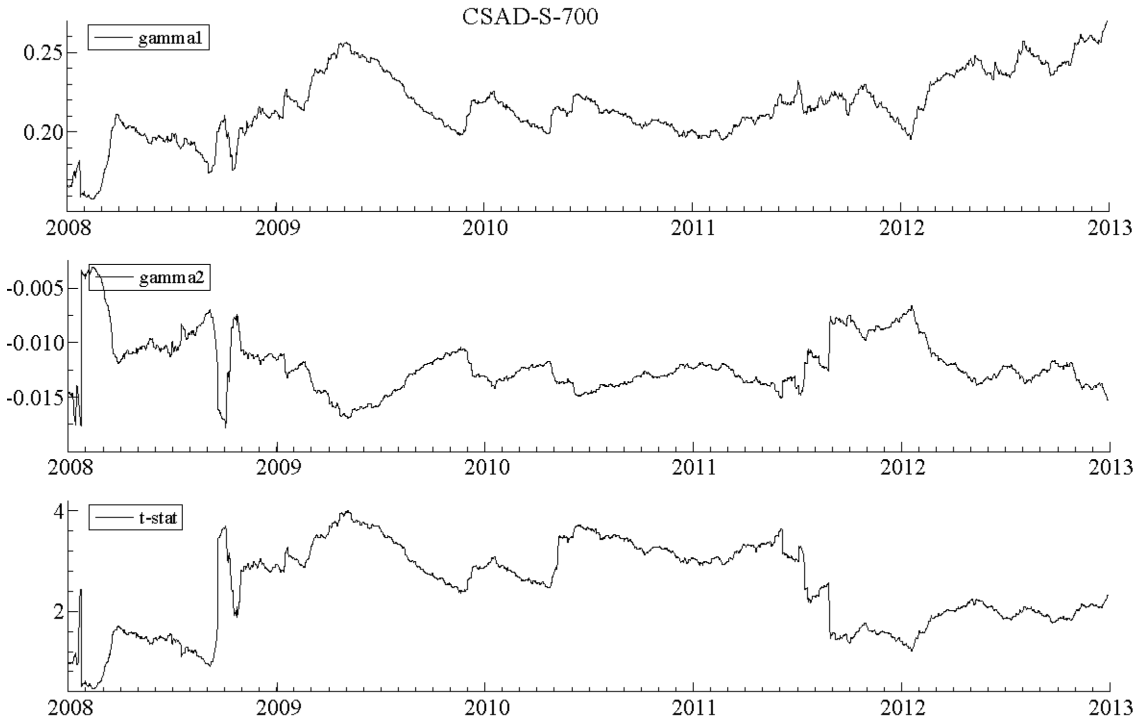

Fig. (8) Results of the rolling window of 700 points size for the South dataset showing the gamma1 coefficient (top), the gamma2 coefficient (middle), and the t-statistics significance of the gamma2 coefficient (down).

The coefficient γ_2 is significant and positive indicating the absence of herding behavior during low market stress, and that traders are trading away from the market consensus for this two subsets in periods of low market stress. This is in agreement with the peaks observed in the CSAD measure at points 300 and 1300, as shown in Fig. (2). There is a similar pattern for the South too, but we cannot consider it significant since the associated t-statistics is always less than 3. The slow time scale window of 700 points also shows a smoothed version of the fast time scale window for the EU and North. In contrast, the South subset shows significant herding behavior throughout the crash.

5 Conclusion

In this work we have examined the herding behavior of the major European indices. The results indicate strong herding behavior of the South countries during the crash period, supporting the argument that herding effects if any are more pronounced during the days of market stress, defined as the days of extreme negative returns. Analysis of the markets microstructure via rolling window regression of varying size indicates herding behavior for the South countries throughout the crash period, and there is also evidence for significant positive herding behavior of the EU and the North countries subsets in periods of low market stress.

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