Herd Behaviour in Extreme Conditions: an evidence from Spanish Market

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Abstract
This paper aims at exploring the effect of financial crises which started in 2008 on the herding behaviour of market participants using the Spanish financial market as a case. We conduct this study to Investigate Herd behaviour in Financial Market of Spain an Ex-ante and Ex-post analysis of financial crises of 2008 considering daily returns of all stocks market index during market stress, a period between 2002 and 2011. The 2008 financial crises which were triggered by the inappropriate use of mortgages in the subprime market have led to recessions among the major economies in the world. Considering that Spain is one of the most affected countries by the financial meltdown, the Spanish recession continued to deepen until this point in time and the consequences were reflected in high volatility and pessimistic downward movement in the stock market. We expect to find positive and significant coefficient values of the dummy variables used to detect the extreme movements in the dispersions of the individual stocks, where significant and negative beta coefficients would indicate the presence of the herd formation. The study concludes that the Spanish market investors, either before or after the crises, do not tend to abandon their private information and form a herd hence making a rational investment decision.
Keywords: Herd Behaviour; Financial Markets; Financial Crises; Spain

Herding, when considered in financial decision making, is phenomenon where an economic agent tends to imitate the investment choice of other investors, or a group, and forsakes his/her own private information. This individual action when imitated by many will form a herd that clusters around the overall market return (Hwang and Samon 2004). In some studies, for example Christie and Huang (1995), it is argued that market stress can be described as the period of extreme, high as well as low. And, this unison participation decreases the dispersion between the individual return and market return. Chang *et al.* (2000) conclude that this dispersion increases with a decreasing rate and if the herding effect is severe then it reduces significantly. This phenomenon leads to a situation where the investors forsake their private information, if any, no matter how accurate that may be, in favour of the group choice of action. This outcome may be a conscious or an unconscious decision which can be a cognitive bias or even a strategic move (Van-Campenhout and Verhestraeten, 2010). This may be a rational or a profitable move for the time being for a single investor but may generate an inefficient outcome in the market as a whole (Bikhchandani et al. 1992), with an increased “ex-ante inefficiency” in general equilibrium. Herding does not always have to be irrational; it may sometimes be the only rational move an investor could take against the uncertainty in the market, huge market volatility and when the investor’s own information is either poor or incomplete. Bikhchandani and Sharma (2000) have discussed this in detail.

We conduct this study to investigate the herd behaviour in financial market of Spain an ex-ante and ex-post analysis of financial crises of 2008 considering daily returns of all stocks market index during market stress, a period between 2002 and 2011. Interestingly herding phenomenon has mixed results that occurs where there is an increased price movement especially the up market (Henker et al. 2006) and where volatility is substantially low or in down market where investors’ confidence is not as high, as shown by Chang *et al*. (2000). As a result the 2008 financial crises which were triggered by the inappropriate use of mortgages in the subprime market have led to recessions among the major economies in the world. However, for some European countries the recession had a devastating impact to the extent that governments were led to the bankruptcy.

Given the fact that Spain is one of the most affected countries by the financial meltdown, the Spanish recession continued to deepen until this point in time and the consequences were reflected in high volatility and pessimistic downward movement in the stock market. It is hence important to examine whether the herding behaviour in the Spanish market is reduced during the recession period as suggested by Christie and Huang (1995) and or is increased as in Chang *et al*. (2000). Therefore, the state of the Spanish market provides a suitable testing sample for herding behaviour at extremely high volatile periods.

While previous research has looked at the potential dominance of market volatility over herding behaviour in explaining risk of individual securities. This study looks at the varying levels of herding during the pre and post crises periods. To conduct this research, we use a fairly simple, yet a strong theoretical framework and model developed by Christie and Huang (1995) which explains that stock evaluations based on rational asset pricing model causes an individual stock to invest in the risk during market stress. Thus, it becomes more volatile and dispersed away from the overall mean market return.

We conclude that Spanish market investors, either before or after the crises, do not tend to abandon their private information and form a herd hence making a rational investment decision. Our conclusion remains consistent with this type of methodology used by Christie and Huang (1995). The volatility in the down market increases making it more uncertain to predict leading to an increased reliance in rational asset pricing models. Our study revealed similar results where the standard deviation of the market return rose from 1% pre-crises to 1.9% post- crises resulting in an increase of 90% volatility after the crises. Similarly, consistent to Christie and Huang (1995), our results show that the individual stocks volatility was also raised by 45% after the crises, from 0.35% to 0.51%, this increases investors' anti-herd behaviour where they perform more rationally and that investor have a tendency to herd more during the up market movement as compared to the down market.

The structure of our remaining paper begins with second section as the literature review and theoretical framework of herd behaviour. In third section we develop and describe our dataset and methodology to illustrate the construction of the measure of dispersions and Variable choice. Fourth section gives us a liberty to discuss our findings and present results, while fifth section concludes the study and suggests some potential constraints and recommendations to improve it.

Literature Review and Theoretical Framework

Correlated Trading or "Herd Behaviour", as described by Bikhchandani *et al*. (1992), and Bikhchandani and Sharma (2001), is the behaviour of an individual investor who forsakes his private information to investment decision against that of the market, referring the situation as forming an "*informational cascade"*. This decision, however may quite often, be suboptimal and inefficient resulting in forming a herd and sometimes making a wrong choice (Benerjee, 1992)**.** Asch (1952) first describes the phenomenon where individuals sometimes abandon their own opinion, albeit correctly, against the group decision. Based on the team theory of Radner (1962), Vives (1995) learns about the, asymptotic, convergence of private information, which may or may not be correct into the precision of the public information since the informational externality will refrain from the agents to rely less on their private information, even if relying on private information in a single period is not optimal. Learning from it will lead to an aggregate welfare gain of "precise" public information. Radner (1962) and Vives (1995) argue this convergence will be slow, but asymptotically viable.

Besides Fama's (1970) ground breaking theory of Efficient Market Hypothesis (EMH), Increasing need of better explanations of the human behaviour, making financial decisions is felt by many authors. Shiller (1987); Bikhchandani *et al*. (1992); Banerjee (1992); Scharfstein & Stein (1990) are among the first few to present their seminal works in formulation of models for herd behaviour in financial market and its consequences if investors follow a pattern where they abandon their private signals in favour of the market. As this is not a rational behaviour and does not depict the actual value of the stocks based on the rational asset pricing model. It rather artificially inflates the stock prices and a bubble may be created with the potential devastating effects of, not only, a material welfare loss and inefficiency leading to the whole transaction as "ex-ante inefficient" but it also indicts the good managers in general equilibrium (Allen *et al*., 1992).

The Information dissemination among the investors is due to the various sources including their private information concluded from their own research about the investments including "Technical Analysis" and "Fundamental Analysis" with the help of rational asset pricing models e.g. CAPM (Van Campenhout, 2010). Truman (1994) finds that correlated trading not only leads to inefficient decision making but also suboptimal use of resources, which should otherwise have reflected the true stock valuations by means of capital asset pricing model, where analysts consider risk matrix in order to determine the true price of the securities.

Olsen (1996) investigates a rather small, but detailed, window of analysts' forecast submissions from 1985 to 1987 and finds out that between 52% to 72% of the analysts submitted a correlated forecast and herding increases with the increase in the uncertainty or prediction ability of the forecasts increases. Hirshleifer & Teoh (2003) however explain that analysts do not always hold a rational stance when making the investment decisions and may deviate from the optimal choice, which may arise from miscalculation of the risks and uncertainties attached to the stock valuation including systematic risk in favour of the more optimistic one. Ciccone (2005) also calculates up to 40% deviation from the optimal choice and shows too optimistic results that lead to a 20% higher forecast errors. This deviation from the rationality may sometimes be the most rational decision under certain circumstances.

Investors may not always use rational asset pricing model or tick the boxes of their risk and reward matrix. Instead, sometimes, they simply form their investment decisions on overall market trend, and an up market, for example, would entail an optimistic view and vice versa (Bange, 2000). Or sometimes they continue to invest in overvalued stock as long as it is performing well. Shiller (1989) explains that this number can be as high as 93% of the rational investors making such decisions. This phenomenon could also hold if investors are afraid to stand out from the crowd. Nevertheless, this behaviour may not be efficient from the social perspective but holding a contrarian view may be detrimental to their career in labour market hence leaving this the only rational choice (Scharfstein and Stein 1990).

Investors having little information and ability to perform fundamental or technical analysis may contract risky investments by following smarter investors in their decisions and exit the market at the time of bad news (Bikhchandani and Sharma 2001). On the same note (Chiang et al, 2010) explain the devastating effect of the herd investors following each other's signals and collectively force the stock prices away from fundamental value where arbitragers are the only one profiting from such opportunities and just like a diamond scheme when it falls petty investors lose out creating huge pareto - inefficiency and the effects are even worse when the markets do not make any corrections on time which will then allow the fundamental values to converge and economy as a whole is in shambles. Investors tend to herd more in low turnover stocks and when the markets are down as compared to the high turnover stocks (Fu 2010). Welch (1999) measures that the effect of the leader's decision on at least next two managers, whether this is to protect the reputation, or it is relatively safe to lose, if at all, in the group hence "sharing the blame" effect.

Saving the reputation in manager's decision to follow copying other's action may not be efficient but it is rational for the managers who have a reputation to maintain. Sometimes it is rational and optimal to follow the actions of the crowd once the herd starts for example in the case of a "payoff externalities" where a rumour brakes out (a run on the bank, for instance). Here it is better to follow the herd because everyone else follows that action since the liquidity of the bank is only limited. Here private information, no matter how accurate, does not play much role.

Herding can be unintentional and spurious where investors may follow similar investment decision only by extracting the same investment signal from the same source of information (Griffin et al, 2003). Similarly when the information of the analysts or a private investor is noisy then it is assumed that the information of the leader is better. Once the leader is followed by second and third analysts especially smart ones, a herd is formed attracting every one even including the smart ones having a better informational signal or having a winning recipe for making good investments, then the power of group urges them to make the same choice as he others.

Christie and Huang (1995) revisit the empirical work that are done to find out herding in financial market and explain that the support for herd behaviour is inconclusive and has a mixed outcome. Herding is more prominent in emerging market and not so much significant in the developed markets. Even in emerging markets some stocks attract more herding than the others and individuals tend to herd more in a down market compare to a bull market (Gebka et al 2009), extreme markets and rumour mongering may be a driving force for correlated trading. Kallinterakis (2010) however finds significant herd formation in an emerging market but the effects may fade away and herding becomes less significant once it is adjusted for the thin trading. Shiller and Pound (1989) and Cristie and Huang (1995) find the evidence of herd behaviour among the institutional investors: The investors in down markets are more likely to follow advice of others during the bear market as compare to a bullish trend.

A fairly simple model, yet with strong theoretical background, to test for the herd behaviour is one used by the Christie and Huang (1995) which understands the nature and impact of the phenomenon on data gives us an intuitive measure where herding would create dispersion in the returns since the prices are more volatile and driven away from the fundamental value. Hence it measures the dispersion which can be defined as *the Cross – Sectional standard deviation of returns (CSSD)* (Christie and Huang, 1995). When the returns correlate with that of the market then these returns will have dispersion closer to zero. When the stocks are traded without herding then the dispersion has a higher mean.

Hwang and Salmon (2004) estimate the same model of CSSD used by Christie and Huang (1995) with the same data type of 10 years daily stocks of US and Korean market during Asian crises and divide it into pre- crises, post- crises and during crises. They use Fama and French (1993) factor model of CAPM instead of the Cross-sectional Returns of the individual stocks. Nevertheless, they use the cross sectional sensitivity of factor variability instead of stock returns. They argue that the cross-sectional average return betas do not ingest the risk factor properly as described in rational asset pricing models. On the other hand, factor’s used by Fama and French (1993) show that Size and B/M factors explain the market variability better than the Cross sectional Average Returns (Huang and Salmon, 2004). There results, however, showed no significant down market herding found in their model, except they find idiosyncrasy in the quite market when the market is about to move back to normal after recession.

Chang, Chen and Khorana (2000) use the same Cross-sectional Absolute Deviation (CSAD) measure but their model was non-linear as contrary to the linear model proposed by Christie and Huang (1995). They found that the relationship between the betas and the market return is linear if there is no herding; but becomes increasing with a decreasing rate in order to account for the herding and if the herding measure is prominent then it will fall down significantly. Their results were based on 4 stock markets around the world with daily and monthly data analysed from 1963 to 1997 found no herding in developed market such as Hong Kong and US, partial herd behaviour in Japan but a significant amount of herding was found in Taiwan and Korean stock exchanges. They concluded that the downmarket stock tend to herd more than the upward movements. Caparrelli et al. (2004) replicated the Christie and Huang model for Italian stock exchange for 1988 to 2001. They did not find any presence of correlated trading in Italian stock market. Demier and Kutan (2006) investigated herd behaviour in Chinese stock market using the same model. They tested firm level as well as the sector level daily data from 1999 to 2002 and checked if Asian crises did cause the herd formation. However, they did not find any significant impact on Cross-sectional Standard Deviation ruling out the herding behaviour in their sample.

Economou et al. (2010) analysed four Mediterranean stock markets from 1998 and 2008, a 10 years daily stock, window and applied Christie and Huang (1995) and Chang et al. (2000) methodology. They found no evidence of herding in Spain, Italy and Greece but some evidence of herding was present in Portuguese stock market. Caporale et al. (2008) tested the Christie and Huang (1995) and Chang et al. (2000) models for Athens stock market and tested for the extreme conditions and the stock were grouped in semi-annual sub periods and the testing for the herd formation during the stock price bubble in 1999. Their results indicated the presence of herding in the market. Kallinterakis and Lodetti (2009), however, applied Christie and Huang (1995) and Chang et al. (2000) models to Montenegro stock exchange. They used the sample period from 2003 to 2008, and even after correction for the thin trading they found no evidence of Herding.

In aggregate the literature on the herd formation remains mixed and at least not at the level of Cross-sectional Mean Returns and the measure of dispersion using CSSD or CSAD which itself may be inefficient to capture inherent risk of the individual stock in their beta coefficients in the model.

Data and Methodology

Data

The data for 145 stocks that are used for research are collected from the Spanish stock exchanges and financial markets known as Bolsasy Marcedos Espanoles (BME) have a market value of \$1.031 billion as of the end of 2011. The BME is ranked at 14th in the world and 5th in Europe in terms of its stock market capitalisation. To undertake this research we collect daily stock prices of Spanish firms. We download data from "*Datastream International*" daily stock returns, whole index, of Spanish Market from January 2002 to 25th July 2011. We use closing price of the stocks to calculate daily logarithmic stock returns. Out of 2452 total observations, we exclude the companies which ceased trading either before or after the sample base year 2002. Our sample reflects a 10 years window giving us a detailed overview of Spanish market movement and, interestingly, to learn the phenomenon of market performance during extreme movements.

Figure 1: An Overview of Spanish Market from January 2002 to July 2011.

Figure 1 explains the general trend in the Spanish market during the period taken as our sample. From the figure we can witness an upward trend from 2003 until 2008 subprime crises, mainly due to the property boom. The upward market trend remained prominent until 2008 but became more volatile since 2008 with large market movements. Eurozone crises remained pervasive until the end of our sample period i.e. until August 2011. An ideal scenario to test for our main hypothesis is that market participants can abandon their own signals and herd formation becomes prominent during the market stress.

Table 1 explains the descriptive statistics of our Market Returns, Cross-sectional Standard Deviation (CSSD) and Cross-Sectional Absolute Deviations (CSAD) as explained by eq. The data are daily stock returns that range from 08 January 2002 to 22 July 2011, both days inclusive. CSSD and CSAD measure of mapping dispersions as proposed by Christie and Huang (1995) and is explained in equation (1) and equation (3) below, where there are $\boldsymbol{N}$ number of stocks in a market portfolio with market return $\boldsymbol{(R_{mt})}$ is the cross-sectional average return of all $\boldsymbol{N}$ returns in the market portfolio.

$$CSSD_t = \sqrt{\frac{\sum_{i-1}^{n}(R_{it}-R_{mt})^2}{n-1}}$$

$$CSAD_t = \frac{\sum_{i-1}^{n}|R_{it}-R_{mt}|}{N}$$

Table 1
Descriptive Statistics

	CSSD	CSAD	Market Return
Mean	0.0191968	0.012107	0.000085
Standard Deviation	0.0091239	0.004782	0.014249
Skewness	5.0186526	1.463053	0.232741
Excess Kurtosis	62.565235	5.950308	8.842401
Minimum	0	0	-0.09679
Maximum	0.1731087	0.052675	0.137370

Table 1 gives the descriptive statistics of our whole data along with the different measures of dispersions from the mean including Cross-sectional Standard Deviation, which measures the proximity of stock returns compared to the average market returns. We have the average dispersion of CSSD in our descriptive statistics which is 1.91% higher than the market mean returns with lower standard deviation but highly skewed and very highly populated around the tails which is an indication that most of the stock returns are dispersed away from the average market returns. Our market returns show more extreme movements from mean at 22% from minimum to the maximum value which is 5% higher than our CSSD series.

Column 2 of Table 1 represents the Cross-sections Absolute Deviation (CSAD), which takes the absolute value of the dispersion and controls for the large fluctuations in the data. This tackles the important problem in Cross-sectional Standard Deviation which is, although, a natural and intuitive measure to capture the influence of the correlated trading but is affected by the presence of extreme values that may affect the robustness of the test. Table 1 compares CSAD with CSSD which is more uniform series with 44% smaller standard deviation, better distribution and less affected by the large movements.

Methodology

We study the phenomenon described by Christie and Huang (1995) in Spanish market, carefully choosing the data with a 10 years window, from 2002 to 2011, in which the market stress and price movement were most pronounced. We analyse daily stock returns of 145 all shares index giving us 2549 observations over 10 years period. We first test for the Cross-sectional Standard Deviation (CSSD) of the returns of entire sample period and then test and adopt a better measure of Cross-sectional Absolute Mean Deviation (CSAD) that is suggested by Christie and Huang (1995) and endorsed by Chang et al. (2000), in order to adjust for the extreme single stock movements, the outliers. Along with the entire sample period analysis we also conduct further research to divide the sample into before and after the market stress caused by the subprime bubble burst.

The empirical specifications of Christie and Huang (1995) CSSD model is as follows:

$$\boldsymbol{CSSD_t = \sqrt{\frac{\sum_{i-1}^{n}(R_{it} - R_{mt})^2}{n-1}}} \qquad (\mathbf{1})$$

Where $\mathrm{R_{it}}$ observes stock return of firm ***i*** at time ***t***, whereas $\mathrm{R_{mt}}$ is the market portfolio of ***n*** firms, which is the cross-sectional average of ***n*** returns on market portfolio. In our hypothesis in order to differentiate between the rational asset prices model versus the herd behaviour we divide the market returns distribution into two extreme tails. We use two dummies in order to test for these two extremes which measures the level of dispersion caused by CSSD. These dummies will capture the individual asset returns that are significantly different from the unison market return clustering around the mean. We regress CSSD returns, a dependent variable, against the two dummies, D^L and D^U, measuring the up and down movements having extreme dispersions. Since the extreme movement is not clear so we apply the tests at 1% and 5% of the tails. The regression equation used in our model is in order to perform these test is written as:

$$\boldsymbol{CSSD_t = \alpha + \beta_1 D_t^L + \beta_2 D_t^U + \epsilon_t} \qquad (\mathbf{2})$$

Where we have;

D_t^L = 1 if the market returns on a particular day ***t*** lies in the extreme lower tail, 1% and 5%, of the return distribution.

D_t^L = 0 ranked otherwise.

And

D_t^U = 1 if the market returns on a particular day ***t*** lies in the extreme upper tail, 1% and 5%, of the return distribution.

D_t^U = 0 ranked otherwise.

α is the coefficient which represents the average dispersion of the sample which excludes the regions covered by the two dummy variables D^L and D^U. According to rational asset pricing models the significantly positive betas coefficients will encompass the volatility in the asset returns which does not follow the herd; whereas negative β_1 *and* β_2 will correspond to the presence of herd behaviour, since the individual asset return is different in sensitivity than the market return which tends to cluster around the mean with low dispersions.

Keeping the main essence of the model Christie and Huang (1995) as well as Chang et al. (2000) recommended a better measure of mapping the dispersion to detect the herd behaviour, the Cross-sectional Absolute Deviation, (CSAD). It takes the absolute value of the dispersion and controls for the large fluctuations in the data. This tackles the important problem in Cross-sectional Standard Deviation which is, although, a natural and intuitive measure to capture the influence of the correlated trading but is affected by the presence of extreme values which may affect the robustness of the test.

Christie and Huang (1995) described Cross-section Absolute deviation as follows:

$$\boldsymbol{CSAD_t} = \frac{\sum_{i-1}^{n} \left| \boldsymbol{R_{it}} - \boldsymbol{R_{mt}} \right|}{\boldsymbol{N}} \qquad (\mathbf{3})$$

Where

Where $\mathrm{R_{it}}$ is the observed stock return of firm ***i*** at time ***t***, whereas $\boldsymbol{R_{mt}}$ is the market portfolio of ***N*** firms, which is the cross-sectional average of ***N*** stocks return on market portfolio. Similar to our equation (2) devised for CSSD we can write the same equation for CSAD as follows:

$$CSAD_t = \alpha + \beta_1 D_t^L + \beta_2 D_t^U + \epsilon_t \qquad (4)$$

Equation (4) follows the same methodology which is used in CSSD, developed by Christie and Huang (1995). In addition to this, the equation also treats for the problem of extreme values and is more robust in nature. We use the same dummy variables viz. D^L and D^U, upper and lower dummies, to capture the upward and downward movements in stock returns. β_1 *and* β_2 are the coefficients which will measure magnitude of the dispersions. We will mainly test for the relationship of CSAD of the individual stock with the market and how close is the individual stock with the market return. If large price movements lead to the asymmetric movement in the CSAD dispersions then the investors do tend to herd, on the contrary this relationship is linear and increasing in nature, that is the increase in the market return will increase the CSAD.

The sample period is 08 January 2002 –22 July 2011, both days inclusive, representing the whole sample period under study.

Results and Discussions

We estimate the regression using the equation (2), where CSSD is regressed on two dummy variables to capture extreme movements in the dispersion measure, the CSSD. Top and bottom tails of the distribution is replicated with the 1% and 5% criteria of extreme market movements. Rational asset pricing models suggest that during the increase in market risk and volatility, market participants tend to act rationally and use their own as well as public signals to make investment decisions, as fear of losing money may overcome the joy of earning it.

Measuring Herd Behaviour using CSSD

This section present the regression model based on CSSD measurement of Kristie and Huang (1995) as well as results that are obtained using on Standard Ordinary Least Squared (OLS) econometric technique. The standard model used is as follows:

$$CSSD_t = \alpha + \beta_1 D_t^L + \beta_2 D_t^U + \epsilon_t \qquad \mathbf{(2')}$$

Where **α** captures the average dispersion of the sample excluding the regions corresponding to the two dummy variables. **β1** and **β2** are the coefficients of the two dummy variables that extreme high and low market movements. The sample period is 08 January 2002 –22 July 2011, both days inclusive, representing the whole sample period under study.

Table 2

Regression Estimates for $CSSD_t$

PANEL A - at 1% level of Significance			
Coefficients	α	β_1	β_2
Value	0.018745	0.01345	0.015214
t-stats	59.86385	5.445565	4.543616
p-values	0.000	0.000	0.000
R- squared	0.075334		
PANEL B - at 5% level of Significance			
Coefficients	α	β_1	β_2
Value	0.018556	0.008995	0.015403
t-stats	61.85466	8.498821	6.127704
p-values	0.000	0.000	0.000
R- squared	0.081321		

This table 2 reports the parameters of the regression of cross-sectional standard deviation on high and low market dummies. That same table explains the regression estimates of our overall sample period from 2002 to 2011 using daily data. The methodology used here is Cross-sectional Standard Deviation (CSSD) as proposed by Christie and Huang (1995) and Blasco et al. (2009). We use dummy variables D^L and D^U to capture extreme market movement as already described in Equation (2). We use 1% and 5% criterion to capture the extreme movements, which are an arbitrary measure. Blasco et al. (2009) for example propose a 3% measure to capture the upper and lower tail of market return distribution. We will, however, confine to the conventional 1% and 5% criterion, respectively. We use newey - west test for statistical inference for t-distribution, which is an autocorrelation and heteroskedesticity robust test.

Our coefficients are positive and statistically significant both at 1% as well as 5% criterion, which means that our dispersions are significantly higher than the average during the daily return calculations affected by the large movements. Our results are consistent with the rational asset pricing and reject the presence of any herd behaviour, similar to what originally presented by Kristie and Huang (1995).

Our results continue to produce significantly positive betas at both criteria of extreme price movements. Our CSSD measures, in Table 1, present positively skewed and non normal distribution with fatter tails which means higher dispersion that is away from the mean market returns, as explained by Hwang and Salmon (2004). Christie and Huang (1995) present another litmus test that beta coefficients should be significantly larger in 1% criterion compared to 5% which means that they are further away from the mean market return proving evidence against the herd behaviour.

Table 2 presents statistically significant $\boldsymbol{B_1}$ estimates at 1.345% at 1% level as compared to 0.899% at 5% criterion which is about 50% higher estimate during the down market price. This suggests that investor tend to act more rationally during the down market stress, which supports the Christie and Huang (1995), Henker et al. (2006) finding against the Chang et al. (2000) results.

Kristie and Huang (1995); Chang et al. (2000); Economou et al. (2010) suggest that CSSD can give us biased outputs affected by the outlier that is similar to the robust measure CSAD, which encompasses the absolute values of the returns and are less affected by the outliers. We have, therefore, used CSAD over CSSD throughout our study.

Descriptive Statistics of Data using CSAD

This section presents and estimates CSSD model of developed by Kristie and Huang (1995). Like previous section, the standard OLS regression technique is used and the results are reported in table 3. The follow model is used for the analysis:

$$\boldsymbol{CSAD_t = \frac{\sum_{i-1}^{n} |R_{it} - R_{mt}|}{N}} \qquad \textbf{(3')}$$

Table 3 explains the descriptive statistics of our Market Returns and Cross-sectional Absolute Deviations (CSAD) as explained in equation (3’). The data are daily stock returns that range that from 08 January 2002 to 22 July 2011 both days inclusive. CSAD is a measure of mapping dispersions as proposed by Christie and Huang (1995). There are ***N*** numbers of stocks in a market portfolio with market return ***(R_{mt})*** as the cross-sectional average return of all ***N*** returns in the market portfolio.

Table 3

Descriptive Statistics CSAD versus Market Dispersion

Descriptive Statistics	CSAD	Market
Mean	0.012107079	0.000085
Median	0.011299106	0.000678
Maximum	0.052675899	0.137371
Minimum	0	-0.096798
Standard Deviations	0.00478206	0.014252
No. of Observations	2452	2452
Average No of Firms	121	NA

We use cross-sectional absolute deviations, as suggested by Christie and Huang (1995), Chang *et al.* (2000) and Economou *et al*. (2010), which measures the proximity of stock returns compared to the average market returns and adjusts them for any extreme movements by taking absolute values. We have average dispersion at 1.21% as compared to 1.91% in CSSD from table 1 where mean market returns are not significant from 0. Our CSAD data is more consistent with minimum value at 0 and maximum value ranging only to 5%. These values are substantially larger in CSSD that range to 17.3% at maximum, whereas market returns are more volatile with (-0.0967) to a maximum of (0.014), a substantial variation in data range. Comparing to CSSD, the CSAD is more normally distributed and with smaller, yet positive skewness 5.95 as the excess kurtosis value with fatter tails. We have 121 average numbers of firms trading each day with 2452 daily data observations over the period.

Measuring Herd behaviour using CSAD

We use equation (4) devised by Kristie and Huang (1995) to capture the regression estimates using CSAD. The equation can be written as follows:

$$\boldsymbol{CSAD_t = \alpha + \beta_1 D_t^L + \beta_2 D_t^U + \epsilon_t} \qquad \textbf{(4')}$$

Table 4
Regression Estimates for CSAD

PANEL A			
Coefficients	α	β_1	β_2
Value	0.01171	0.012752	0.012146
t-stats	*61.15613	*10.28333	*8.523086
p-values	0.000	0.000	0.000
R- squared	0.20998		
PANEL B			
Coefficients	α	β_1	β_2
Value	0.011383	0.008907	0.008444
t-stats	**63.38966	**11.81124	**10.01473
p-values	0.000	0.000	0.000
R- squared	0.253062		

Note. ** denotes level of significance at 1% criterion and ** at 5%.*

Table 4 explains the regression estimates of our overall sample period from 2002 to 2011 using daily data. Our coefficients are positive and statistically significant both at 1% as well as 5% criterion, which means that our dispersions are significantly higher than the average during the daily return calculations affected by the large movements. Our results are consistent with the rational asset pricing and reject the presence of any herd behaviour. The results are consistent with the literature presented Kristie and Huang (1995) among others.

Our results continue to produce significantly positive betas at both criterions of extreme price movements. Our CSAD measures, in Table 4, present positively skewed, non-normal distribution with fatter tails which means higher dispersion, away from the mean market returns as explained by Hwang and Salmon (2004). Christie and Huang (1995) present another litmus test that beta coefficients should be significantly larger in 1% criterion compared to 5% which means that they are further away from the mean market return proving evidence against the herd behaviour. Table 4 presents statistically significant B_1 estimates at 1.27% at 1% level as compared to 0.89% at 5% criterion. B_2 have estimates at 1.21% and 0.84% at 1% and 5% criterions. Our estimates in CSAD are more consistent and are more uniformly distributed further away from mean as compared to CSAD in Table 3. Our betas at 1% criterion are significantly higher than the betas at 5% criterion which means that more stocks are dispersed away from mean farther than

5% region hence giving strong evidence against the presence of intentional herding and that, investor tend to act more rationally during the market stress, giving evidence for Christie and Huang (1995).

Similar results are shown in our study with beta coefficients are uniformly distributed with ***B_1 and B_2*** being significantly identical at a particular criterion. Our ***B_2*** estimates from table 2 of CSSD at 5% region have decreased substantially in table 4 from 1.54% to 0.84% making it more uniformly distributed away from mean in CSAD, leaning towards an inconclusive differentiation of up market or downmarket herding behaviour.

Herd Behaviour before Subprime Crises

In order to test for herd behaviour using equation (4') during up and down market stress we have divided our sample period before and after subprime financial crises in order to conclude whether investor herd is more during up market or during down market. Our sample period is carefully chosen to test for the presence of herd behaviour in good times when stocks are going up, after the dot com bubble the subprime lending coupled with the CDS, with international exposure, increased significantly giving a boost to property market around the world, Spain was no exception rather it was one of the most benefiting economies.

Table 5
Herding Behaviour during the Pre- Crises Period

PANEL A - at 1% level of Significance			
Coefficients	α	β_1	β_2
Value	0.010208	0.006853	0.008544
t-stats	*63.45	*10.71	*10.26
p-values	0.000	0.000	0.000
R- squared	0.058575		
PANEL B - at 5% level of Significance			
Coefficients	α	β_1	β_2
Value	0.01001	0.00676	0.006064
t-stats	**66.91	**12.54	**9.244
p-values	0.000	0.000	0.000
R- squared	0.147759		

*Note. * denotes level of significance at 1% criterion and ** at 5%.*

Table 5 explains the regression estimates using CSAD, measurement of dispersion, and maps the proximity of individual stock returns to the mean. We test the sample period from January 2002 to December 2007 the period before the subprime crises hit the market, but this period enjoyed a substantial upward movement.

Our results in Panel A, show significant, but low and positive coefficients β_1 and β_2, where β_1 is 0.68% and β_2 the up market dummy coefficient remains at 0.85% significant at 1% criterion. Panel B however show that our down market dummy β_1 coefficients remain same at 5% criterion but β_2 reduces to 060%, a 20% decrease indicating that there are more upmarket stocks dispersed at 1% extreme.

Herd Behaviour after the Subprime Crises

It is believed that Spanish market was one of the most affected due to its exposure to the subprime lending and escalated property market, after January 2008 stock markets around the world entered in to a bearish trend affecting Spanish markets as well.

Table 6

Herding behaviour during the post-crises period

PANEL A - at 1% level of Significance			
Coefficients	α	β_1	β_2
Value	0.014429	0.011725	0.011469
t-stats	54.82731	10.32728	6.429454
p-values	0.000	0.000	0.000
R- squared	0.319429		
PANEL B - at 5% level of Significance			
Coefficients	α	β_1	β_2
Value	0.014017	0.008079	0.007718
t-stats	55.58036	9.40169	7.359117
p-values	0.000	0.000	0.000
R- squared	0.304557		

Table 6 shows the CSSD measurement from January 2008 to July 2011 a period where a substantial bearish trend continued in the Spanish market. Panel A shows that the at 1% significance level both beta coefficients β_1 and β_2, representing down market and up market dummies respectively, showed increased dispersion to 1.17% and 1.14% respectively, a 95% increase from pre-crises period in down market β_1 and 46% increase in β_2, an up market dummy coefficient both of these estimates are significant.

Panel B shows a reduced variability to 0.08% for β_1 and 0.077% for β_2 both of these estimates are, however, significant at 5% criterion. These results give us evidence that during downward market movement with substantial volatility investors tend to follow rational asset pricing models and do not involve in intentional herding. Our post crises dispersion is more positively skewed with higher excess kurtosis than the pre crises dispersion, which is also positively skewed and higher kurtosis. We can conclude that in any market conditions be it up or down investors tend not to follow herd while making investment decision but follow investment decision more rationally during the downward market movement as compared to the upward movements. Our results are similar to Kristie and Huang (1995) and Henker et al. (2006) against the Chang et al (2000) finding that investors tend to herd during the downward market.

Conclusion

We carried out tests to spot herd formation during various market states, both during upward as well as downward movements. Our choice of sample was interestingly divided into pre-crises and post-crises periods corresponding to the subprime turmoil starting from 2008. We followed the conceptual framework of Christie and Huang (1995); Chang et al. (2000) who first formulated the model to test for the herd behaviour during market stress, if investors tend to abandon the their private signals and follow the market consensus; this behaviour can be detected by mapping the temporal path of their investments which will cluster around the mean of the market returns.

The literature on herd formation is mixed as more dynamic models have been used to detect for the herd behaviour but the results remain inconclusive at least in the developed markets. Some of the non-linear models have found herding under extreme circumstances but the evidence is short lived. Some results including Caparrelli et al. (2004) tested C-H model in Italian stock markets and found no herding behaviour similarly Kallinterakis and Lodetti (2009) replicated the Chang et al. (2000) model with thin trading adjustments; their results were consistent with our results as they found no sign of Herding even when they tested it for thin trading. Kallinterakis (2010), for example found herd formation in emerging market but the effects faded away when they adjusted for thin trading.

Consistent with the previous studies, for example, Christie and Huang (1995); Fotini et al. (2010); Damirer and Kutan (2006), we have not found any evidence of herding behaviour in Spanish stock market, independently of the market states, that is either before or after the subprime crises. we used CSSD and CSAD measures of dispersions in locating proximity of individual stock returns to the mean market return, although we stuck to CSAD in order to avoid biasedness caused due to the extreme values, which is in the line of argument proposed by (Henker (2006); Damirer and Kutan (2006); Christie and Huang (1995). Our results are consistent with the methodology used, where both of our betas (βs) coefficients being positive with significant "t- stats" even after applying tests at a stringent 1% criterion, significance level persist. Our distributions are "Non-Gaussian" with positive skewness and significantly high excess kurtosis which shows that individual stock returns do not cluster around the mean market return.

Our carefully chosen pre-crises and post-crises samples show a difference in the level of volatility in the return of the individual stock with increased volatility of 45% cross-sectional dispersions of individual return, whereas post-crises market return volatility increased by 84%.

We maintain our hypothesis that during increased market volatility uncertainty in the asset return increases and there is more incentive to gain more private information including following the rational asset pricing models to make investment decisions. These findings draw our attention to important evidence on the policy implication which suggests that the Spanish investors tend to invest according to the rational asset pricing models and "Do Not" herd during the market stress in downward motion; however, the tendency is lower during up market movement.

Our choice of sample was, although, sufficient to detect any pattern in the investment style but our model did not capture the non-linearity as in Chang et al. (2000). Kallinterakis and Lodetti (2009), however, replicated the Chang et al. (2000) model with thin trading adjustments; their results were consistent with ours. Kallinterakis (2010), for example found herd formation in emerging market but the effects faded away when they adjusted for thin trading.

Further improvements in the model can be made by dividing the data into industry specific daily, monthly and intraday basis. Blasco et al. (2011) discussed the importance of the frequency of data points and its impact on herd formation. The use of dummy variables is very subjective to use "extreme" values and the use of Cross-sectional Standard Deviation is highly correlated with the time series volatility so is it difficult to distinguish the causality of the two.

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