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THE CASE OF THE SPANISH STOCK MARKET

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JEL codes: G14, G10

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THE IMPLICATIONS OF HERDING ON VOLATILITY. THE CASE OF THE SPANISH STOCK MARKET

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ABSTRACT:

According to rational expectation models, uninformed or liquidity trading make market price volatility rise. This paper sets out to analyze the impact of herding, which may be interpreted as one of the components of uninformed trading, on the volatility of the Spanish stock market. Herding is examined at the intraday level considered the most reliable sampling frequency for detecting this type of investor behavior, and measured using the Patterson and Sharma (2006) herding intensity measure. Different volatility measures (historical, realized and implied) are employed. The results confirm that herding has a direct linear impact on volatility for all of the volatility measures considered except implied volatility.

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

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1. Introduction

Price volatility in capital markets is a key topic in finance: the basis of pricing models, investment and risk management strategies and market efficiency models is accurate volatility measurement. In an ideal world where the market is efficient, prices instantaneously adjust to new information. Therefore volatility is only caused by the continuous adjustment of stock prices to new information. There is nevertheless abundant evidence, both in the literature and among practitioners, of price adjustments that are due not to the arrival of new information but to market conditions or collective phenomena such as herding (Thaler [1991], Shefrin [2000]). Thus, we cannot talk of efficient pricing or indeed of an efficient market, at least in the strict traditional sense. The market may operate under a limited rationality paradigm in which historical information is open to investors' subjective interpretation.

Herding is said to be present in a market when investors opt to imitate the trading practices of those they consider to be better informed, rather than acting upon their own beliefs and private information. Herd trading, therefore, despite sometimes being rational, cannot therefore be considered an informed trading strategy, since herders imitate other investors even when in possession of their own information. Some of the main ideas advanced to explain this behavior are based on: how the information is transmitted (Banerjee [1992], Bikhchandani, Hirshleifer and Welch [1992], Hirshleifer, Subrahmanyam and Titman [1994], Gompers and Metrick [2001] or Puckett and Yan [2007]), reputation costs (within agency theory and only in developed markets, Scharfstein and Stein [1990], Trueman [1994]) and finally, agent compensation based on performance relative to a benchmark (Roll [1992], Brennan [1993], Rajan [1994] or Maug and Naik [1996]). Some authors have recently suggested new explanations such as the degree of institutional ownership, the quality of the information released, dispersion of investor beliefs or the presence of uninformed investors, among others (see Patterson and Sharma [2006] henceforth PS, Demirer and Kutan [2006], Henker, Henker and Mitsios [2006] and Puckett and Yan [2007]).

Generally speaking, most of the studies carried out to test for herding in capital markets have proved inconclusive. Hence, in recent years various measures have been proposed with a view to overcoming the limitations of past research (Lakonishok, Schleifer and Vishny [1992], Christie and Huang [1995], Wermers [1999], Chang, Cheng and Khorana [2000], Hwang and Salmon [2004], PS[2006]). Radalj and McAleer (1993), note that the main reason for the lack of empirical evidence of herding may lie in the choice data frequency, in the sense that too infrequent data sampling would lead to intra-interval herding being missed (at monthly, weekly, daily or even intradaily intervals). For the purposes of our investigation we used the PS(2006) measure, which we consider the most suitable, since it overcomes this problem by being based on intraday data. We are aware of the risks attached to opting for one measure or another since it is difficult to isolate herding from other variables. We nevertheless feel that this should not raise any obstacles and that it is the line to follow if we are to continue advancing the research into investor behaviour.

The link between investor behaviour and market volatility was first noted by Friedman (1953) who found that irrational investors destabilized prices by buying when prices were high and selling when they were low, while rational investors tended to move prices towards their fundamentals, by buying low and selling high. Following Friedman and the theory of Noisy Rational Expectations, Hellwig (1980) and Wang (1993) claimed 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; a behavior that we might consider tantamount to herding. Wang (1993) reports that, although it is uninformed trading, this behavior may be rational in less informed investors if it takes place in a context of asymmetrical information. Froot, Scharfstein and Stein (1992) also concluded that investors tend to imitate one another, and that this drives volatility. More recently this relationship has been documented by Avramov, Chordia and Goyal (2006), who claim that both herding and contrarian trading have a strong impact on daily volatility [1].

Following the authors who have observed the behavior of market agents to have a certain influence on existing volatility, we set out to assess the effect of different levels of herding intensity on the degree of market volatility. As a first stage in the procedure, we take series of the various volatility measures used in the literature, such as absolute return residuals, realized volatility (Andersen et al [2001]), historical volatility (Parkinson [1980] and Garman and Klass [1980]) and implied volatility from

[1] For further information on the relationship between uninformed investors and volatility, see also Black (1976), De Long et al (1990) and Campbell and Kyle (1993).

the options market. Given that the literature has documented volume traded effects (Lamoureux and Lastrapes [1990]) and day-of-the-week effects (French, [1980], Agrawal and Tandon [1994]) on volatility, the volatility series have been purged of both these effects. In this way we are able to study the herding effect on our volatility series without running the risk of confusing other previously known effects with the one we wish to analyze. In a second stage we analyze both the linear and non-linear relationships between the volatility variables and herding.

The study focuses on the Spanish stock exchange's benchmark index, the Ibex-35, which tracks the 35 most traded shares, and which we consider to be representative of the market as a whole. The Spanish market is a suitable framework in which to centre this analysis because it is one with documented evidence of herding (see Blasco and Ferreruela [2007, 2008] and Lillo et al [2007]).

Fundamentally this study contributes to provide an explanation for that portion of volatility that is not due to changes in fundamentals or other known effects, while also adding to the literature on herding behavior of investors and advancing the understanding of the phenomenon and the search for the possible implications of different levels of herding on the market, since empirical relationships are established between herding intensity and market volatility. The results could prove highly relevant in achieving a better understanding of market functioning and serve both academics and practitioners, given that an understanding of which variables affect volatility and the nature of their influence could contribute to much more accurate forecasting and, furthermore, to the definition of new risk measures or new hedging strategies. In fact, some authors (e.g. Crépey 2004) explain how the different volatility regimes exhibited in certain markets may require especially useful alternative volatility measures, and how market complexity and incompleteness of the volatility measures are drawbacks that call for a recalibration of the models used for risk management. Other authors (Demetrescu, 2007) find that volatility clusters can appear as a consequence of the volatility forecasting activity itself. Traders use different models to evaluate stock volatility. An increase of recently observed volatility leads to higher estimates of current volatility and thus higher perceived market risk. The higher the risk perceived, the higher the price correction. Hence, present and past volatility estimates are linked in a feed-back loop that might be worthy of analysis.

At this point we should ask ourselves whether that part of volatility due to herding, if present, could be hedged or diversified or, in other words, whether implied volatility in derivatives includes the herding component or only future information or uncertainty. All these aspects are key factors in investment decision-making and portfolio or risk management.

Other important features of the study are the use of an intra-daily herding measure, since intra-daily data are thought to be the most appropriate when trying to detect herding behavior and the use of several volatility indicators in the analysis of the effects on volatility, both which will increase the robustness of our results. Lastly, the time period analyzed is long enough to dilute any biases due to temporary market fluctuations.

The remainder of the paper is structured as follows: section two presents the database used in the analysis with some descriptive statistics for the Spanish stock market. Section three describes the methodology and presents the main findings. Section four summarizes the main conclusions derived from the study.

2.- Database

The sample period runs from January 1st 1997 to December 31st 2003. The data were supplied by the Spanish Sociedad de Bolsas SA. The intraday data used to calculate the herding variable include the date, exact time in hours, minutes and seconds, stock code, price and volume traded in number of titles of all trades executed during the above-mentioned period.

The Ibex-35 index tracks the movements of the 35 most liquid and most traded stocks in the Spanish continuous market. For the purposes of our analysis we used the composition of the Ibex-35, the volume in Euros traded and the number of trades for each of the listed stocks, together with the daily opening, closing, maximum and minimum price series for the period. Further, we used Ibex-35 15 minute price data also supplied by the Spanish Sociedad de Bolsas SA.

We exclude from the analysis all trades executed outside normal trading hours (10 a.m. to 5 p.m. for the whole of 1997, later extended by stages to 9 a.m. to 5:30 p.m. by 2003). Hence, the data used in this analysis cover all trades executed on Ibex-35 stock at any time during normal stock exchange trading hours.

The implied volatilities of the options on the Ibex-35 were drawn from a database containing historical close of trade data for the derivatives market, provided by MEFF (the official Spanish futures and options market), including the date of trade, the underlying of the contract (in our case the Ibex-35), contract expiry date, exercise price and volatility at the close of trading.

3.- Methodology and results

3.1- Herding intensity measure

To measure herding intensity in the market, this study uses the measure proposed by PS(2006), which is based on the information cascade models of Bikhchandani, Hirshleifer and Welch (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 we consider this to be the ideal frequency of data to test for the presence of this kind of investor behaviour. This has the further advantage for our purposes, that it does not assume herding to vary with extreme market conditions, and considers the market as a whole rather than a few institutional investors.

In the model developed by Bikhchandani, Hirshleifer and Welch (1992) information cascades occur when investors base their decisions on the actions they observe in others, which they allow to override their own information. The probability of an information cascade is very high even if only a few early traders have made their investment decision.

PS(2006), who developed an index based on these theories, asserted that, empirically, an information cascade will be observed when buyer-initiated or seller-initiated runs last longer than would be expected if no such cascade existed and each individual investor were to base his trading decisions exclusively on private signals. These authors propose a statistic that measures herding intensity in terms of the number of runs. If traders engage in systematic herding, the statistic should take significantly negative values, since the actual number of runs will be lower than expected.

$$x(s,j,t)=\frac{\left(r_s+1/2\right)-np_s\left(1-p_s\right)}{\sqrt{n}} \tag{1}$$

where r_s is the actual number of type *s* runs (up runs, down runs or zero runs), *n* is the total number of trades executed on asset *j* on day *t*, ½ is a discontinuity adjustment parameter and p_s is the probability of finding a type of run *s*. Under asymptotic conditions, the statistic *x(s, j, t)* has a normal distribution with zero mean and variance

$$\sigma^2(s, j, t) = p_s(1-p_s) - 3p_s^2(1-p_s)^2 \tag{2}$$

Finally, PS(2006) define their herding intensity statistic as:

$$H(s, j, t) = \frac{x(s, j, t)}{\sqrt{\sigma_s^2(j, t)}} \xrightarrow{a.d} N(0,1) \tag{3}$$

where *s* takes one of three different values according to whether the trade is buyer-initiated, seller-initiated, or zero tick, such that we have three series of H statistics. Ha denotes the series of statistic values for up (buyer-initiated) runs, Hb denotes those for down (seller-initiated) runs, and Hc those for runs with no price change, also known as zero runs. To categorize trades as buys or sells PS use the tick test[2]. In our analysis we follow the same method.[3] .

To construct the herding intensity measures required for our study, we begin by sorting the trades for each day (having excluded all those executed outside normal trading hours) by stock code and measuring the number of (up, down or zero) runs that took place that day, and then calculating the PS(2006) statistic. We find the Ha, Hb and Hc statistics for each day for all Ibex-35 listed stocks at that point of time, which finally leaves us with the Ibex-35 Ha, Hb and Hc statistic series.

Table I shows the descriptives for the herding intensity measures, where it can be seen that, on average, herding intensity is significantly negative across all types of run (up runs, down runs, and zero runs), but that a notable difference can be observed between the first two (-8.8152 and -8.7263 respectively) and the last (-4.0399), with much higher herding intensity levels emerging when there are price changes (up runs and down runs) than where there is no price change (zero runs). In fact, if we look at the maximum values of the series, the highest value in the down runs is -1.5433, which comes very close to being significant. In other words, significant herding took place on Ibex-35 stock throughout practically the whole of the sample period.

[2] A trade is classed as a buy if the price is higher (an *up-tick)* than the most recent previous trade, and as a sell if the price is lower (a *down-tick)* than the most recent previous trade. If the price is the same as the most recent previous trade, the trade is classed as a *zero-tick*.

[3] There are different means to identify a transaction as a buy or a sell. Finucane (2000) demonstrates how this method yields similar results to others. This, together with the unavailability of a database that included the bid-ask spread, led us to opt for the tick test to categorise trades.

3.2- Volatility measures

3.2.1- Absolute return residuals

The first of the volatility measures considered in this paper is the absolute return residual, which is obtained from the following regression:

$$R_{it} = \sum_{k=1}^{5} \alpha_{ik} D_{kt} + \sum_{j=1}^{12} \omega_{ij} R_{it-j} + \varepsilon_{it} \tag{4}$$

where R_{it} is the index return *i* on day *t,* which can take one of four values: AA if it is the return calculated from opening on day *t* to opening on day *t+1,* AC if what is being measured is the return from opening to closing on day *t*, CC if it is the return from closing on day *t-1* to closing on day *t,* and finally, CA if we are measuring the return from closing on day *t* to opening on day *t+1*. Following French (1980) and Keim and Stambaugh (1984) we include the variable D_{kt} to represent the day-of-the-week dummies in order to capture differences in mean returns that are due exclusively to variations in market performance on different days of the week. Finally, to remove autocorrelation from the return series, we include the variable R_{it-j} as the lagged return variable. $|\varepsilon_{it}|$ provides a volatility measure for each of the series used.

The first four columns of Table II give the descriptive statistics for the four resulting volatility measures. On average there are no major differences, the highest value being that of $|\varepsilon_{AA}|$ at 0.0129, and the lowest that of $|\varepsilon_{CA}|$, at 0.0061. This is consistent with market functioning since $|\varepsilon_{CA}|$ is the only one of these measures that captures exclusively volatility over non-trading hours and, generally speaking, news likely to trigger volatility is more likely to emerge during trading hours than during non-trading time.

3.2.2- Realized volatility

The second of the volatility measures considered is realized volatility. Merton (1980) already showed that accurate volatility estimators can be obtained using fixed-interval data, as long as the intervals tend towards zero, given that prices follow a geometric Brownian motion and estimation error in the return variance is proportional to the length of the interval, such that it decreases with shorter intervals. Andersen et al. (2001) show that by summing the squares of intraday returns calculated from high frequency data it is possible to obtain an accurate volatility estimator and find that, when the frequency of the data tends towards infinity, it is possible to obtain a volatility estimator that is error free and equal to real volatility. The variance of the discrete returns measured at numerous intervals is known in the literature as the integrated variance $\overline{\sigma_t^2}$ which is a natural measure of real volatility[4] where $\overline{\sigma_t^2} = \int_0^1 \sigma_{t-\tau}^2 d\tau$.

The integrated volatility estimator, known as realized volatility, is obtained by summing intraday squared returns (m) according to the following expression:

$$\sigma_R = \overline{\sigma}_t^2(m) = \sum_{k=1}^{m} r_{t+k/m} \tag{5}$$

Where $r_{t+k/m}$ is the return for each of the short intervals into which the trading session is divided[5].

Following this methodology, this paper uses two measures of realized volatility: one is realized volatility, measured from opening to closing of trade on day *t*, which we will denote by σ_{R-AC}; the other is realized volatility including overnight data, that is, events occurring from opening of trading on day *t* to opening of trading on day *t+1*, which we denote by σ_{R-AA}.

Columns five and six in Table II show the descriptive statistics for the daily series of these two realized volatility measures. On average, the results are similar to those obtained in the previous measures, with slightly higher values of realized volatility being observed when overnight data are taken into account. (0.0120 for σ_{R-AC} and 0.0142 for σ_{R-AA}). While the minimum values are similar for both measures, the opening to opening realized volatility measure shows the higher maximum value.

3.2.3- Historic volatility: Parkinson and Garman-Klass

Thirdly we use the historical volatility measures proposed by Parkinson (1980) and Garman and Klass (1980).

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[4] For further information on realized volatility, see French, Schwert and Stambaugh (1987), Schwert (1989) and Ferland and Lalancette (2006).

[5] Bandi and Russell (2008) obtain optimal intervals for the calculation of realized volatility and show errors for 5-minute intervals to be approximately equal to those of the optimal interval, where the 5-minute interval is the one used to calculate realized volatility in the majority of empirical studies. We were forced by the lack of superior data to use 15-minute intervals to calculate this measure of volatility. Nevertheless, Andersen et al. (2000) showed in an experiment that volatilities start to stabilize at 30 minute intervals. Our results can therefore be considered free of significant error, thanks to the data frequency used.

Parkinson's measure takes the maximum and minimum daily prices of an asset (in our case we take the Ibex-35 as one more asset). The collection of these prices is more effort-intensive than that of the opening and closing prices used in the construction of other measures of historic volatility, since it requires continuous observation of the market, but, since extreme price data is more informative than opening and closing price data, the extra effort may provide added value to the results. The reason for this is that volatility reverts to the mean once it reaches extreme values, and this estimator therefore facilitates the tracking of extreme volatilities and enables forecasting.

We calculate Parkinson's estimator according to the following expression:

$$\sigma_P = \frac{1}{2\sqrt{\ln 2}}\sqrt{\frac{1}{n}\sum_{t=1}^{n} P_t^2} \tag{6}$$

where $P_t = \ln\frac{H_t}{L_t}$, and H_t and L_t are, respectively, the maximum and minimum Ibex-35 prices on day *t*.

Garman and Klass suggest a slightly different approach to estimate historical volatility, in which opening and closing prices as well as extreme prices are included. We calculate historical volatilities according to the following expression:

$$\sigma_{GK} = \sqrt{\frac{1}{n}\sum_{t=1}^{n}\left[\frac{1}{2}P_t^2 - (2\ln 2 - 1)Q_t^2\right]} \tag{7}$$

where $Q_t = \ln\frac{C_t}{O_t}$, and C_t and O_t are, respectively, the Ibex-35 opening and closing prices on day *t*.

The next two columns of Table II show the descriptive statistics for the time series volatilities calculated by these measures. No major differences emerge between the two. On average (0.012 for Parkinson's estimator and 0.0117 for the Garman-Klass estimator) the two are very similar to the measures presented so far. The level of leptokurtosis in the distribution is lower than in most of the other measures presented. The coefficients (11.30 for Parkinson's estimator and 10.10 for the Garman-Klass estimator) are similar to that of $|\varepsilon_{AC}|$ the only lower one being that of $|\varepsilon_{CC}|$ (3.89).

3.2.4- Implied volatility

All the volatility measures presented so far use spot market data. Nevertheless, several studies of the S&P100 index coincide in stating that implied volatility in at-the-money (henceforth ATM) options is a more efficient volatility estimator than those based exclusively on historical data. Fleming (1998) and Christensen and Prabhala (1998) among others, and more recently, for the Spanish stock market, Corredor and Santamaría (2001, 2004) show that implied volatility is a reliable predictor of future volatility versus other volatility measures. There are also numerous studies showing that the implied volatility indexes currently being constructed in several countries across the world possess significant power to predict future volatility in the stock market (Fleming, Ostdiek and Whaley [1995], Simon [2003], Giot [2005]).

Some recent papers have claimed that implied volatility also reflects investor sentiment (Baker and Wurgler [2006]). This led us to ask ourselves whether this measure may be sensitive to the presence of herding behavior in the stock market. We believe that the inclusion of this variable as an additional volatility measure in this paper will help to obtain a much more detailed and broader picture of the impact of herding on volatility.

Implied volatility measures resulting from the inversion of Black and Scholes (1973) (henceforth BS) pricing model are used. The main reason to use them is the convenience, given that those measures are available in the market (which can also make them affect investor expectations). In a theoretical framework, Fleming (1998) argued that in short term and ATM options, BS model gives estimations virtually identical to the ones given by other stochastic volatility models. Following the above literature, we now focus on the implied volatility in short-term (ST) ATM call options on the Ibex-35 (with 30 days or less to maturity).

The last column of Table II shows observable differences between descriptive statistics for implied volatility and the historical volatility measures. Implied volatility presents a slightly higher average than the previous measures (0.0165) and a closer to normal distribution, with a short-run asymmetry coefficient of 0.0493 and a kurtosis level of 1.7191.

Table III shows the existing correlation between the various volatility measures used in this paper. The correlation is low in overall terms, suggesting that it makes sense to use different measures because each one may supply additional information to the analysis. Not surprisingly, in view of the way in which they are constructed, the most highly inter-correlated are the Parkinson and Garman Klass measures, with a correlation coefficient of 0.8962. They are followed by σ_{R-AC}, with a correlation coefficient of 0.8794 with σ_{R-AA} (which is also foreseeable from the method used in their calculation), 0.8167 with σ_P and 0.8638 with σ_{GK}.

3.3- Volatility and herding

3.3.1- Obtaining series free of day-of-the-week and volume effects.

Having obtained the volatility measures described above, the second stage of the study is to purge them of the volume and day-of-the-week effects documented in the literature. We did this by running a series of regressions in which each of the above-described volatility measures was made to depend on the Monday effect and on a proxy for the daily trading volume and then corrected for autocorrelation. Thus, and subsequently taking the residuals of these regressions, we obtained series in which the only effects would be due to factors other than volume or the day-of-the-week effects, which, if present, would be captured by the coefficients of the variables considered.

There is a vast amount of evidence to show that volume traded and return volatility are positively correlated (Karpoff [1987], Gallant, Rossi and Tauchen [1992], Jones, Kaul and Lipson [1994]). The two paradigms that attempt to explain this relationship are the mixture of distributions (Epps and Epps, [1997]) and the microstructure paradigm (O´Hara, [1995]). Among a number of empirical studies that use different measures of volume to test these paradigms, we find Jones, Kaul and Lipson (1994) and Chan and Fong (2000, 2006). Following these papers, we use three different measures of volume: the traditional measure of volume traded in Euros, the number of trades, and the average trade size in Euros.

Table IV gives the correlations between the various volume measures considered; volume traded in Euros (*V*), number of trades (*NT*) and average trade size (*ATS*). Most notable in the table are the high correlation between *V* and *NT* (0.8149) and the negative correlation between *NT* and *ATS* (-0.2256). Given the existing controversy in the literature over which of these factors actually have an impact on volatility, we believe it makes sense to consider all of these measures, in order to lend more robustness to the results.

The estimated regressions may be written as follows:

$$\sigma_{it} = \alpha_i + \alpha_{im} M_t + \sum_{j=1}^{12} \rho_{ij} \sigma_{it-j} + \phi_i V_{it} + \upsilon_{it} \tag{8}$$

$$\sigma_{it} = \alpha_i + \alpha_{im} M_t + \sum_{j=1}^{12} \rho_{ij} \sigma_{it-j} + \theta_i NT_{it} + \eta_{it} \tag{9}$$

$$\sigma_{it} = \alpha_i + \alpha_{im} M_t + \sum_{j=1}^{12} \rho_{ij} \sigma_{it-j} + \gamma_i ATS_{it} + \tau_{it} \tag{10}$$

where σ_{it} is the value on day *t* of each of the volatility measures considered, where *i* can take ten different values; M_t is a dummy variable that takes a value of 1 for Mondays and zero for the remaining days of the week; *V*, *NT* and *ATS* are the volume measures described above. υ_{it}, η_{it} and τ_{it}, the residuals of the regressions, are the new volatility series after the removal of Monday and volume effects, which, if present, are captured by the coefficients of the variables in question.

Table V gives the coefficients of the volume proxies used in expressions (8), (9) and (10). Similar results are found for the first two volume measures considered. When the variable included in the regression is volume traded in Euros, it can be seen to have a positive influence on volatility for all the measures of historical volatility. Similarly, when trading volume is measured in terms of the number of trades, it is also observed to have a significantly positive effect on volatility in all the terms in which it was measured. However, when volume is measured in terms of average trade size, all the significant effects of volume on volatility ($|\varepsilon_{AA}|$, $|\varepsilon_{CA}|$, realized volatility and ST implied volatility) that emerge are negative. In other words, volatility increases with increases in volume traded, but decreases with increases in trade size. Both Easley and O'Hara (1987) and Admati and Pfeiderer (1988) suggest that informed traders engage in higher volume trading than uniformed traders do. Thus, the larger observed trade size, the higher the amount of informed trading and therefore the less volatility we can expect to find in the market, Hellwig (1980) or Wang (1993)[6].

3.3.2- The effect of herding on volatility.

Having obtained the "clean" volatility series, we can now examine them to determine the extent of the linear effect of herding intensity on calculated volatility on day *t*.

[6] Nevertheless, despite the observed differences across the three volume measures considered, if we focus on the adjusted R^2, we find no major differences between V, NT and ATS within each volatility measure.

To do so we run the following regressions:

$$\upsilon_{it} = \omega_{it} + H_{ist} + \lambda_{it} \tag{11}$$

$$\eta_{it} = \omega_{it} + H_{ist} + \lambda_{it} \tag{12}$$

$$\tau_{it} = \omega_{it} + H_{ist} + \lambda_{it} \tag{13}$$

where υ_{it}, η_{it} and τ_{it} are the residuals of the expressions (8), (9) and (10), ω_{it} is a constant and H_{ist} is the PS(2006) herding intensity measure on day *t*, where *s* can take three different values, according to whether the herding has occurred during an up run, a down run or a zero run.

Table VI shows the coefficients for the different measures of herding intensity (Ha, Hb and Hc). Overall, we find all three types of herding to have a significantly negative effect on all the volatility measures except implied volatility. Given that the level of herding intensity increases as H_s becomes more negative, the negative coefficients found for the herding intensity variable in regressions (11), (12) and (13) suggest that markets exhibiting higher levels of herding intensity will also present higher volatility. This result is consistent with that obtained by Avramov, Chordia and Goyal (2006).

The results for the measures of historical and realized volatility are very similar, irrespective of which volume proxy is used, and also unanimous. The variable used to measure herding intensity appears to affect the volatility generated that day, the effect being observed in practically all the volatility measures based on stock market data[7].

Overall, the results for the measures of historical and realized volatility show that a higher level of herding (which might be interpreted as uninformed trading) leads to greater price changes (volatility), that is, less stability. Herding traders either add momentum to price changes or cause prices to overshoot the fundamental price, resulting in more volatile and, perhaps, less informative prices. Nevertheless, these traders also provide liquidity to markets

The results for the implied volatility measure are not so clear. The differences found between the results for implied volatility and the rest of the measures used show that the presence of herding affects current volatility but not expected volatility, which is measured by implied volatility. The most frequent interpretation of implied volatility is as the market's future volatility forecast. Implied volatility mainly collects

[7] There are some exceptions: certain types of herding do not impact significantly on volatility captured by $|\varepsilon_{AA}|$, $\sigma_{R\text{-}AC}$, $\sigma_{R\text{-}AA}$ y σ_{GK}.

expectations about factors such as market price, fear of sharp drops or interest rate which, in turn, depend on future information. The option prices, and therefore the implied volatility estimates, also involve other factors such as the expiration date, the strike price, the bearish/bullish state of the market, liquidity problems in the options traded, volatility price skews due to buy/sell fees, excessive leverage effects or wide bid/ask spreads (see, among others, Peña et al. (1999) or Serna (2004). The results indicate that implied volatility, by definition, does not account for herding effects.

Our results are partially consistent with prior literature, as already mentioned. Several studies have found volatility to increase with uninformed or liquidity trading (Hellwig [1980] and Wang [1993]) and some have directly linked volatility increases to herd trading (Froot, Scharfstein and Stein [1992], Avramov, Chordia and Goyal [2006]). Nevertheless, our results using the short-term implied volatility provide new information that has not be presented in former studies. We believe that our study contributes to the robustness and novelty of the herding literature through the number of volatility measures and types of volume considered and the explicit use of a measure of intraday herding.

3.3.3- Non-linear causality

Since there is no reason why the relationships between variables need not be exclusively linear, we test for possible non-linear causality between the different measures of volatility and the herding level. Using the procedure described in Hiemstra and Jones (1994), we find no evidence at all of non-linear causality in the results.

A different pattern emerges, however, in the results for implied volatility in the prices of call ATM options. The values of the statistic are positive but non-significant at the standard levels of significance and higher when the cause variable is sell-side herding. This positive sign is robust to different values of the parameters in the Hiemstra and Jones (1994) procedure. For the remaining volatility measures, the sign of the non-linear causality statistic is negative, which is a clear indication that the herding level hampers, rather than facilitates, the prediction of non-linear volatility. This difference in the direction of the results could be interpreted as the already mentioned conceptual difference between the various volatility measures and as being somewhat coherent with the different sign (positive) of the coefficients for the linear effect of the intensity of sell-side herding on the implied volatility. For ease of reading, the results tables are not presented, given the lack of significance[8] of the results.

4.- Conclusions

This paper examines the way in which market volatility is affected by the presence of herding behavior. The relationship between investor behavior and market volatility has been examined in prior research in various financial markets, the majority of the findings supporting the idea that volatility increases with uninformed or liquidity trading. Information asymmetry can raise volatility and uninformed traders very frequently follow the market trend, buying when prices rise and selling when they fall, thus exhibiting a type of behavior that we might equate with herding.

The herding intensity measure used in this paper is that proposed by PS(2006), which is based on the information cascade models described in Bikhchandani, Hirshleifer and Welch (1992) where then intensity of herding in the market is measured in both buyer- and seller-initiated trading sequences. It is a measure constructed from intraday data, which we believe to be the most suitable data frequency for the detection of possible herding behavior among traders in the market.

We also use various measures of market volatility: absolute return residuals, historical volatility (Parkinson and Garman-Klass), realized volatility (Anderson et al, 2001) and implied volatility. All of these are purged for possible day-of-the-week or volume effects that might confound the findings.

The results presented in this paper are consistent with prior literature in revealing a clear effect of herding on market volatility: the higher the observed level of herding intensity, the greater volatility we can expect to find. This result (which comes from lineal relations) is homogeneous across two of the measures (historical and realized volatility) considered but does not apply in the case of implied volatility, where the herding effect is not significant at all. This suggests that the presence of herding affects current market volatility, but has no impact on expected future volatility, which is what implied volatility is intended to measure. Hence, imitation trading in stock markets does not transfer significant volatility effects to the option markets, given that it

[8] Nonetheless they are available from the authors upon request. The linear and non-linear analysis has been repeated adding to the volatility model the leverage effect (throughout the asset's returns). The results are similar to those presented here and are available from the authors upon request.

only affects stock market dynamics when traders have the means to identify each other in the trading environment.

The results of the assessing of the non-linear relations between herding and volatility indicate that there is no such relation between the said variables.

The overall results of this paper may be useful for interpreting the concept of risk and for defining risk management strategies. The choice of a specific type of volatility measure may be relevant, given that volatility estimates calculated with stock market data are “contaminated” by herding effects, whereas this is not the case with expected implied volatilities.

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TABLES

Table I. Descriptive data for the herding measures across up, down and zero runs.

	Ha Ibex35	*Hb Ibex35*	*Hc Ibex35*
Mean	-8.8152	-8.7263	-4.0399
Median	-8.8950	-8.7773	-3.9789
St. Dev.	2.1277	2.1499	1.3820
Asymmetry	0.1095	0.0059	-0.2661
Kurtosis	-0.3768	-0.2709	-0.3547
Minimum	-14.3633	-15.5900	-8.9243
Maximum	-1.0853	-1.5433	0.2202

Table II. Descriptive data for the different volatility measures considered

	$\lvert \varepsilon_{AA} \rvert$	$\lvert \varepsilon_{AC} \rvert$	$\lvert \varepsilon_{CC} \rvert$	$\lvert \varepsilon_{CA} \rvert$	σ_{R-AC}	σ_{R-AA}	σ_{P}	σ_{GK}	*ST ATM Call*
Mean	0.0129	0.0108	0.0122	0.0061	0.0120	0.0142	0.0120	0.0117	0.0165
Median	0.0101	0.0087	0.0096	0.0045	0.0107	0.0125	0.0105	0.0103	0.0160
St. Dev..	0.0126	0.0091	0.0104	0.0071	0.0059	0.0081	0.0065	0.0061	0.0065
Asymmetry	3.8175	2.0839	1.6419	7.8360	2.9336	6.3570	2.4582	2.3132	0.0493
Kurtosis	34.1569	10.8448	3.8602	135.7490	18.1877	94.9509	11.3010	10.1018	1.7191
Minimum	0.0000	0.0000	0.0000	0.0000	0.0030	0.0034	0.0022	0.0020	0.0000
Maximum	0.1898	0.1118	0.0694	0.1588	0.0787	0.1744	0.0687	0.0693	0.0411

Table III. Correlation between the different volatility measures considered

	$\lvert \varepsilon_{AA} \rvert$	$\lvert \varepsilon_{AC} \rvert$	$\lvert \varepsilon_{CC} \rvert$	$\lvert \varepsilon_{CA} \rvert$	σ_{R-AC}	σ_{R-AA}	σ_{P}	σ_{GK}	*ST ATM Call*
$\lvert \varepsilon_{AA} \rvert$	1.0000								
$\lvert \varepsilon_{AC} \rvert$	0.2767	1.0000							
$\lvert \varepsilon_{CC} \rvert$	0.5861	0.3070	1.0000						
$\lvert \varepsilon_{CA} \rvert$	0.2452	0.6986	0.3485	1.0000					
σ_{R-AC}	0.5642	0.5376	0.4678	0.4061	1.0000				
σ_{R-AA}	0.6764	0.5021	0.8076	0.4492	0.8794	1.0000			
σ_{P}	0.4177	0.7536	0.3727	0.5552	0.8167	0.7114	1.0000		
σ_{GK}	0.4313	0.5271	0.3479	0.4039	0.8638	0.7261	0.8962	1.0000	
ST ATM Call	0.3100	0.3107	0.3137	0.3043	0.5305	0.4997	0.4490	0.4847	1.0000

Table IV. Correlation between the different trade volume measures. The data shown are the coefficients of correlation between daily trading volume in (*V*), number of trades (*NT)* and trade size in Euros (*ATS*) for Ibex-35 stocks.

	V	*NT*	*ATS*
V	1.0000		
NT	0.8149	1.0000	
ATS	0.3301	-0.2256	1.0000

Table V. Coefficients for the trade volume measures. The data shown are the coefficients for the trading volume proxies in the following regressions:

$$\sigma_{it} = \alpha_i + \alpha_{im} M_t + \sum_{j=1}^{12} \rho_{ij} \sigma_{it-j} + \phi_i V_{it} + \upsilon_{it}$$

$$\sigma_{it} = \alpha_i + \alpha_{im} M_t + \sum_{j=1}^{12} \rho_{ij} \sigma_{it-j} + \theta_i NT_{it} + \eta_{it}$$

$$\sigma_{it} = \alpha_i + \alpha_{im} M_t + \sum_{j=1}^{12} \rho_{ij} \sigma_{it-j} + \gamma_i ATS_{it} + \tau_{it}$$

where σ_{it} is the value on day *t* of each of the volatility measures considered, where *i* can take ten different values, M_t is a dummy variable that takes a value of 1 for Mondays and 0 the remaining days of the week, *V* is volume traded in Euros, *NT* is volume traded in number of trades and *ATS* is average trade size. The values shown in parentheses are the t-statistics.
*** denotes significance at 1%, ** denotes significance at 5% and * denotes significance at 10%.

		V	*NT*	*ATS*
$\mid \varepsilon_{AA} \mid$	*Coeff.*	0,0027***	0.0041***	-0.0000**
	t-stat.	(4.2554)	(5.8815)	(-2.3565)
	Adj.R^2	0.1159	0.1268	0.1074
$\mid \varepsilon_{AC} \mid$	*Coeff.*	0.0030***	0.0036***	-0.0000
	t-stat.	(7.9540)	(8.3335)	(-0.5168)
	Adj.R^2	0.1237	0.1296	0.0994
$\mid \varepsilon_{CC} \mid$	*Coeff.*	0.0033***	0.0035***	0.0000
	t-stat.	(7.4908)	(7.1902)	(0.4152)
	Adj.R^2	0.1520	0.0097	0.1291
$\mid \varepsilon_{CA} \mid$	*Coeff.*	0.0012***	0.0016***	-0.0000*
	t-stat.	(3.3684)	(4.1415)	(-1.8255)
	Adj.R^2	0.1165	0.1204	0.1111
$\sigma_{R\text{-}AC}$	*Coeff.*	0.0018***	0.0024***	-0.0000**
	t-stat.	(9.4258)	(10.8723)	(-2.1845)
	Adj.R^2	0.4900	0.5005	0.4712
$\sigma_{R\text{-}AA}$	*Coeff.*	0.0023***	0.0029***	-0.0000**
	t-stat.	(8.0573)	(9.3204)	(-2.5015)
	Adj.R^2	0.4073	0.4154	0.3911
σ_P	*Coeff.*	0.0025***	0.0029***	-0.0000
	t-stat.	(10.5253)	(10.9319)	(-0.3594)
	Adj.R^2	0.3712	0.3779	0.3409
σ_{GK}	*Coeff.*	0.0022***	0.0027***	-0.0000
	t-stat.	(9.6087)	(10.3834)	(-0.7774)
	Adj.R^2	0.3968	0.4053	0.3656
ST ATM Call	*Coeff.*	0.0000	0.0004*	-0.0000***
	t-stat.	(-0.1058)	(1.7880)	(-3.0927)
	Adj.R^2	0.6457	0.6466	0.6486

Table VI. Results of herding on the volatility measures. The data shown are the coefficients for the effect of the herding intensity measures on the volatility measures purged of volume effects and sorted by type of volume measure, where υ_{it} is the volatility measure after removing the volume variable *V*, η_{it} is the volatility measure after removing the volume variable *NT* and τ_{it} is the volatility measure with *ATS* removed. The expressions of the regressions are as follows:

$$\upsilon_{it} = \omega_{it} + H_{ist} + \lambda_{it}, \qquad \eta_{it} = \omega_{it} + H_{ist} + \lambda_{it} \qquad \tau_{it} = \omega_{it} + H_{ist} + \lambda_{it}.$$

The values in parentheses are the t-statistics. *** denotes significance at 1%, ** denotes significance at 5% and * denotes significance at 10%.

	υ			η			τ		
	Ha	*Hb*	*Hc*	*Ha*	*Hb*	*Hc*	*Ha*	*Hb*	*Hc*
$\lvert \varepsilon_{AA} \rvert$	-0.0003**	-0.0003**	-0.0006**	-0.0001	-0.0001	-0.0004	-0.0007***	-0.0006***	-0.0010***
	(-2.3048)	(-2.0132)	(-2.3473)	(-0.5291)	(-0.4523)	(-1.5127)	(-5.2466)	(-4.7914)	(-3.7803)
$\lvert \varepsilon_{AC} \rvert$	-0.0004***	-0.0004***	-0.0008***	-0.0003***	-0.0003***	-0.0007***	-0.0009***	-0.0008***	-0.0013***
	(-4.3493)	(-3.8370)	(-4.6714)	(-3.3157)	(-2.9763)	(-4.0911)	(-8.6158)	(-7.9008)	(-7.1050)
$\lvert \varepsilon_{CC} \rvert$	-0.0005***	-0.0004***	-0.0010***	-0.0005***	-0.0004***	-0.0014***	-0.0010***	-0.0008***	-0.0015***
	(-4.4316)	(-3.8502)	(-5.8713)	(-4.0491)	(-3.5522)	(-5.6488)	(-8.6295)	(-7.4927)	(-8.1886)
$\lvert \varepsilon_{CA} \rvert$	-0.0004***	-0.0002***	-0.0008***	-0.0003***	-0.0003***	-0.0007***	-0.0008***	-0.0008***	-0.0012***
	(-4.4393)	(-3.8093)	(-4.6677)	(-1.1910)	(-2.9722)	(-4.0958)	(-8.6829)	(-7.9172)	(-7.1009)
σ_{R-AC}	-0.0002***	-0.0001*	-0.0002**	-0.0001***	0.0000	-0.0001	-0.0005***	-0.0003***	-0.0005***
	(-4.5607)	(-1.6341)	(-2.4242)	(-2.6368)	(0.1209)	(-1.4227)	(-9.7689)	(-6.6011)	(-5.0129)
σ_{R-AA}	-0.0003***	-0.0002**	-0.0005**	-0.0002**	-0.0001	-0.0004*	-0.0006***	-0.0005***	-0.0008***
	(-4.0727)	(-2.1338)	(-2.5507)	(-2.4517)	(-0.7552)	(-1.9616)	(-8.9463)	(-6.5252)	(-4.2876)
σ_{P}	-0.0003***	-0.0002***	-0.0005***	-0.0003***	-0.0001**	-0.0004***	-0.0007***	-0.0005***	-0.0008***
	(-5.2837)	(-3.2672)	(-4.5096)	(-4.0851)	(-2.1971)	(-3.8023)	(-10.8609)	(-8.8246)	(-7.6602)
σ_{GK}	-0.0003***	-0.0001*	-0.0003***	-0.0002***	-0.0000	-0.0002**	-0.0006***	-0.0004***	-0.0006***
	(-4.5445)	(-1.7829)	(-2.9430)	(-3.1187)	(-0.4224)	(-1.9833)	(-9.7758)	(-7.1587)	(-6.3098)
ST ATM Call	-0.0001	0.0000	-0.0000	-0.0000	0.0001	0.0001	-0.0001	0.0000	-0.0000
	(-1.5932)	(0.0411)	(-0.2574)	(-0.1928)	(1.3376)	(0.6454)	(-1.2876)	(0.2544)	(-0.1159)