

HERDING, VOLATILITY AND MARKET STRESS

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ABSTRACT:

Herding behavior in stock markets is tightly linked to market stress and also to volatility (both directly and indirectly through the variation of the latter during market stress periods). This article analyzes the relationship between herding and volatility during market stress days. The study has been carried out in the Spanish market, given that a significant level of herding has already been detected there. The herding measure implemented (Patterson and Sharma, 2006) is based on intraday data and both realized volatility measures and conditional volatility models have been used. The results show evidence of the asymmetric effect of herding on volatility during extreme market movements, something that is in line with the different psychological implications of extreme up and down market movements.

Key words: *Herding*, behavioral finance, volatility, market stress

JEL codes: G14, G10

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HERDING, VOLATILITY AND MARKET STRESS

1-Introduction

The existence of collective phenomena such as herding (Thaler [1991], Shefrin [2000]) can be studied in the framework of investor behavior on financial markets. This area of finance suggests that stock prices are not the only relevant information in the market. Therefore some shades can be given to the usual definition of market efficiency within a bounded rationality paradigm.

There is herding in a market when investors opt to imitate the observed decisions of other agents in the market, who they suppose to be better informed, instead of following their own information and beliefs. Avgouleas (2009) says that herding also means that disclosed information is ignored in favour of the safer “follow the herd” strategy. Thus, herding places a very powerful limitation to rational reaction to all kinds of disclosed information. The main causes for herding pointed out in the literature up to now are imperfect information (Puckett and Yan [2007]), reputation (Trueman [1994]), and compensation schemes (Scharfstein and Stein [1990], Roll [1992], Brennan [1993], Rajan [1994] or Maug and Naik [1996]).

Herding can be regarded as a rational strategy for less sophisticated investors, who try to imitate the activities of successful investors since the use of their own information and knowledge lead to greater cost (Khan *et al.* [2011]), thus the presence of extreme market movements could exacerbate this behavior. The cost and time of processing the amount of information generated during those periods would be higher than usual, increasing the incentives to herd. Extreme down market movements and periods of stress have been linked to herding both directly and indirectly through market volatility (Schwert (1990), Patev and Kanaryan (2003) or Karunanayake *et al.* (2010) show that crises significantly increase market volatility). Kodres and Pristsker (1998) claim that bad news and financial crises increase informational asymmetries and generate contagion and imitation. Policymakers also suggest that the herding behavior of market participants exacerbates market volatility, destabilizes markets and increases financial system fragility, and in fact it is one of the potential explanations for simultaneous market drops. Brock (1999) indicates that some explanations for financial crises focus on the idea that market participants who invest by imitation specially worry about the short term, which occasionally can lead to panic situations in the market. Avgouleas

(2009) argues that institutional herding has been recognized as one of the main builders and amplifiers of crises and especially as one of the causes of the global financial crisis of 2008.

In this vein, some herding measures suggested in the literature (Christie and Huang [1995], Chang, *et al.* [2000] among others) presuppose that, if the phenomenon appears, it would be stronger under extreme market conditions, that is to say, when sharp rises and falls are taking place. This idea is confirmed by several papers focused on the effects of the Asian crisis (Choe *et al.* [1999] or Ghysels and Seon [2005] among others). However, Hwang and Salmon (2004) conclude right the opposite for the market index. They find that herding behavior is more intense during market calm periods.

The link between volatility and investor behavior is not new in the literature. Friedman (1953) was the first to suggest that irrational investors destabilize markets, by buying when prices are high and selling when they are low, whereas rational investors move the prices closer to their fundamental value, by buying when they are low and selling when they are high. More recently, several authors have pointed out the influence on volatility of investors that imitate other investors (Froot, *et al.* [1992], Choe, *et al.* [1999], Alper and Yilmaz [2004]). This relationship has been documented by Avramov, *et al.* (2006) who claim that the activity of some investors (those showing herding behavior and those showing contrarian behavior) has a noticeable effect on daily volatility. However, Bohl, *et al.* (2009) conclude that herding and positive feedback trading behavior are not necessarily evidence in favor of a destabilizing effect on stock prices.

In line with the authors who suggest that there is a link between herding and volatility, Blasco *et al.* (2012) find a direct linear impact of herding on volatility in the Spanish market. We aim to test whether that existing relationship is affected by extreme conditions in the market (abnormally large average price movements), and whether the effects hold for both bullish and bearish extreme market periods. Given the different psychological implications of extreme bullish markets (e.g. disposition effect) and extreme bearish markets (e.g. panic), we expect to find asymmetrical effects of herding on volatility. We choose the Spanish Stock market because it is a suitable framework, it is a developed stock market where the existence of herding and the influence of this behavior on volatility has already been tested and confirmed, Blasco and Ferreruela (2007, 2008) and Blasco, *et al.* (2011).

In order to achieve our objective this paper focuses on two main questions. The first one is to test whether investors' herding intensity rises significantly during crisis periods. The second question is to measure the impact of herding behavior on volatility during both bullish and bearish extreme market periods. During stress periods, the financial system stability and the effectiveness of portfolio management are questioned, so assessing what happens in the markets during those periods can be useful for both portfolio managers (who diversify to minimize risks) and policymakers (who need to calibrate market system functioning). Additionally we consider that this kind of studies where the influence of human behavior on financial markets is shown is of great interest in the sense that they help to understand market reactions that cannot be explained by fundamentals.

This paper contributes to financial literature in various aspects. First, it directly analyzes investor behavior during several extreme market situations with different intensities and implications (following Christie and Huang [1995] we use two criteria to define extreme market movements: the 1 percent (5 percent) criterion restricts extreme days as 1 (5) percent of the lower tail and 1 (5) percent of the upper tail of the market return distribution) which significantly contributes to enrich the results, assessing how herding intensity reacts to both bearish and bullish market situations. Secondly, the implications of herding (which can be regarded as a form of uninformed trading) on market volatility during extreme market periods are studied. In order to do so realized volatility and conditional volatility models are used, which improves the robustness of the results. Moreover, we use conditional volatility models because they offer a wider perspective of the concept of volatility. These models, to our knowledge, have not been applied to the problem posed here. On the third place, a measure of herding which does not presuppose a higher level of herding during stress moments is applied. That prevents our results from biases providing them a higher reliability and robustness. Some of the papers which have studied the relationship between market stress and herding show a major drawback when trying to test it, since the models used impliedly add extreme market movements to the herding measure.

The reminder of the paper is structured as follows: section 2 describes the database used, section 3 shows the methodology and the construction of the different variables considered as well as the main results. Section 4 summarizes the main conclusions derived from the paper.

2-Data

Our data set contains the Ibex-35 index as well as the stocks belonging to that index during the sample period. The period under analysis goes from 1st January 1997 to 31st December 2003, a total of 1750 trading days. The analysis focuses on the Ibex-35 index of the Spanish market. The Ibex-35 Index is a capitalization-weighted index comprising the 35 most liquid Spanish stocks traded in the Continuous Market. A substantial amount of data is necessary to construct the herding intensity measure. The liquidity of the assets belonging to the Ibex-35 index allows us to calculate the measure chosen. The Ibex-35 index is not a closed set of stocks. Conversely the index is revised every six months, adding the most liquid stocks of the semester and removing those which are not so liquid. In order to select the most liquid, both the volume traded and its quality are taken into account.

The data have been provided by the Spanish Sociedad de Bolsas SA. Two databases are used: one related to individual stocks and the other one related to the market index. The former has intraday frequency and is used in the construction of the herding intensity measure. It contains, for each and every transaction in the period under study, the date, the time in which it takes place measured in hours, minutes and seconds, the stock code, the price and the volume traded (measured in number of stocks). We need to highlight that the number of data fluctuates between 25.000 and 150.000 a day, so the computational effort needed for processing the intraday frequency dataset is intense. The data used refer to transactions on the stocks belonging to the Ibex-35 during the official trading hours of the Spanish market. We exclude from the analysis all trades executed outside regular trading hours (10 a.m. to 5 p.m. for the whole of 1997, later extended by stages from 9 a.m. to 5.30 p.m. by 2003). Hence, the data used in this analysis cover all trades executed on Ibex-35 stocks at any time during regular stock exchange trading hours.

For the purposes of our analysis we used daily data of the composition of the Ibex-35, the volume traded in both Euros and number of stocks, together with the daily closing price series for the period. Further, we use Ibex-35 15 minute price data.

Table I shows some descriptive statistics for the Ibex-35 index. More precisely it shows the percentage variation in returns year by year, the volume traded and the number of trades, as well as the volatility measures used. The evolution in the level of herding intensity in accordance to the next section is also shown.

3-Methodology and results

3.1- Herding intensity measure

Detecting the existence of herding and its effects is not an easy task. There have been multiple attempts to measure it: e.g. Lakonishok, *et al.* (1992) suggest a measure which has been specially used in the study of herding among institutional investors, Christie and Huang (1995), Chang, *et al.* (2000), or Patterson and Sharma (2006) (henceforth PS). However, in practice, empirically distinguish between intentional herding (deliberately following other investors) and spurious herding (individuals behaving in the same way when facing the same information set) is not a simple task. There are a plethora of factors which can potentially affect an investment decision. However that cannot excuse us from trying to enrich this field of research by analyzing the effects of those acts.

To measure herding intensity in the market, this study uses the measure proposed by PS, which is based on the information cascade models of Bikhchandani, *et al.* (1992), where herding intensity is measured in both buyer- and seller-initiated trading sequences. This measure has a major advantage over others in that it is constructed from intraday data, that is, a daily indicator is obtained but from intraday data, since this has been considered to be the ideal frequency of data to test for the presence of this kind of investor behavior (Henker, *et al.* [2006]). It also has the further advantage for our purposes that it does not assume herding to be revealed only under extreme market conditions as occurs in other methodological proposals, and that it considers the market as a whole rather than a few institutional investors as has been usual practice in the empirical literature.

Following Bikhchandani, *et al.* (1992) model, market participants receive an imperfect signal G (good news which can make stock prices rise) or B (bad news which can make stock prices fall) about the future value of an asset. Investors know their own signal, but they do not know other investors' signal although they can infer which was the signal received by others by observing their investment decisions. In this model investment decisions are made sequentially, hence the observation of preceding acts can become crucial when taking your own investment decision. Information cascades occur when investors base their decisions on the actions they observe in others, which they allow to override their own information.

Following the scheme presented in Bikhchandani and Sharma (2001), the simplest operative sequence could be summarized as follows: the first agent to make a decision (I#1) only has his own signal to go by; having no other investor to observe, he acts upon his own private information. The second investor (I#2) has, in addition to his own signal, the information revealed by I#1's decision. If I#1 invested and I#2's signal is G, he will buy. If the two signals are contradictory, Bayes' theory tells us that there is 0.5 probability of a positive return. In this case, the second investor will decide completely at random whether or not to buy. When it is I#3's turn to decide, if the first two investors have invested, he will know that I#1's signal was G, and that I#2's was also most probably positive; he will therefore invest even if his signal is B. After I#3, no new information regarding investment decisions will be passed on to later investors, since all the existing information is based on the decisions of the first investors. This is the point at which the investment cascade begins, since people will invest whatever signal they receive. An investment cascade will therefore commence if, and only if, the number of previous investors that decide to invest is two or more than the number of those who do not invest. The probability of a cascade is very high even when only a few of the earliest investors have made their decision. If an investment cascade starts then we would expect to observe long sequences of buy or sell trades. In particular, we would expect to see fewer buy or sell runs than we would in the case where each investor followed his or her own signal.

PS propose a statistic to establish the measure of herding intensity in the market by comparing the number of sequences. For the purposes of the analysis we need to infer the direction of trade using intraday trading data. Following PS we use the tick-test with respect to traded prices to infer if a trade is buyer or seller initiated. In particular, a trade is classified as buyer-initiated if the current trade price is higher than the previous trade price (up-tick). Similarly, a trade is classified as seller-initiated if the current trade price is lower than the previous trade price (down-tick). In a traditional tick-test, if there is no change in the current trade price with respect to the previous trade price (zero-tick) then the trade is classified using the last trade price which differs from current trade price. However, as the sequence of zero-ticks gets longer, it may be difficult to justify the use of above method to classify zero-tick trades. Therefore, we separate the zero-ticks from up-ticks and down-ticks.

So formally we define $\{Tr_{jt}\}$ as the whole of all the trades on stock j throughout all the t_k moments of the t -eth trading session.

$$\{Tr_{jt}\} = \{Tr_{jt_k}, \dots, Tr_{jt_m}\} \quad \text{with} \quad k \leq \dots \leq m \quad (1)$$

Let PTr_{jtk} be the trade price. We define sequences $S_{jt} = \{Tr_{jt_k}, Tr_{jt_{k+1}} \dots Tr_{jt_{k+l-1}}\}$ as a subgroup of consecutive trades on stock j on day t . We identify buyer initiated, seller initiated and zero tick sequences (S_{ijt} , i = buyer initiated, seller initiated, zero tick) if, respectively,

$$\begin{aligned} PTr_{jt_k} &< PTr_{jt_{k+1}} < \dots < PTr_{jt_{k+l-1}} \\ PTr_{jt_k} &> PTr_{jt_{k+1}} > \dots > PTr_{jt_{k+l-1}} \\ PTr_{jt_k} &= PTr_{jt_{k+1}} = \dots = PTr_{jt_{k+l-1}} \end{aligned} \quad (2)$$

In order to determine the significance of the sequence test we follow a procedure commonly used in this kind of analysis. We call $x(i, j, t)$ the estimated difference in the number of sequences of a certain type i . This difference is calculated by comparing the real number of sequences in the market (r_i) to those which should be found in theory.

$$r_i = \sum I_i(S_{jt}) \quad (3)$$

where $I_i(S_{jt})$ is an indicator which takes value 1 if the sequence S_{jt} is of type i , and 0 otherwise.

$$x(i, j, t) = \frac{(r_i + 1/2) - np_i(1 - p_i)}{\sqrt{n}} \quad (4)$$

where r_i is the real number of sequences of type i (upward, downward or zero tick), n is the total number of trades executed in security j during the trading day t , $1/2$ is a discontinuity adjustment parameter and p_i is the probability of finding a sequence of type i (a priori $p_i = 1/3$)¹. The variable $x(i, j, t)$ is asymptotically normally distributed with zero mean and variance:

$$\sigma^2(i, j, t) = p_i(1 - p_i) - 3p_i^2(1 - p_i)^2 \quad (5)$$

¹ Under the null hypothesis that stock prices follow a random walk the probability assignable to each type of price sequence should be the same. However, Blasco, *et al.* (2012) show that stock markets may reflect other tendencies or phenomena than herd behaviour that may influence such probability, although the significance and the conclusions do not change significantly, so we use the case of $p_i = 1/3$.

Let $H(i,j,t)$ be a measure of buyer-initiated or seller-initiated herding for stock j on date t . This measure could be computed as:

$$H(i, j, t) = \frac{x(i, j, t)}{\sqrt{\sigma_i^2(i, j, t)}} \xrightarrow{a.d} N(0,1) \quad (6)$$

where i can take one of three different values according to whether the trade is buyer-initiated, seller-initiated or zero tick, which gives three series of H statistics. H_a is the statistic value series in upward (buyer-initiated) and H_c is the statistic value series in zero tick sequences. We calculate H_c as a different measure in order not to make H_a and H_b artificially higher which could lead us to say that there is herding where it actually is not, but for the purposes of the analysis we only show the results for H_a and H_b . If investors herd, then the actual number of buyer initiated/seller initiated runs would be lower than expected. This would result in a statistically significant negative $H(i,j,t)$. Therefore, the more negative $H(i,j,t)$, the greater the probability of herding is. For large samples, $H(i,j,t)$ is normally distributed with mean 0 and variance 1 under the twin assumptions that the variable under study is *iid* and continuously distributed.

We then obtain H_a and H_b statistics for each day of the study period on all the stocks listed in the Ibex-35 and finally obtain average H_a and H_b statistic series for the Ibex-35.

The appropriate way to detect herding is to compare the fraction of the sample having statistically significant herding intensity to what is expected by pure random chance. The results of the herding intensity measures for both the whole sample period and each of the years under study are shown in Table I. On average, the herding measure is negative and significant for buyer initiated, seller initiated and zero tick sequences. It should be highlighted that the average level of herding intensity is significant all the years in the sample, increasing considerably during the last two years of the sample.

3.2- Financial crisis and herding intensity

Herding behavior and other collective phenomena can be exacerbated when the market shows extreme conditions. Hence they can contribute to increase the effects of a crisis because that is when the contagion effect is most likely to be at its peaks. Kodres and Pristsker (1998) argue that in those moments more intense herding behavior is likely to appear due to the confluence of information asymmetries and bad news.

Additionally, the reasoning of the information cost and its effect on herding behavior may become more relevant during crises. Herding can be also affected by the existence of extreme bullish periods, when great amounts of information are generated in the market and the less sophisticated investors do not have the time or the instruments to process it.

In this section we set out to assess whether that phenomenon takes place in the Spanish market. Further, we analyze whether it holds for up and down market situations considering the market as a whole. In order to do so the level of herding is modeled including variables representing the precise moments under study.

The period under study contains several dates that have been considered extreme up market days and extreme down market days. Following Christie and Huang (1995) we consider two different criteria to determine what an extreme market day is: the 5% criterion restricts extreme days as 5% of the lower tail and 5% percent of the upper tail of the market return distribution. The one percent criterion is more restrictive, it only considers extreme days the 1% of the lower tail and 1% percent of the upper tail. Globally speaking the 5% criterion characterizes as extreme days 174 days (87 up and 87 down), 27% of them during 2002. The more restrictive 1% criterion detects 34 extreme days during the period under study, of which 32% belong to the year 1998 and 29% belong to year 2002 (see Table II). The months of September and October of 1998 deserve a special mention, given that the falls were larger than 7%.

Taking into account these periods, four fictitious variables are created: two related to extreme falls and the other two related to extreme rises. The variables related to significant falls take value 1 for those days when extreme negative returns were recorded and 0 otherwise (for the 5% lower tail the variable is D_{B5} , when we apply the 1% criterion the variable is called D_{B1}). The variables related to extreme rises take value 1 when extreme positive returns were recorded and 0 otherwise (D_{A5} takes value 1 for the 5% upper tail of the distribution of returns and 0 otherwise and D_{A1} is the dummy variable for the 1% criterion).

Therefore we set out to determine whether extreme falls or extreme bullish days affect the herding level of the market, and whether they do it in a similar way and with the same intensity. In order to do so we pose a system of equations taking into account the two kinds of herding described above (H_a and H_b) and we solve it following the SUR methodology (Seemingly Unrelated Regression):

$$\begin{aligned}
H_{at} &= \alpha_{a0} + \delta_{aj} \sum_{j=1}^k H_{at-j} + \alpha_{a1} D_{ijt} + u_{at} \\
H_{bt} &= \alpha_{b0} + \delta_{bj} \sum_{j=1}^k H_{bt-j} + \alpha_{b1} D_{ijt} + u_{bt}
\end{aligned} \tag{7}$$

Where H_{at} , and H_{bt} mean respectively upward and downward herding intensity. D_{ijt} is the dummy variable considered (D_{A5} , D_{B5} , D_{A1} or D_{B1}). In addition some lags of the dependent variable are included to control for the autocorrelation of the series.

The results of the estimation are shown on Table III. It only gives the coefficients of the dummy variables under study. The results indicate that the level of herding behavior increases during stress periods, but the influence of extreme up markets and extreme down markets is not the same. Extreme bullish days affect herding in seller initiated sequences (Ha) more intensely than herding in buyer initiated sequences (Hb), whereas during extreme bearish days herding in buyer initiated sequences grows more than in seller initiated sequences. It seems that investors follow the different more than usual, that is to say, when the prices are falling and the returns are negative, herding is more intense on the buy side, and when prices rise and the returns are positive then herding takes place on the sell side. That trades are seen as something extraordinary given the market situation those days, and therefore, they are intensely followed. It seems that the relevant actions on a bad day are buyer initiated trades, and the relevant on a good day are seller initiated trades, and that is why they are followed more keenly than usual. This phenomenon is more intense when we look at the dummy variables calculated with the 1% CH criterion. That makes sense given that those dummy variables refer to the most extreme days of the period.

3.3-Volatility measure

The volatility measure used in this paper is realized volatility. It is obtained by summing the squares of intraday returns calculated from high frequency data. Andersen, *et al.* (2001) prove that under general conditions, the variance of these discrete returns over a day, conditional on the sample path $\{\sigma_{t-\tau}^2\}_0^1$ is $\overline{\sigma_t^2} = \int_0^1 \sigma_{t-\tau}^2 d\tau$. In the literature $\overline{\sigma_t^2}$ is known as integrated variance and is a natural measure of the true daily volatility. The estimator of that variance is known as realized volatility and is obtained as follows:

$$\overline{\sigma_t^2}(m) = \sum_{k=1,2,\dots,m} r_{t+k/m}^2$$

(8)

where m is the number of intervals within a day. Andersen, *et al.* (2001) show that under weak regularity conditions $\overline{\sigma_t^2}(m)$ converges in probability to the integrated variance, as $m \rightarrow \infty$. Hence, it seems that the higher the data frequency, the closer to true volatility the estimator will be. Most papers consider 5 minute intervals to be a good frequency. The availability of data for the Ibex35 only allows us to calculate realized volatility through 15 minute data. Anyway, since Andersen, *et al.* (2000) find that volatilities start to stabilize at 30 minute intervals, the results obtained can be considered free of significant error, thanks to the data frequency used. Table I gives the annual average of the volatility measure.

3.4 -Volatility, herding intensity and financial crises

Following the theory of Noisy Rational Expectations, Hellwig (1980) and Wang (1993) assert that volatility is driven by uninformed or liquidity trading, given that price adjustments arising from uninformed trading tend to revert. The latter author observes that information asymmetry may drive volatility and that uninformed investors largely tend to follow the market trend, buying when prices rise and selling when they fall; uninformed trading is not equivalent to herding, but we could say that herding is a type of uninformed trading, given that investors ignore their own information and beliefs and act following the actions of other investors. Hellwig (1980), Wang (1993) or Avramov, *et al.* (2006) find a relationship between volatility and herding (or non informed trading) in a more or less direct way, thus indicating that collective behavior is a volatility enhancing factor. In this sense Blasco, *et al.* (2012) using several volatility measures, confirm that herding has a direct linear impact on volatility for all of the volatility measures considered (the higher the observed level of herding intensity, the greater volatility is expected), although the corresponding intensity is not always the same. They also find that herding variables seem to be useful in volatility forecasting.

French and Roll (1986) argue that trading entails volatility. This means that we always need to include a measure of the traded volume in any study of the market volatility. There is a vast amount of literature regarding the relationship between traded volume and volatility. Jones, *et al.* (1994) take apart daily volume into the number of

trades and the average trade size and observe that the former affects volatility to a higher degree. Chan and Fong (2000) consider that the important factor on volatility is order imbalance. Given that it is not clear which is the best volume measure for these purposes, following Chan and Fong (2006) we consider both the volume traded and the number of trades, in order to obtain robust results.

Having said that, our next step is to determine whether herding affects volatility in a different way during extreme market periods. Previously we have detected an influence of those extreme days on the herding level, hence, intuitively we think that this effect could have a reflection on volatility which, as well as the effect of herding, does not need to be symmetrical. In order to carry out this analysis we estimate the following models for the realized volatility measures:

$$RV_t = \alpha_0 + \alpha_1 M_t + \sum_{j=1}^{12} \rho_j RV_{t-j} + \alpha_2 V_t + \alpha_3 H_{i,t} + \alpha_4 D_{ijt} H_{it} + \mu_{it} \quad (9)$$

$$RV_t = \alpha_0 + \alpha_1 M_t + \sum_{j=1}^{12} \rho_j RV_{t-j} + \alpha_2 NT_t + \alpha_3 H_{i,t} + \alpha_4 D_{ijt} H_{it} + \mu_{it} \quad (10)$$

where RV_t is realized volatility as described previously, M_t is the Monday dummy variable, which takes value 1 on Mondays and 0 otherwise. V_t is the volume traded on day t , NT_t is the number of trades on day t and H_{it} are two variables related to the herding level in the market (H_a and H_b). D_{ijt} is the variable representing the extreme market period under study and it takes the four different values already explained. Hence, each of these equations is estimated eight times, considering a different kind of herding intensity every time and also the different extreme market variables that we have described above.

Table IV gives the results of these regressions. The coefficients of the herding variables in the stress moments considered are shown. If we observe the effect of extreme bullish days, the results show that herding increases volatility less than the rest of the days, regardless of the volume measure considered, the type of herding and the criterion used to determine what is extreme. On the other hand, during extreme down market days herding makes volatility rise more than usual. This result holds for both herding measures and for both the 1% and the 5% criterion.

These results are consistent with the idea of volatility as destabilization or turbulence, which are probably larger in bearish periods, when investors may panic, than during bearish days, when investors are more relaxed. Schwert (1990) study the October 1987 crash and show that stock volatility jump dramatically during and after

the crash. Platev and Kanaryan (2003) study four Central Europe markets and find strong evidence of huge influence over market volatility caused by the Asian and Russian crises. Karunanayake *et al.* (2010) show that both the Asian crisis and the more recent global financial crisis significantly increased the stock return volatilities across all of the four markets in their study.

We find that it is during the extreme down market days and not during bullish days when the behavior of investors, imitation or of other kind, affects volatility to a higher degree.

3.5-Conditional volatility models and herding

This section sets out to analyze whether the effect of herding on conditional volatility can be significant during crisis periods. In order to carry out this analysis we propose the conditional volatility model Garch(1,1)² in which we include the variables related to herding and its effect during extreme market days. This inclusion is in line with Lamoreux and Lastrapes (1990a) and the incorporation of traded volume in the conditional volatility model.

$$R_t = \beta_0 + \beta_1 * R_{t-1} + \beta_2 * D_{ijt} + u_t \text{ where } u_t \text{ follows a } N(0, \sigma_t^2) \quad (11)$$

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \alpha_2 \sigma_{t-1}^2 + \alpha_3 H_{i,t} + \alpha_4 H_{i,t} D_{ijt} \quad (12)$$

In addition, model GJR(1,1)³ is estimated. The average specification is similar and the variance is as follows:

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \alpha_2 \sigma_{t-1}^2 + \alpha_3 H_{i,t} + \alpha_4 H_{i,t} D_{ijt} + \alpha_5 S_{t-1}^- u_{t-1}^2 \quad (13)$$

Where S_t^- equals 1 when u_t is smaller than zero and equals 0 when u_t is larger than or equal to 0.

Table V shows the results of the estimations. The coefficients related to the impact of herding on the conditional volatility during extreme days as well as the variable herding itself are shown. For the bearish days the conclusions are similar to those of the realized volatility previously analyzed, whereas in the case of extreme positive returns days the coefficient of the effect of herding on volatility, both alone and the joint effect of extreme days and herding, are no longer significant. The coefficient of the joint effect of extreme negative returns days and herding appears significant and negative

² Following Lamoreux and Lastrapes (1990b) this model is a parsimonious representation of the conditional variance which adequately adjust to financial series.

³ This model takes into account the possibility of non symmetrical impacts of information on volatility Glosten *et al* (1993).

regardless of the criterion used to determine the extreme days and the type of herding under analysis. The results for the bearish days agree with those obtained for the other volatility measure. This confirms that conditional volatility is also increased with regard to herding levels at the defined moments.

4-Conclusions

This paper sets out to analyze in depth a question of remarkable relevance as the effect that herding behavior has on the market and how it is affected by extreme positive or negative returns days, something that we may call market stress. In order to do so first of all we analyze the influence of extreme market days on the mimicking behavior of investors, and we conclude that during those days investors follow each other more intensely than when the market is calm or bullish, but the effect is not homogenous. During extreme bullish days investors follow more intensely on the sell side, while during extreme bearish days investors are more prone to follow the buys. We also assess whether herding significantly affects the market volatility during stress periods. The results point out the great importance of this factor, especially in those moments. We observe an asymmetrical effect of herding on volatility. When the market is undergoing extreme rises in prices, herding affects volatility less than a non-extreme day, whereas investor behavior has a greater influence on volatility during those moments which can be considered extreme falls.

Colander, *et al.* (2008) blame the economists of their participation in crises for not including abnormal situations in their models. They support the introduction of contagion and herding behavior in the macroeconomic models as well as the posing of those models outside calm environments. In this sense this work also supports its inclusion. Conversely, this paper sheds light on a totally relevant and current question. During extreme bearish days psychological biases may arise affecting the whole financial system and a greater need for assessing investment risks appears. Adding elements which include behavioral factors on that valuation can be a highly valuable tool in the risk management field.

Table I: Annual descriptive of Ibex-35 return series, volume traded in thousands (Vol), number of trades (NT), realized volatility (VR) and herding intensity measures (Ha and Hb).

Year	Variation % Rent.	Vol	NT	VR	Ha	Hb
1997	40,75%	572.858	14.089	0,0095	-6,023	-6,204
1998	35,58%	935.926	25.351	0,013715	-8,468	-8,490
1999	18,35%	853.401	25.804	0,010529	-7,620	-7,309
2000	-21,75%	1.522.887	40.456	0,012326	-8,798	-8,479
2001	-7,82%	1.411.571	34.802	0,013575	-9,347	-9,282
2002	-28,11%	1.279.675	38.074	0,014854	-10,941	-10,800
2003	28,17%	1.283.267	34.292	0,009677	-10,526	-10,535
Average	9,31%	1.122.383	30.397	0,01202	-8,815	-8,726

Table II: Number of extreme market days by year. The first two columns show the extreme days identified taking the 5% upper and lower tails of the distribution of the returns as extreme days. The last two columns show the number of extreme days by year when we take the 1% upper and lower tails of the distribution as extreme.

Year	Extreme up days (5%)	Extreme down days (5%)	Extreme up days (1%)	Extreme down days (1%)
1997	7	6	1	2
1998	17	15	4	7
1999	4	4	2	1
2000	12	15	1	1
2001	16	19	2	3
2002	25	22	7	3
2003	6	6	0	0

Table III: Results of the SUR (Seemingly Unrelated Regression) estimation of the herding intensity levels regarding extreme market periods * significant at 10%, ** significant at 5%, *** significant at 1%. Ha and Hb are respectively the herding intensity measures for upward and downward sequences. D_{ij} takes 4 different values depending on the hypothesis under study: D_{A5} , D_{B5} , D_{A1} and D_{B1} . Model:

$$H_{at} = \alpha_{a0} + \delta_{aj} \sum_{j=1}^k H_{at-j} + \alpha_{a1} D_{ij} + u_{at}$$

$$H_{bt} = \alpha_{b0} + \delta_{bj} \sum_{j=1}^k H_{bt-j} + \alpha_{b1} D_{ij} + u_{bt}$$

	Ha	Hb
D_{A5}	-0,3213	-1,8082
t-statistic	(-1,99)**	(-11,27)***
D_{B5}	-1,6297	-0,3208
t-statistic	(-10,98)***	(-2,02)**
D_{A1}	-0,6056	-2,0044
t-statistic	(-1,66)*	(-5,38)***
D_{B1}	-2,1775	-0,7849
t-statistic	(-6,76)***	(-2,32)**

Table IV: Results of the estimation of the influence of herding on volatility during market stress

$$RV_t = \alpha_0 + \alpha_1 M_t + \sum_{j=1}^{12} \rho_j RV_{t-j} + \alpha_2 V_t + \alpha_3 H_{it} + \alpha_4 D_{ijt} H_{it} + \mu_{it} \quad (9)$$

$$RV_t = \alpha_0 + \alpha_1 M_t + \sum_{j=1}^{12} \rho_j RV_{t-j} + \alpha_2 NT_t + \alpha_3 H_{it} + \alpha_4 D_{ijt} H_{it} + \mu_{it} \quad (10)$$

Equation 9				
	D_{A5}	D_{B5}	D_{A1}	D_{B1}
α_{3Ha}	-0,0005	-0,0003	-0,0005	-0,0004
t-statistic	(-5,83)***	(-4,02)***	(-5,87)***	(-4,96)***
α_{4Ha}	0,0001	-0,0004	0,0004	-0,0010
t-statistic	(2,34)**	(-8,37)***	(3,14)***	(-10,14)***
α_{3Hb}	-0,0002	-0,0002	-0,0002	-0,0002
t-statistic	(-2,78)***	(-2,21)**	(-2,64)***	(-2,50)**
α_{4Hb}	0,0001	-0,0006	0,0004	-0,0013
t-statistic	(2,42)**	(-9,50)***	(3,12)***	(-11,35)***
Equation 10				
	D_{A5}	D_{B5}	D_{A1}	D_{B1}
α_{3Ha}	-0,0002	-0,0001	-0,0003	-0,0002
t-statistic	(-2,92)***	(-1,32)	(-2,96)***	(-1,85)*
α_{4Ha}	0,0001	-0,0004	0,0004	-0,0010
t-statistic	(2,38)**	(-8,54)***	(2,99)***	(-10,49)***
α_{3Hb}	0,0000	0,0000	0,0000	0,0000
t-statistic	(-0,18)	(0,18)	(-0,04)	(0,23)
α_{4Hb}	0,0001	-0,0005	0,0003	-0,0013
t-statistic	(2,04)**	(-9,08)***	(2,84)***	(-11,47)***

Table V: Results of the estimation of the influence of herding and financial crises on conditional volatility. Models follow:

$$R_t = \beta_0 + \beta_1 * R_{t-1} + \beta_2 * D_{ct} + u_t \text{ where } u_t \text{ follows a } N(0, \sigma_t^2) \quad (11)$$

$$\text{GARCH}(1,1) \text{ model} \quad \sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \alpha_2 \sigma_{t-1}^2 + \alpha_3 H_{i,t} + \alpha_4 H_{i,t} D_{ct} \quad (12)$$

$$\text{GJR}(1,1) \text{ model} \quad \sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \alpha_2 \sigma_{t-1}^2 + \alpha_3 S_{t-1}^- u_{t-1}^2 + \alpha_4 H_{i,t} + \alpha_5 H_{i,t} D_{ct} \quad (13)$$

Where S_t^- equals 1 when u_t is smaller than zero and 0 otherwise.

GARCH				
	D_{A5}	D_{B5}	D_{A1}	D_{B1}
$\alpha_3 H_a$	-0,00000727	0,00000004	-0,00000031	-0,00000031
z-statistic	(-13,51)***	(0,29)	(-1,20)	(-1,31)
$\alpha_4 H_a$	0,00001010	-0,00000547	0,00000309	-0,00001440
z-statistic	(17,93)***	(-3,49)***	(0,59)	(-2,13)**
$\alpha_3 H_b$	-0,00000021	0,00000009	0,00000002	-0,00000005
z-statistic	(-0,77)	(0,78)	(0,13)	(-0,30)
$\alpha_4 H_b$	0,00000129	-0,00000624	0,00000172	-0,00001630
z-statistic	(1,14)	(-3,45)***	(0,34)	(-2,13)**
GJR				
	D_{A5}	D_{B5}	D_{A1}	D_{B1}
$\alpha_3 H_a$	-0,00000056	0,00000012	-0,00000020	-0,00000005
t-statistic	(-1,47)	(1,17)	(-0,73)	(-0,17)
$\alpha_4 H_a$	0,00000233	-0,00000486	0,00000415	-0,00001420
t-statistic	(1,69)*	(-3,57)***	(0,78)	(-2,40)**
$\alpha_3 H_b$	-0,00000034	0,00000012	-0,00000007	0,00000001
t-statistic	(-1,00)	(1,24)	(-0,28)	(0,08)
$\alpha_4 H_b$	0,00000185	-0,00000557	0,00000235	-0,00001670
t-statistic	(1,53)	(-3,50)***	(0,43)	(-2,42)**

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