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The Information Environment, Informed Trading and Volatility

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Abstract

The relation between informed trading and volatility is analysed using the change in the proportion of informed transactions calculated through the Probability of Informed Trading variable (PIN). The analysis relates to the Spanish market during 1997-2010, given that the Spanish market covers a very diverse range of listed companies. Some companies are comparable to companies listed on U.S. markets while others are smaller in size and have a lower trading volume and inferior quality of information. The methodology is based on a modification of the model proposed by Avramov *et al* [2006]. Our proposal incorporates the change in the proportion of informed transactions, calculated with intraday data, into the volatility model. The results are also presented using a conditional volatility model in which the change in the proportion of informed transactions is incorporated. These results attest to the influence of informed trading as a price stabilising factor in heavily traded and highly capitalized stocks (familiar stocks). Informed trading leads to a marked decrease in volatility for these particular stocks both in periods of calm and crisis.

JEL codes: G01, G02, G14

Keywords: Behavioural finance; time series; microstructure; informed trading; volatility

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1.-Introduction

Volatility is a key factor in financial analysis given its importance for, inter alia, stock valuation, risk management, portfolio formation and market efficiency. In fact, unexpected price fluctuations, depending on their intensity, can confound the most carefully thought-out expectations and render expert recommendations useless. In an ideal world, volatility could be explained through the arrival of unexpected information. However, fear, risk aversion and other psychological factors can influence the processing of information on the part of agents in such a way that price variation will be more or less intense depending on subjective perceptions.

The trading in financial assets during a specific session provides a basic time framework for volatility analysis. Each transaction can in fact involve additional unexpected information and psychological biases that in turn generate new price variations. These variations are important for everyday investors' decisions although they do not necessarily induce immediate changes in their views about fundamental pricing variables or in their risk aversion strategies. Sims [1984] and Lehmann [1990] suggest that the prices of assets follow a martingale-like process over very short time intervals, since changes in the fundamentals are barely perceptible during a session in which unexpected information arrives. Cochrane [2001] argues that it is impossible for risk aversion to change on a daily or longer term basis. Therefore, it is possible to think in terms of a close connection between the microstructure of the market and the intensity of asset volatility (see, among others, Amihud *et al* [1990], Bianco and Renò, [2006] or Awartani *et al* [2009]).

The relationship between investor behaviour and market volatility was identified by Friedman [1953]. He pointed out that irrational investors have the effect of destabilising prices, since they buy when prices are high and sell when prices are low, while rational investors move prices towards their fundamentals, as they buy when prices are low and sell when they are high. Along similar lines, and using the theory of Noisy Rational Expectations, Hellwig [1980] and Wang [1993] claim that volatility increases with liquidity or uninformed trading because the price changes generated by uninformed negotiation tend to revert. In Hellwig's model [1980], information arriving in the market is aggregated in the prices through the actions of risk-averse agents, heterogeneously informed agents who individually do not have excessive influence on prices. In general, informed traders influence stock prices by stepping in to profit if they observe that prices temporarily deviate from their fundamentals. The greater the numbers of informed agents, the more precise are the informative signals and their impact on prices reduces the deviations from the fundamentals. However, noisy information aggregation leads to excess price volatility. Wang [1993] observed that information asymmetry can increase volatility because uninformed investors frequently take positions following the trend. This behaviour, despite being uninformed trading, can be rational for less informed investors if they find themselves in an asymmetric information environment. Furthermore, Cutler *et al* [1990] and De Long *et al* [1990] found that positive feedback investment strategies can originate an excess of volatility even in the presence of rational informed investors if, for example, these rational informed investors find it interesting to appear to jump on the bandwagon and not to buck the trend followed by noise traders, in the hope of selling (buying) at a much higher (lower) price tomorrow.

The model developed by Campbell *et al* [1993] is useful for distinguishing between informed and uninformed transactions. This model establishes that a fall in prices may be attributed to new negative information or to excessive selling pressure provoked by herding. In the first case, there is no reason to expect subsequent price changes. In the second case, a subsequent correction to the excessive selling pressure may be expected with an increase in prices. In other words, informed agents will generate null autocorrelation returns, just as uninformed agents or imitators will generate non-null autocorrelation returns.

More recently this relationship has been documented by Avramov *et al* [2006] (hereinafter ACG06). According to these authors, the activities of both imitative and non-imitative investors have a significant effect on day-to-day volatility, although in different directions. ACG06 checks whether the fact that there is herding behaviour causes an increase in volatility while informed trading causes a decrease. It does this by classifying sales transactions as herding or mimetic and contrarian in order to identify each of the above-mentioned types of behaviour. The classification is based on the relation between residual return and sales transactions. The authors establish that contrarian sales are informed sales and that they reduce volatility while imitative sales increase it.

From a different perspective the PIN variable (probability of informed trading) obtained from the microstructure model given by Easley *et al* [1997] has assumed importance as an explanation of several market characteristics and variables such as stock splits, cross-sectional expected returns, ownership structure or market efficiency (see, among others, Dennis and Weston [2001], Easley *et al* [2001], Easley *et al* [2002], or Vega [2006]). The PIN variable captures the degree of asymmetry in trading so that its use can help to better understand the relationship between informed trading and volatility. To the best of our knowledge, three works have dealt with this relationship. Marsh *et al* [2008] analysed the relationship between the PIN variable and asset volatility in the USA and found a negative relation between them. Poskitt [2005], studying the Australian market, detected a negative correlation between PIN and volatility. Indirectly, Lai *et al* [2014] have also found a similar correlation in some international markets.

In line with these studies, the aim of the present paper is to analyse the relationship between volatility and information at the market microstructure level and to attempt to determine whether informed trading influences volatility and how this occurs in the Spanish Stock Market, using the PIN variable for calculating our informed trading measure. From a complementary perspective, the paper of Blasco *et al.* [2012] finds evidence in the Spanish market of how trading through imitation has a significant positive influence on volatility. Furthermore, the greater the level of herding detected, the greater the anticipated volatility. In the light of these results, this study considers the Spanish market to be the ideal setting for reaching the intended objective: to examine in depth the behaviour of daily informed trading as complementary to daily imitative trading. Given the above indications, we might expect to find a negative correlation between the informed trading variable and volatility.

The Spanish market differs from the American market in various other respects which makes its study worthwhile. Informed trading can be conditioned by the informative environment and the characteristics of the stock market. Following the information provided by Lai *et al* [2009], the proxies used as measures of the financial disclosure environment and of the corporate governance environment have values in Spain 50% lower than the equivalent values in the USA (financial transparency factor 0.88 versus 1.59; disclosure requirements index 0.50 versus 1.00 and anti-self-dealing-index 0.37 versus 0.65). This suggests that the Spanish market is more opaque than the traditionally studied USA market. Moreover, considering the assessments of financial analysts as a source of information, the values of errors in their predictions and the differences in their recommendations are more than twice as much in Spain as in the USA. Additionally, as measures of insider ownership and institutional holding and trading, it can be said that the proportion of stocks closely held by insiders and controlling shareholders is much greater in Spain (0.44/0.17). Significant differences are also found when measuring the proportion of stocks held or traded by foreign mutual funds (2.92/0.39 and 1.88/0.92), or when the proportion of stocks held or traded by domestic funds is quantified (3.58/17.77 and 1.09/5.63). All these data reveal a market with inferior informative quality than the American market, which presupposes a greater effect of informed trading on the market in general and on volatility in particular.

While the objective coincides in part with the paper of ACG06, the contribution of this study is threefold. First, it gives a different perspective for studying the concept of informed transactions using an explanatory variable that we consider to be more appropriate than that mentioned in ACG06. This variable is directly influenced by the probability of informed trading (PIN), generally accepted (Easley *et al* [1996, 1997, 2002, 2008 and 2010], among others) as an informed trading measure in the literature. The second contribution is the study of the Spanish market which, as already mentioned, has characteristics different from those of the American market. It is of interest for its greater informative opacity. Thirdly, this work includes an analysis of the relation between volatility and informed trading taking into account the differentiation between types of stock. The relation between volatility and PIN studied in the literature does not consider specific volatility models and has treated stock markets as a whole. Nevertheless, Barberis and Shleifer [2003] suggest that investors are prone to "categorization" and treat certain members of certain groups of stocks (such as small cap stocks) as being more similar than the fundamentals would suggest. As a result, categorization produces common factors in returns to stocks in the same group. Given that the literature has shown that the probability of informed trading is greater for smaller sized stocks, it might be assumed that the stabilising effect of informed trading would be greater for this type of stock than for stocks of greater size. However, taking into account the varying intensity of the presence of institutional investors in the different types of stock, as well as other characteristics of the informative environment, this result might not be so predictable. This work examines this question which is not considered in previous studies.

This paper thus takes the test proposed by ACG06 as a starting point and suggests some variations of the model in order to improve the interpretation and clarity of the results. We use a less constrictive variable for approaching informed trading that involves both current and delayed information: the change in the ratio of informed transactions, calculated using the probability of informed trading. The role of all the transactions undertaken is taken into account so that unlike ACG06 we offer the possibility that both selling and buying activity incorporate information. For the purposes of comparison and in order to test the robustness of the results, the paper also includes conditional volatility models modified by the inclusion of the informed trading variable, enabling the volatility persistence to be incorporated into our analysis.

A further relevant aspect of this study is the use of intraday information to measure the probability of informed trading. As mentioned before, we believe this frequency of data to be the most appropriate for trying to detect the effect of informed and uninformed transactions on volatility. The method selected for classifying the type of transaction includes a separate group for zero tick transactions (no price change) so that possible classification problems can be avoided. In the Spanish market we find that, on average, the probability of rise or fall sequences is 60% while zero-tick sequences occur in the time interval under study with a probability of 40%. For this reason we consider it important to avoid misleading results caused by bias in the classification of transactions. Furthermore, the time period analyzed is long enough to dilute any biases due to temporary market fluctuations, despite the outbreak of the financial crisis.

The results obtained are of particular relevance for gaining a deeper insight into the roles of the market and, given that good prediction of volatility is a key factor in investment decisions, they could be useful for defining new risk measures, for portfolio management or for coverage strategies. In fact, Crépey [2004] explains how market complexity and incompleteness of the volatility measures are drawbacks that call for a recalibration of the models used for risk management. More recently, Andersen *et al* [2011] suggest that the detrimental impact of microstructure noise on the accuracy of forecasting can be substantial. Knowing which variables affect volatility and how they do this could be of considerable help when seeking more accurate predictions of volatility. Furthermore, knowing the relationship between volatility and information is fundamental for both market regulators and academics. On the one hand, regulators need to reduce information asymmetry to make stock markets more transparent. In fact they make regulations and develop institutional infrastructures in order to provide investors with equal access to information. On the other hand, academics have analysed the interaction between informed and uninformed investors, and shown that the relation between them induces informational risk in asset prices. Any progress in this area is thus warranted.

The paper is organised as follows. Section 2 describes the database. Section 3 explains the calculation of the probability of the informed trading variable together with a description of its constituent elements. The methodology and principal results are given in Section 4. Finally, the conclusions are set out in Section 5.

2.-Database

The data used in this analysis were provided by the Sociedad de Bolsas SA and by Datastream (Thomson Financial). The period analysed was from 1 January 1997 to 31 December 2010. The study of the relation between volatility and informed trading was undertaken on a daily frequency basis. This frequency is usual for this type of study, as can be seen in Campbell *et al* [1993], Jones *et al* [1994], Chan and Fong [2000], Chordia *et al* [2001] or Kao and Fung [2012], among others. However, databases with different frequencies, daily and intraday, are used in the paper. The daily database collects the stock returns, calculated through closing prices, the trading volume calculated in two ways (the number of transactions and the number of stocks), capitalisation, turnover, book-to-market and the number of transactions initiated by buyers and sellers necessary for calculating the PIN variable. The latter data does not appear as such in the available databases and has to be estimated using intraday data. Thus intraday information has been used for the calculation of the probability of informed trading. The intraday database collects together all the transactions conducted during the period. For each transaction the date, the exact time in hours, minutes and seconds, the broker code, the price and the trading volume (in number of stocks) are specified. Operations conducted outside the normal market trading hours have been omitted from the analysis, both before the official opening of each session and after the market closed[1]. The usual trading hours at the beginning of the sample period (1997) were from 10.00 am to 17.00 pm. These were extended progressively until being fixed in 2003 from 9:00 am to 17:30 pm.

This information enables the number of daily purchases and sales to be obtained, for which an algorithm needs to be applied in order to determine the type of transactions.

[1] The reason for excluding trades outside normal hours is that these operate under a different trading mechanism than that used during the rest of the day.

Following the lines established by authors such as Lyons [1995] or Sias and Starks [1997], the transactions can be identified with the tick test[2].

Each session has a total number of transactions calculated as the sum of buying transactions, selling transactions, and zero-tick transactions, in other words those which cannot be accurately classified as purchases or sales. The zero-tick division does not appear in ACG06. We have included it in order to avoid our results suffering from an element of bias owing to the inclusion of transactions that cannot strictly be determined one way or the other.

For estimation purposes, we have selected a wide variety of stocks[3] so that their parameters of capitalisation, turnover, return and book-to-market can be considered representative of the diversity of the stock market as a whole. The selection criterion was to identify stocks with the highest, average and lowest values for all the variables mentioned and select those with the highest repetition rate within the whole set of variables. The set of stocks selected represents 94.53% of the market capitalisation of the Spanish stock exchange.

3.-Calculation of the PIN variable

The PIN variable is a function of the flow of abnormal orders (under excessive buying or selling pressure) attributable to private information or to a different interpretation by agents of public information. The usual approach in market microstructure that public information is directly incorporated into prices more than being reflected in the flow of orders does not always appear to be verified, given that there is practical evidence that extraordinary flows also take place when public information exists about which agents have different interpretations. In this case, it may be that private signals received by an agent derive from public information that is difficult to interpret (see Kim and Verrecchia [1994, 1997], Chung *et al* [2005], Saffi

[2] There are alternative ways of classifying a transaction as being initiated by the buyer or by the seller. Finucane (2000) shows that the tick-test method produces similar results to those of other classification methods. Given this finding and the fact that there is no database available which includes the bid-ask differential, we have decided to use the tick-test to classify operations. Specifically, a transaction is classified as being initiated by the buyer if the price of the transaction is higher than that of the previous transaction (up-tick), and as initiated by the seller if the transaction price is lower than that of the previous transaction (down-tick). If there is no price difference between a transaction and the previous transaction, it is classified as zero-tick.

[3] The estimation of the PIN variable with intraday data involves a very high number of iterations and a high computational cost. It was therefore decided to take a representative majority of stocks traded on the Spanish stock exchange. This takes into account criteria including the whole range of traded stocks in terms of size, liquidity and volatility.

[2007] or Chen *et al* [2007]). The present paper takes this approach, proposing that the PIN variable is not exclusively a measure of strictly private information but that it also includes information from investors who are especially adept at processing public information.

Given that information-based trading is unobservable, a model is required for making deductions. This paper follows the market microstructure model proposed by Easley *et al* [1996, 1997] and Easley *et al* [2002]. This can be described as a learning model in which agents observe market data, make inferences about its true underlying value, and incorporate it modifying the values of the stocks they trade. Easley *et al* [2002] model a market in which a competitive market maker trades a stock with informed and uninformed traders[4]. Information events occur between trading days with probability α. The probability of this being bad news is δ and the probability that it is good news is (1-δ). Uninformed investors or liquidity traders buy and sell stocks for reasons exogenous to the model. Their sell and buy orders arrive in the market according to a Poisson-independent distribution with arrival rates ε_b for buy orders and ε_s for sell orders. Informed investors trade for speculative reasons; if they receive good news they will buy the stock and if they receive bad news they will sell it. The arrival rate of orders from informed agents is assumed to follow a Poisson process and is identified as μ.

PIN is defined as the estimation of the arrival rate of informed investors divided by the arrival rate of all investors during a specific time period. PIN can be calculated as follows:

$$PIN = \frac{\alpha\mu}{\alpha\mu + \varepsilon_b + \varepsilon_s} \tag{1}$$

where $\alpha\mu+\varepsilon_b+\varepsilon_s$ is the arrival rate of all transactions and $\alpha\mu$ is the arrival rate of information-based orders. The estimation of the parameters is made following Easley *et al* [2010]. The underlying likelihood function in the model for all purchases and sales on any single trading day is a mixture of three Poisson probabilities weighted by the probability of having good news, bad news or no news on that day. This function is as follows:

[4]The figure of the market-maker does not specifically exist in the Spanish market, but the trades placed through the order book enable solicited transactions to be observed. The experimental study of Bloomfield *et al* (2005) suggests that a market-making role arises endogenously in the electronic markets.

$$L((B,S)\,|\,\theta) = \alpha(1-\delta)e^{-(\mu+\varepsilon_b+\varepsilon_s)}\frac{(\mu+\varepsilon_b)^B(\varepsilon_s)^S}{B!S!} + \alpha\delta e^{-(\mu+\varepsilon_b+\varepsilon_s)}\frac{(\mu+\varepsilon_s)^S(\varepsilon_b)^B}{B!S!} + \\ + (1-\alpha)e^{-(\varepsilon_b+\varepsilon_s)}\frac{(\varepsilon_b)^B(\varepsilon_S)^S}{B!S!} \tag{2}$$

where B is the total number of purchases (operations initiated by the buyer) and S the total number of sales (operations initiated by the seller) for one day and $\theta = \{\varepsilon_s,\varepsilon_b,, \mu, \alpha, \delta\}$ is the initial vector of the structural parameters. Easley *et al* [2010] recommend the factorization of the maximum likelihood function to make its calculation easier, increasing computational efficiency and reducing truncation errors. Following these authors, the likelihood function for T days can be represented as:

$$L((B_t,S_t)_{t=1}^T\,|\,\theta) = \sum_{t=1}^{T}\left[-\varepsilon_b - \varepsilon_s + M_t(\ln x_b + \ln x_s) + B_t\ln(\mu+\varepsilon_b) + S_t\ln(\mu+\varepsilon_{s)}\right] \\ + \sum_{t=1}^{T}\ln\left[\alpha(1-\delta)e^{-\mu}x_s^{S_t-M_t}x_b^{-M_t} + \alpha\delta e^{-\mu}x_b^{B_t-M_t}x_s^{-M_t} + (1-\alpha)x_s^{S_t-M_t}x_b^{B_t-M_t}\right] \tag{3}$$

where $M_t = \min(B_t,S_t) + \max(B_t,S_t)/2$, and

$$X_S = \frac{\varepsilon_s}{\mu+\varepsilon_s} \quad \text{and} \quad X_b = \frac{\varepsilon_b}{\mu+\varepsilon_b}. \tag{4}$$

Maximising the likelihood function with respect to the parameters $\theta = \{\varepsilon_s,\varepsilon_b,, \mu, \alpha, \delta\}$ is done separately for each stock and for each year. This gives us the corresponding parameter estimates per stock and year during the sample period.

Lin and Ke [2011] recommend a different factorization in order to mitigate the downwards bias in PIN estimates. A comparison made by Yan and Zhang [2012] shows that the estimate based on the Easley *et al* [2010] factorization is systematically smaller than the estimate based on the Lin and Ke [2011] factorization. Nevertheless, they also find that boundary solutions appear with a very high frequency when the LK factorization is used. Boundary solutions can cause a systematic bias in the estimate of PIN. Yan and Zhang [2012] suggest that it is necessary to use the LK factorization together with their algorithm to obtain an estimate of PIN using 125 sets of initial values and choosing either the boundary solution or the non-boundary solution, if possible, with the highest value of the objective function as the maximum likelihood estimate. In this paper we have used the proposal by Easley *et al* [2010] [5] together with the Yan and

[5] The Newton-Raphson method has been used for maximizing the likelihood function in equation (3). This method was used by authors such as Brockman and Chung (2003), Brown and Cliff (2004), Pang *et al* (2007) or Lin and Ke (2011), among others.

Zhang [2012] algorithm for choosing initial values[6]. Table I shows the mean estimation of the parameters ε_s, ε_b, μ, α, δ for all stocks at an annual frequency. It can be seen that the estimated parameters have values similar to those found in the literature (see, Benos and Jochec [2007], Li and Zhang [2008], Choi [2009], Duarte and Young [2009], Aslan *et al* [2011] or Lai *et al* [2014], among others). The percentage of boundary solutions for α estimate is 1.28%. The percentage of boundary solutions for δ estimates is 15.86%. We also estimate that the Yan and Zhang algorithm enables us to improve the maximum likelihood estimate in about 14.44% of the cases with respect to a fixed initial combination of reference values ε_b=1.0, ε_s=2.0, δ=0.58, α=0.12 and μ=1.35 selected after various preliminary trials.

Table II shows the PIN estimates aggregated for the stocks classified by size into stocks with higher, medium or lower capitalization. The results in panels A (annual estimation means for the total period) and B (annual estimation means for periods before and during/after financial crisis) clearly show that large companies have lower PIN variable values than small companies. This result is consistent with those obtained by Mohanram and Rajgopal [2009], Marsh and Nagayasu [2009], Popescu and Kumar [2010], Aslan *et al* [2011] or Lai *et al* [2009], among others. These authors have found an apparent inverse ratio between the size of the stocks and their PIN variables. The result is also consistent with results relating to the concentration of uninformed trading (herding) in large companies owing to the familiarity and the quality of the information (Palomino [1996], Sias [2004], Lin, *et al* [2009] or Blasco *et al* [2009], among others). Therefore, the size of the company can be considered as a relevant characteristic for attracting informed trading, given that large companies are greatly preferred by the majority of groups of uninformed investors. These companies are more visible (transparent) and easier to follow, so that uninformed investors are attracted by them. In contrast, small companies, being more opaque, concentrate the activities of informed investors. The cost of finding information, both financial and in terms of time seems to lie behind this phenomenon.

4-Methodology and empirical results.

4.1-Calculating volatility

[6] We have also used the Lin and Ke (2011) factorization. Nevertheless, we do not find higher estimates than the estimates based on the Easley *et al* (2010) factorization, and boundary solutions appear with a very high frequency.

Daily volatility will be obtained in a similar manner to that proposed by Schwert [1990], Jones *et al* [1994], Chan and Fong [2000] or ACG06. It is calculated as the absolute value of the residual obtained from the following regression:

$$R_{it} = \sum_{k=1}^{5} a_{i,k} D_{kt} + \sum_{r=1}^{s} b_{i,r} R_{i,t-r} + c_i \frac{NS_{i,t}}{NT_{i,t}} + u_{i,t} \tag{5}$$

where R_{it} is the return of stock i on day t, D_{kt} are the dummy variables corresponding to each day of the week, NS_{it} is the number of sales transactions of stock i on day t, NT_{it} is the total number of transactions of stock i on day t, and s is the number of lags included to avoid autocorrelation problems[7]. The ratio of both variables (NS and NT) is representative of the sales activity and is a control variable that captures negative return and orthogonalizes the residual variable to this information. Although there are simpler ways of obtaining the residual to approximate volatility, this expression enables some estimation problems revealed in the literature to be overcome and therefore the absolute value of the residual, denominated $|u_{i,t}|$, will be our first volatility estimate.

Table III shows the estimations of the parameters of the proposed equation for obtaining the volatility by means of the absolute value of the residual. The estimation data is shown in disaggregated quintiles in order to examine the results in greater detail. The results are quite uniform for all the stocks analysed. The dummy variables representing the days of the week are basically positive and significant. The lags in return significantly and negatively influence the actual return, this being especially evident in the first lag in the case of small companies. In addition, as would be expected, the significant negative estimate of sales activity logically induces a reduction in prices.

4.2- ACG06 Model

Our first objective is to clarify the influence of informed trading in the model put forward in ACG06.

In this model, the information base to define the type of transaction is found in the residual of the previous regression. The residual $u_{i,t}$ is associated with the unexpected return of stock i on day t. During a trading session with unexpected positive returns, the sales transactions are associated with contrarian or informed transactions. In a trading

[7] This number is not the same for all stocks and depends on the autocorrelation detected. The range varies from 1 to 5 lags.

session with unexpected negative returns, the sales transactions are linked to the mimetic effect or uninformed trading.

Formally, contrarian transactions are denoted as:

$$\frac{NS_{it}}{NT_{it}} * (u_{it} \geq 0) \tag{6}$$

where $(u_{it} \geq 0)$ is a variable with a value of 1 if u_{it} is not negative and zero otherwise. Similarly, herding transactions or uninformed transactions are denoted by:

$$\frac{NS_{it}}{NT_{it}} * (u_{it} < 0) \tag{7}$$

where $(u_{it} < 0)$ is a variable with a value of 1 if u_{it} is negative and zero otherwise.

The underlying idea is that sales transactions in the presence of falling prices are identified with herding transactions, while in the presence of rising prices sales transactions are identified with information showing an opinion opposite to that prevalent in the market at the time. The authors also conjecture that herding trades are uninformed and contrarian trades are informed. Furthermore, when the lagged unexpected return is negative, selling activity governs the increase in subsequent volatility; when the lagged unexpected return is positive, selling activity governs the volatility decline during the next period. This suggests that selling activity is the source of the asymmetric volatility phenomenon.

ACG06 evaluate the impact of informed and uninformed sales transactions by means of the following specification:

$$|u_{i,t}| = \Phi_i + \Psi_i M_t + \sum_{k=1}^{s} \rho_{i,k} |u_{i,t-k}| + c_i NT_{i,t} + \left[\underbrace{d_{i,0} + d_{i,1} \frac{NS_{i,t-1}}{NT_{i,t-1}} (u_{i,t-1} \geq 0)}_{Contrarian} + \underbrace{d_{i,2} \frac{NS_{i,t-1}}{NT_{i,t-1}} (u_{i,t-1} < 0)}_{Mimetic} \right] u_{i,t-1} + \eta_{i,t} \tag{8}$$

where M_t is a dummy variable that has a value of 1 on Mondays and zero on other days, $NT_{i,t}$ is the variable associated with the trading volume in stock i on day t[8] and $NS_{i,t}$

[8] This variable is included because there are numerous papers in the empirical financial literature that show a positive and significant relation between volume and volatility (Karpoff (1987), Gallant *et al* (1992), Jones *et al* (1994), Epps and Epps (1997), O´Hara, (1995) and Chan and Fong (2000, 2006), among others). 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]). From a number of empirical studies that use different measures of volume to test these paradigms, we have taken Jones, *et al* (1994), Chan and Fong (2000, 2006) and ACG06. Following these papers, we use two different measures of volume: the total number of transactions and the total number of stocks traded.

represents the number of transactions initiated by the seller in stock i on day t. The equation also includes the lags (s) of the dependent variable for taking into account the volatility persistence[9].

In this expression the impact of sales transactions on volatility is classified depending on whether the unexpected return is positive or negative, so it can be expected that:

$$d_{i,1} + d_{i,2} < 0 \tag{9}$$

However, it should be remembered that because contrarian transactions, according to the established premises, should reduce volatility while herding transactions should increase it, both coefficients should be negative given the sign of the residuals that accompany them.

Table IV shows the estimations of the model proposed in ACG06. In general the positive correlation of the volatility is shown as well as the importance of volume as an explanatory variable, given that these variables appear significant. However, the ultimate objective of this analysis concerns the issue of whether the parameters associated with informed and uninformed trading influence volatility, and this is not so conclusive. In fact, when studying the effect of informed trading on volatility, parameter d_1, this appears significant in the group of medium-sized companies (quintile 3) but with the opposite sign to that expected. This does not suggest that informed trading reduces volatility. When observing the effect of uninformed trading on volatility, the effect appears significant in the case of companies belonging to the first quintile. In 92% of cases, the presence of mimetic behaviour is observed together with increases in volatility[10]. A look at the results suggests that, in general, the test followed by ACG06 does not allow the starting hypothesis that informed trading induces lower volatility to be accepted, given that the results cannot be generalised when obtaining contrasting evidence. Therefore, in following this study it does not seem entirely clear that the type of trading (specifically informed trading) has a direct effect on volatility. Our results coincide with those given in ACG06 on the negative sign of the coefficient associated with imitative or uninformed trading for stocks in the first quintile. However, in our study significant results are not appreciated for informed trading, while they are

[9] The number of lags included varies for stocks depending on the significance of the correlation.
[10]For reasons of clarity only the results when the volume is approximated by the number of transactions are shown. The conclusions obtained from the results when the volume is approximated by the number of traded stocks coincide with those shown for the number of transactions.

significant in the cited study. These differences could be a result of the Spanish market being different from the American, or that the variables considered in ACG06 as informed and uninformed trading are unable to capture the essence of the type of trading in the Spanish market and therefore do not allow their possible effects to be detected. Furthermore, in the Spanish market the effect of herding on volatility has been demonstrated using alternative measures to those used by ACG06 for all stocks regardless of their size. This raises questions about the general validity of the ACG06 measures for both informed and uninformed trading in markets other than the American market. In our opinion, the proposal of ACG06 suffers from some limitations for more opaque markets and this leads us to put forward the following arguments and an alternative proposal.

4.3-Discussion of the ACG06 model and alternative proposal.

The model presented in ACG06 uses a daily volatility estimate constructed on the basis of the unexpected return of a complete trading session that, in turn, depends on some lagged variables representing informed and uninformed trading. The market microstructure, however, is rich in changes. The arrival of new information drives the dynamics of a trading session. The different reactions of informed and uninformed agents to such new information will induce changes in prices during the session. Glosten and Milgron [1985] and Kyle [1985] claim that the aggregation of transactions of informed and uninformed investors is what produces the trading volume. Therefore, we should take account of this wealth of informational and transactional detail in order to obtain complete and general conclusions.

An agent's decision to buy or sell in the market is generally taken for two reasons: information or liquidity. In the former case, the agent takes a strategic stance in relation to other agents reacting quickly to the arrival of news. In the case of liquidity or lack of information, the agent may act immediately or at the end of a sequence of imitative actions in the light of previous reactions of other agents who have made decisions beforehand, or the agent could even react in later sessions. In other words, not all transactions initiated by buyers or sellers respond to information, independently of the unexpected returns, and not all transactions addressed by liquidity or the herding effect take place in the same session. They could occur after some delay. These reactions and their intensity may be influenced by the information environment of the stock market.

An analysis of the ACG06 model, considering the sales transactions contrary to the unexpected returns of the previous day to be informed transactions, begs the following questions:

- What value is being placed on the adept processing of information? An informed professional agent should react almost immediately to the arrival of new information, and in fact this is what is defined by the concept of market efficiency. Therefore, informed trading should have a negative impact at least on volatility generated during the same session. More precisely, as the number of informed transactions increases during the trading session, volatility should decrease as informed traders move prices to their fundamental value.

- As regards the lagged explanatory variables in the ACG06 model, what can explain the unexpected positive return in a session when informed sales transactions have occurred? There are two probable explanations: new positive information has arrived during the session and sequences of informed buy transactions and rising prices have been more intense, or there are buy transactions governed by liquidity or imitation of a previous informed buy negotiation (even from a previous session). Furthermore, agents governed by imitative criteria imitate the decision, not the price. This suggests that perhaps part of the sales decisions that were contrary to unexpected returns were not addressed by information, but by imitation. According to the findings of Kittiakaraskun et al [2011], sales activity during a trading session is not necessarily dominated by a specific type of operator (informed or uninformed) and the price formation process occurs through the actions of different groups of agents with heterogeneous opinions and criteria. Thus, lagged contrary sales transactions may not be exclusively a good proxy for informed trading, particularly in those environments with an intense herding level. In fact, the wide variety of circumstances deriving from the arrival of good and bad news and the subsequent reaction of informed traders, as well as the interaction of informed and uniformed traders who respond to liquidity needs both from a buying or a selling perspective, may make it difficult to state categorically that there is a correspondence between contrarian and informed trading and that sell trades when returns are negative represent uninformed activity.

Given the above considerations, we think that today's volatility depends on contemporary and lagged variables. The results of Chen and Daigler [2008] or Kao and Fung [2012] show that information is a key factor in the relationship between volatility and volume and that those theories which explain this relationship are not exclusive, but complementary. These authors, using intraday data, find a significant contemporaneous relationship between volume and volatility, consistent with the mixture-of-distributions hypothesis that links volume of trading with the arrival of new information events (Clark, [1973], Epps and Epps [1976], and Tauchen and Pitt [1983]). They also find a significant relationship between lagged volume and volatility, behaviour that is consistent with the hypothesis of sequential information arrival in the markets (Foster [1995], Wang and Yau [2000]). In turn, both the mixture-of-distributions hypothesis and the sequential information arrival hypothesis are consistent with both the hypothesis of dispersion of expectations (Harris and Raviv [1993], Shalen [1993]) in which informed and uninformed agents react to the same information in different ways, and the asymmetric information hypothesis (Daigler and Wiley [1999], Downing and Zang [2004]) which suggests that informed agents position themselves at one side of the market, reducing volatility.

Therefore, to maintain this structure of complementary hypotheses we consider both contemporary and lagged relationships to be relevant (which is why we incorporate the change in the proportion of informed transactions into the model), together with the separation between informed agents both for buy and sell positions, given that both types of transaction derive from different information events or alternative processing of the same information.

Furthermore, the ACG06 model uses sales transactions assuming a complementary behaviour to that of buying transactions. This is because transactions without price changes are included in one of the two classifications (buy or sell). However, the so-called “zero-tick” transactions are more difficult to classify as informed or imitative. We therefore think it is important to exclude them from the group and consider them separately. When separating transactions without a change in price, the buy and sell transactions are no longer complementary and thus we need to find an alternative proposal for the variable representing informed trading. Given that we have the probability of informed trading available, we can calculate the number of informed transactions multiplying the PIN estimate by the number of strictly buy and sell transactions.

Our proposal for the informed trading variable is what we might call the “variation of the proportion of informed transactions”, that is the ratio between strictly informed buy or sell transactions (leaving aside zero-tick transactions) and the total number of transactions completed in the trading session. The intention is to use a measure free of the bias that could be introduced by transactions with no price change or by transactions that may respond to mimetic behaviour or to other reasons than good or bad news arriving in the markets during the same session.

The specific model is as follows:

$$|u_{it}| = \phi_i + \sum_{k=1}^{s} \rho_{ik} \, |u_{i,t-k}| + \gamma_i NT_{it} + \varphi_{i1}\left(\frac{NS_{it} + NB_{it}}{NT_{it}} PIN_{it} - \frac{NS_{it-1} + NB_{it-1}}{NT_{it-1}} PIN_{it-1} \right) + \zeta_{it} \tag{10}$$

where NS_{it} is the number of sales transactions of stock i on day t, NB_{it} is the number of buying transactions of stock i on day t and NT_{it} is the total the number of buying transactions of stock i on day t and NT_{it} is the total number of transactions of stock i on day t. The model incorporates in a manner analogous to that of ACG06 the volatility persistence that is determined by the coefficients ρ_k and the element associated with trading volume NT_{it}. The expression $\frac{(NS_{it} + NB_{it})PIN_{it}}{NT_{it}}$ encapsulates our proposal for the "minimal proportion of informed transactions" variable. Note that this variable is included in the model in incremental terms. The object of the proposal is to determine how variations in informed trading influence volatility during a session. Also note that PIN_{it} is an annual estimation calculated using intraday data. The use of daily data in eq. 10 requires daily information about the number of transactions so that the proportion of informed transactions can be calculated at this frequency leaving aside zero-tick transactions.

Following the premises set out above, increases in informed trading might be expected to reduce volatility on approximating the prices to their fundamentals and correcting possible deviations caused by uninformed trading.

Panel A in Table V shows the results of our alternative proposal, in which informed trading is calculated as the variation of a minimal proportion of informed transactions through the PIN variable. The results of the estimations obtained provide more convincing conclusions than those obtained previously. In addition to the autocorrelation of volatility and the importance of volume, already observed in the ACG06 approximation, the variable associated with informed trading is significant and negative in larger-sized stocks. Examining the stocks analyzed by capitalization, we see that all the stocks belonging to the first quintile unanimously suggest that informed transactions tend to reduce volatility. This effect falls to 89% in the second quintile. That is, the volatility of those stocks that exhibit lower PIN values is significantly reduced when informed investors trade. The percentage of significant negative estimates notably decreases for those quintiles formed by smaller capitalization stocks. Then, we can conclude that there is a noticeable relationship among volatility changes, informed trading and firm size. Therefore, our estimations lead to the conclusion that informed trading, in accordance with a strict definition of market efficiency, contributes to the reduction in volatility and the movement of prices towards their fundamentals, particularly in large capitalization stocks that are more familiar to investors.

The results are consistent with the suggestions of Poskitt [2005], Marsh *et al* [2008] and Lai *et al* [2014] who show a negative relationship between volatility and informed trading. Moreover, the result is also consistent with the findings of Blasco *et al* [2012] for the Spanish market in which it was found that the presence of herding increased market volatility, particularly in familiar stocks. According to our results in this paper, informed trading should correct this reaction, reducing volatility. This means that in those stocks where herding is more likely to occur, the corrective effect of informed traders is easily appreciated.

Informed trading is lower when there is greater informative transparency (Lai *et al* [2009, 2014]) and it therefore depends on the informative quality surrounding it. The greater the informative transparency, the lesser the incentive to dedicate additional efforts to achieving more accurate and higher quality information. We have detected a lower degree of informative efficiency in our market so that the expected effect of the PIN and the informed transactions would be greater than in other markets such as the American market. The result obtained is not so clear when we observe the market as a whole, but it is clear in relation to the group of stocks with higher capitalisation gathered in the larger size quintiles.

The result may also be compatible with that obtained for the USA market as a whole. The size of companies in the American market is greater than the size of Spanish companies. In the USA, informed trading affects stocks as a whole. If in the Spanish market the range of company sizes is more varied and, in general, Spanish companies are smaller in size, it is possible that for Spanish companies as a whole the effect is undetected. However, it is detected for those companies whose size approaches that of American companies. Therefore, size can be not very significant in the USA market when the influence of informed trading is analysed, but in smaller markets this variable is an important element to be considered.

Given that in the Spanish market the larger companies with better informative quality, i.e. those with similar characteristics to American companies, are those which offer results similar to those of American companies, it is worth reflecting on the need for a minimum size, a minimum level of informative transparency and perhaps a minimum transaction size in order to be able to detect the influence of variations in informed trading on volatility.

Thus, the effect of informed trading on volatility in stock markets with a wide range of listed companies is particularly noticeable in those stocks with better informative quality that, in turn, induces uninformed traders to participate, even following herding strategies. This is because they consider that the specialized processing of information does not provide significant economic profits. In contrast, those stocks that are listed in such stock markets and exhibit lower informative quality basically attract informed investors and their marginal effect on volatility is hardly detected.

The time period analysed has various sub-periods marked by the outbreak of the financial crisis at the end of 2007. We therefore consider it appropriate to study the robustness of the results obtained repeating the analysis for the period 2008-2010. The results are shown in panel B in Table V. It can be seen that the results obtained confirm the robustness of the estimations included in panel A. The intensity of the effect of the volatility correction on the stocks belonging to the first quintile is clear, as are the general conclusions with respect to the other quintiles.

4.4- Results using autoregressive conditional variance

An alternative estimation is proposed using autoregressive conditional heteroskedasticity models. Specifically, the following GARCH(1,1) model is used, corrected with the elements to be analysed:

$$R_{it} = \sum_{k=1}^{5} a_{ik} D_{kt} + \sum_{k=1}^{s} b_{ik} R_{it-k} + c_i \left(\frac{NS_{it} + NB_{it}}{NT_{it}} PIN_{it} - \frac{NS_{it-1} + NB_{it-1}}{NT_{it-1}} PIN_{it-1} \right) + u_{it} \tag{11}$$

$$u_{it} \approx N(0, \sigma^2)$$

$$\sigma^2_{it} = \theta_i + \beta_i u^2_{it-1} + \varpi_i \sigma^2_{it-1} + \varphi_i NT_{it} + v_i \left(\frac{NS_{it} + NB_{it}}{NT_{it}} PIN_{it} - \frac{NS_{it-1} + NB_{it-1}}{NT_{it-1}} PIN_{it-1} \right) \tag{12}$$

The mean and variance equations include the usual elements in addition to the variables described above. This proposal attempts on the one hand to simplify into one step the two-step estimation procedure of the previous test and, on the other hand, to provide complementary information about the influence of informed trading on returns when using conditional volatility. This all serves to add robustness to the results of the previous proposal.

Table VI shows the model estimation results, including the variation in the informed trading variable both in the mean and in the variance equations. For the mean equation only the results relating to the lags in returns and to informed trading are shown. These enable us to detect on the one hand the correlation of the negative sign of the return in the mean equation. On the other hand, the variable used to measure informed trading does not provide clear evidence about its influence in this equation, so it is difficult to interpret. However, when analysing the variance equation, the coefficients obtained corroborate the previous results given that a significant influence of informed trading on price variations is clearly shown. The inferences of the results on this variable coincide almost entirely with those obtained in the previous section, despite the differences in the volatility estimation procedure. The analysis following the capitalization criteria leads us to similar conclusions to those suggested for Table V. Therefore, it can be said that the volatility of heavily traded stocks is seen to be affected by informed trading. Highly capitalized and heavily traded stocks, that is, familiar stocks that usually attract higher herding levels, correct their higher volatility levels when informed traders move prices towards their fundamentals.

Bandi and Russell [2006] suggest that asset prices can be written as the sum of efficient prices and a noise component that is induced by microstructure frictions. Then, the variance of returns depends on both the variance of the underlying efficient returns and the variance of the microstructure noise components. Whereas the variance of the efficient return process is a crucial ingredient in the practice and theory of asset valuation and risk management, herding is considered a microstructure component that can be used to consistently estimate the microstructure noise variance. Informed traders should help to reduce the microstructure component of volatility and to determine the proper asset valuation of those stocks that are herding attractors.

These results confirm the need for greater accuracy in the measurement of informed trading since, as can be seen, the results vary depending on the approximation considered. The proposal here represents progress in this direction, trying to resolve limitations detected in previous studies by not having to make assumptions about investor behaviour and considering as a marker of informed trading the variation in the proportion of informed transactions, calculated through a variable already accepted in the literature, the PIN variable (Easley *et al* [1996, 1997, 2002, 2008 and 2010] among others).

5-Conclusions

The empirical evidence revealed in this paper represents a contribution to the literature that combines microstructure and investor behaviour in the financial markets. The main objective is to analyse the relationship between informed trading and volatility using an alternative proposal to that previously used in the literature. This proposal includes the PIN variable in the calculation of informed transactions. The Spanish market from January 1997 to December 2010 was analysed. This market provides an ideal setting for the analysis because the existence of herding and its influence on volatility in this market has been demonstrated (Blasco *et al* [2012]). Furthermore, the lower degree of informative transparency in the Spanish market compared to the American makes for interesting results from the perspective of examining the relation between volatility and informed trading in more opaque markets than those usually studied.

The methodology is based on the proposal of ACG06 which is modified by transforming the informed trading variable by means of the proportion of informed transactions calculated through the probability of informed trading (PIN). The idea is to find a less restrictive measure of informed trading that can be applied in stock markets with different informative environment. Additionally, a model of autoregressive conditional heteroskedasticity is tested incorporating a representation of informed trading. As well as changes in the methodology, the work discusses types of stocks and their effect on the relation between volatility and informed trading, an aspect which has proved to be of great significance.

The results obtained using the ACG06 proposal does not show that informed trading affects volatility. This leads us to suppose that the differences between the conclusions reached by these authors and our own results are due to the fact that the methodology used by ACG06 is not appropriate for capturing this effect in all markets. However, using the change in the proportion of informed transactions through the PIN variable in the classification of the trading produces results which are much more consistent with those expected. It can be said that, in general, the effect of informed trading is to reduce volatility during the trading session for familiar stocks, these being highly capitalized and heavily traded. The results are the same when the influence of the crisis is analysed, when estimations of informed trading over different time periods are used and when the estimation of volatility is made using the conditional volatility model. Informed trading seems to be particularly significant for stabilizing prices of those large stocks traded by uninformed traders who usually prefer familiar stocks which, in the case of the Spanish market, are those which, at least, maintain a size and an informative quality comparable with large markets. This is because uninformed traders consider that the specialized processing of information for these stocks does not provide significant economic profits. However, the presence of informed traders does not influence the volatility of those stocks already traded by informed traders, usually small firms. In this case, the marginal effect of informed trading on volatility is hardly detected.

The results are of interest in so far as they can help to improve the prediction of future volatility. This will enable more accurate interpretation of risk and a clearer definition of management strategies. If investors are able to include this information in their volatility prediction models, they will then be able to improve investment decision-making and portfolio or risk management. The regulators will have a better understanding of the variables which affect information asymmetries and will then be able to propose regulations or changes in the market designed to reduce such asymmetries.

References

Andersen T.G., T. Bollerslev and N. Meddahi. "Realized volatility forecasting and market microstructure noise" *Journal of Econometrics*, 160 (1), (2011), pp. 220-234.

Amihud Y., H. Mendelson and M. Murgia. "Stock market microstructure and return volatility. Evidence from Italy" *Journal of Banking and Finance*, 14, (1990), pp. 423-440.

Aslan H., D. Easley, S. Hvidkjaer and M. O´Hara. "The characteristics of informed trading: Implications for Asset Pricing" *Journal of Empirical Finance*, 18, 5, (2011), pp. 779-992.

Avramov D., T. Chordia and A. Goyal. "The impact of trades on daily volatility" *Review of Financial Studies*, 19, (2006), pp. 1241-1277.

Awartani B., V. Corradi and W. Distaso. "Assessing Market Microstructure Effects via Realized Volatility Measures with an Application to the Dow Jones Industrial Average Stocks" *Journal of Business & Economic Statistics*, 27, (2), (2009), pp. 251-265.

Bandi F.M. and J.R. Russell. "Separating microstructure noise from volatility*", Journal of Financial Economics*, 79, (2006), pp. 655-692.

Barberis N. and A. Shleifer. "Style investing", *Journal of Financial Economics* 68, (2003), pp. 161-199.

Benos E. and M. Jochec. "Testing the PIN variable" *working paper series. Business Illinois,* 2007.

Bianco S. and R. Reno. "Dynamics of intraday serial correlation in the Italian futures market". *Journal of FuturesMarkets*, 26 (1), (2006), pp. 61-84.

Blasco N., P. Corredor and S. Ferreruela. "Generadores de comportamiento imitador en el mercado de valores español" *Revista Española de Financiación y Contabilidad*, 38, 142, (2009), pp. 265-291.

Blasco N., P. Corredor and S. Ferreruela. "Does herding affect volatility? Implications for the Spanish stock market" *Quantitative Finance,* 12(2), (2012), pp. 311-327.

Bloomfield R., M. O'Hara and G. Saar. "The make or take decision in an electronic market: Evidence on the evolution of liquidity" *Journal of Financial Economics,* 75, (2005), pp. 165-199.

Brockman P. and D.Y. Chung. "The inter-temporal behavior of informed and uninformed traders" *Review of Quantitative Finance and Accounting*, 21 (3), (2003), pp. 251-265.

Brown G. and M.T. Cliff. "Investor sentiment and the near-term stock market" *Journal of Empirical Finance*, 11 (1), (2004), pp. 1-27.

Campbell J.Y., S.J. Grossman and J. Wang. "Trading volume and serial correlation in stock returns" *The Quarterly Journal of Economics,* 108, (1993), pp. 905-939.

Chan K. and W.M. Fong. "Trade size, order imbalance and the volatility-volume relation" *Journal of Financial Economics,* 57, (2000), pp. 247-273.

Chan K. and W.M. Fong. "Realized Volatility and Transactions" *Journal of Banking and Finance*, 30 (7), (2006), pp. 2063-2085.

Chen Q., I. Goldstein and W. Jiang. "Price Informativeness and Investment sensitivity to stock price" *The Review of Financial Studies*, 20 (3), (2007), pp. 619-650.

Chen L.T.W. and R.T. Daigler. "An examination of the complementary volume-volatility information theories" *Journal of Futures Market*, 28, (2008), pp. 963-992.

Choi J. "The economics of politically-connected firms" *International Tax and Public Finance*, 16 (5), (2009), pp. 605-620.

Chordia T., A. Subrahmanyam and V. Anshuman. "Trading activity and expected stock returns" *Journal of Financial Economics,* 59, (2001), pp. 3-32.

Chung K.H., M. Li and T.H. McInish. "Information-based trading, price impact of trades and trade autocorrelation" *Journal of Banking and Finance*, 29 (7), (2005), pp. 1645-1669.

Clark P.K. "A subordinated stochastic process model with finite variance for speculative prices", *Econometrica*, 41, (1973), pp. 135-155.

Cochrane J.H. "A rehabilitation of stochastic discount factor methodology" The National Bureau of Economic Research, Working Paper 8533, 2001.

Crépey S. "Delta-hedging vegarisk?" *Quantitative Finance*, 4, 5, October, (2004), pp. 559-579.

Cutler D. M., J.M. Poterba and L.H. Summers. "Speculative dynamics and the role of feedback traders" *American Economic Review,* 80, (1990), pp. 63-68.

Daigler R.T. and M.K. Wiley. "The impact of trader type on the futures volatility-volume relation" *Journal of Finance,* 54, (1999), pp. 2297-2316.

De Long B. J., A. Shleifer, L.H. Summers and R.J. Waldmann. "Positive feedback investment strategies and destabilizing rational speculation" *Journal of Finance,* 45, (1990), pp. 379-395.

Dennis P. J. and J.P. Weston. "Who's informed? An analysis of stock ownership and informed trading" Working Paper, Rice University, 2001.

Downing C. and F. Zhang. "Trading activity and price volatility in the municipal bond market" *Journal of Finance,* 59, (2004), pp. 899-931.

Duarte J. and L. Young. "Why is PIN priced?" *Journal of Financial Economics,* 91 (2), (2009), pp. 119-138.

Easley D., R. Engle, M. O´Hara and L. Wu. "Time varying arrival rates of informed and uninformed trades" *Journal of Financial Econometrics*, (2008), pp. 171-207.

Easley D., S. Hvidkjaer and M. O´Hara. "Is information risk a determinant of asset returns?" *The Journal of Finance*, 57 (5), (2002), pp. 2185-2221.

Easley D., S. Hvidkjaer and M. O´Hara. "Factoring information into returns" *Journal of Financial and Quantitative Analysis*, 45 (2), (2010), pp. 293-309.

Easley D., N. M. Kiefer and M. O'Hara. "One day in the life of a very common stock" *Review of Financial Studies,* 10, (1997), pp. 805-835.

Easley D., N. M. Kiefer, M. O'Hara and J. Paperman. "Liquidity, information and infrequently traded stocks" *Journal of Finance,* 51, (1996), pp. 1405-1436.

Easley D., M. O'Hara and G. Saar. "How Stock Splits Affect Trading: A Microstructure Approach" *Journal of Financial and Quantitative Analysis,* 36, (2001), pp. 25-51.

Epps T. and M. Epps. "The stochastic dependence of stochastic price changes and transaction volume: Implications for the mixture of distribution hypothesis" *Econometrica*, 44, (1976), pp. 305-321.

Epps T.W. and M.L. Epps. "The stochastic dependence of security price changes and transaction volumes: Implications for the Mixture-of-Distributions Hypothesis" *Econometrica*, 44, (1997), pp. 305-321.

Finucane T.J. "A Direct Test of Methods for Inferring Trade Direction from Intra-Day Data" *Journal of Financial and Quantitative Analysis,* 35, (2000), pp. 553-576.

Foster A.J. "Volume-volatility relationships for crude oil futures markets" *Journal of Futures Markets*, 15, (1995), pp. 929-951.

Friedman M. "The case for exigible exchange rates" in Milton Friedman ed.*: Essays in Positive Economics.* University of Chicago Press.Chicago, IL*,* 1953.

Gallant R.A., P.E. Rossi and G. Tauchen. "Stock prices and volume" *Review of Financial Studies*, 5, (1992), pp. 199-242.

Glosten L.R. and P. Milgron. "Bid, ask and transaction prices in a specialist market with heterogeneously informed traders" *Journal of Financial Economics*, 14 (1), (1985), pp. 71-100.

Harris M. and A. Raviv. "Differences of opinion make a horse race" *Review of Financial Studies,* 6, (1993), pp. 473-506.

Hellwig M.F. "On the aggregation of information in competitive markets" *Journal of Economic Theory,* 22, (1980), pp. 477-498.

Jones C., G. Kaul and M. Lipson. "Transactions, volume and volatility" *Review of Financial Studies,* 7, (1994), pp. 631-651.

Kao E.H. and H-G. Fung. "Intraday trading activities and volatility in round-the-clock futures markets" *International Review of Economics & Finance,* 21, (2012), pp. 195-209. doi:10.1016/j.iref.2011.06.003.

Karpoff J.M. "The relation between price changes and trading volume: A survey" *Journal of Financial and Quantitative Analysis*, 22, (1987), pp. 109-126.

Kim O. and R. Verrecchia. "Market Liquidity and Volume around Earnings Announcements" *Journal of Accounting and Economics*, 17, (1994), pp. 41-67.

Kim O. and R. Verrecchia. "Pre-Announcement and Event-Period Private Information" *Journal of Accounting and Economics*, 24, (1997), pp. 395-419.

Kittiakaraskun J., Y. Tse and G. Wang. "The impact of trading activity by traders types on asymmetric volatility in Nasdaq-100 Index Futures" Working paper WP#0021FIN-257-2010. University of Texas at San Antonio, 2011.

Kyle A. "Continuous Auctions and insider trading" *Econometrica*, 53 (6), (1985), pp. 1315-1336.

Lai S., L. Ng and B. Zhang. "Informed trading around the world?" *Working paper*. Australian School of Business. (Previous title of Lai S., Ng L., Zhang "Does PIN affect Equity Prices Around the World?" *Journal of Financial Economics*, 114, (2014), pp. 178-195), 2009.

Lai S., L. Ng and B. Zhang. "Does PIN affect Equity Prices Around the World?" *Journal of Financial Economics*, 114, (2014), pp. 178-195.

Lehmann B. "Fads, martingales, and market efficiency" *Quarterly Journal of Economics,* 105, (1990), pp. 1-28.

Li M. and S.X. Zhang. "Underpricing, ownership dispersion and aftermarket liquidity of IPO stocks" *Journal of Empirical Finance Economics*, 91 (2), (2008), pp. 119-138.

Lin H.W. and W.E. Ke. "A computing bias in estimating the probability of informed trading" *Journal of Financial Markets*, 14 (4), (2011), pp. 625-640.

Lin W., S. Tsai and D. Sun. "What Causes Herding: Information Cascade or Search Cost?" MPRA Paper, Nº 21204. http://mpra.ub.un-muenchen.de/21204, 2009.

Lyons R.K. "Tests of Microestructural Hypotheses in the Foreign Exchange Market" *Journal of Financial Economics*, 39, (1995), pp. 321-351.

Marsh I.W., J. Nagayasu and J. Wandrin. "Some evidence on the effectiveness of a securities transaction tax from the U.S. equity market" *Proceeding of the Asian Finance Association-Nippon Finance Association 2008 International Conference.* Yokohama, 2008.

Marsh I.W. and J. Nagayasu. "Determinants of the PIN: Evidence from the Japanese Stock Exchange Market" Working paper Cash Business School London, 2009.

Mohanram P. and S. Rajgopal. "Is PIN priced risk?" *Journal of Accounting and Economics*, 47 (3), (2009), pp. 226-243.

O'Hara M. "*Market Microstructure Theory.*" Blackwell, UK, 1995.

Palomino F. "Noise trading in small Markets" *Journal of Finance*, 51(4), (1996), pp. 1537-1550.

Pang W., S.H. Hou, M.D. Troutt, W.T. Yu and K.W.K. Li. "A Markov chain Monte Carlo approach to estimate the risks of extremely large insurance claims" *International Journal of Business and Economics*, 6 (3), (2007), pp. 225-236.

Popescu M. and R. Kumar. "An ex ante measure of the probability of informed trading" working paper available at http:// ssrn.com/abstract=891717*,* 2010.

Poskitt R. "Disclosure regulation an information risk" *Accounting and Finance*, 45, (2005), pp. 457-777.

Saffi P.A.C "Differences of opinion, information and the timing of trades" Working paper series, available at http://ssrn.com/abstract=967696, 2007.

Schwert G. W. "Stock volatility and the crash of '87" *Review of Financial Studies,* 3, (1990), pp. 77-102.

Shalen C.T. "Volume, volatility and the dispersion beliefs" *Review of Financial Studies,* 6, (1993), pp. 405-434.

Sias R.W. and L.T. Starks "Institutions and Individuals at the Turn-of-the-Year" *Journal of Finance*, 52, (1997), pp. 1543-1562.

Sias R.W. "Institutional Herding" *Review of Financial Studies,* 17(1), (2004), pp. 165-206.

Sims C. A. "Martingale-like behavior of prices and interest rates" Discussion Paper No. 205. Center for Economic Research. University of Minnesota, 1984.

Tauchen G. and M. Pitt "The price variability-volume relationship on speculative markets" *Econometrica*, 51, (1983), pp. 485-505.

Vega C. "Stock price reaction to public and private information" *Journal of Financial Economics*, 82(1), (2006), pp. 103-133.

Wang J. "A model of competitive stock trading volume" *Journal of Political Economy,* 102, (1993), pp. 127-168.

Wang G. and J. Yau. “Return volatility, trading imbalance and the information content of volume” *International Review of Economics and Finance*, 8, (2000), pp. 375-397.

Yan Y. and Z. Zhang. “An improved estimation method and empirical properties of the Probability of Informed Trading” *Journal of Banking and Finance,* 36, (2012), pp. 454-467.

Table I. Mean estimation of the parameters α, δ, ε_b, ε_s, and μ of the PIN variable. Period 1997-2010 and subperiods.

	Annual Mean 1997-2010	Standard deviation	Annual Mean 1997-2007	Annual Mean 2008-2010
α	0.3483	16.28%	0.3599	0.3072
δ	0.4793	14.99%	0.4716	0.5097
ε_b	119.3713	23.79%	116.9655	129.1942
ε_s	132.7937	42.09%	110.4391	211.8458
μ	128.3956	53.29%	103.1744	218.1432

Table II. Estimation of the PIN variable for stocks according to capitalization.
Panel A. Period 1997-2010. Annual frecuency.

	Annual Mean	Mean Standard deviation	Standard deviation
Large Stocks (First and second quintiles)	12.44%	4.16%	7.17%
Medium Stocks (Third quintile).	14.51%	4.51%	5.70%
Small Stocks (Fourth and fifth quintiles)	21.50%	8.61%	15.36%

Panel B. Period 1997-2010 split into before and during/after financial crisis periods. Annual frecuency.

	1997-2007	2008-2010
Large Stocks (First and second quintiles)	12.19%	13.50%
Medium Stocks (Third quintile).	13.58%	17.49%
Small Stocks (Fourth and fifth quintiles)	20.65%	28.33%

Table III.-Results of regression of returns R_{it} of stock i on day t, where D_{kt} are the dummy variables corresponding to each day of the week, R_{it-k} are the lags in returns, NS_{it} is the number of sales transactions of stock i on day t and NT_{it} the total number of transactions of stock ion day t. α_1=Monday,α_2=Tuesday,α_3=Wednesday,α_4=Thursday,α_5=Friday. β_1 and β_2 are the coefficients of the first and second lags in returns, respectively. Stocks are ranked by capitalization.

$$R_{it} = \sum_{k=1}^{5} a_{i,k} D_{kt} + \sum_{r=1}^{2} b_{i,r} R_{i,t-r} + c_i \frac{NS_{i,t}}{NT_{i,t}} + u_{i,t}$$

Capitalization		a_1	a_2	a_3	a_4	a_5	b_1	b_2	c
Large Quintile 1	Mean estimate	0.0099	0.0108	0.0101	0.0099	0.0102	0.0374	-0.0427	-0.0718
	Standard deviation	0.99%	0.94%	1.04%	0.93%	0.94%	5.20%	1.91%	6.01%
	Mean p-value	0.1877	0.2027	0.2133	0.1861	0.2158	0.1425	0.1669	0.1973
	%of 10% sig. estim.	78%	78%	78%	78%	78%	69%	74%	78%
Quintile 2	Mean estimate	0.0185	0.0190	0.0195	0.0192	0.0197	-0.1015	-0.0409	-0.1158
	Standard deviation	0.99%	0.99%	0.99%	1.05%	1.07%	18.83%	5.91%	6.12%
	Mean p-value	0.0167	0.0063	0.0083	0.0066	0.0262	0.1910	0.1842	0.0160
	%of 10% sig. estim.	100%	100%	100%	100%	81%	61%	64%	100%
Quintile 3	Mean estimate	0.0252	0.0238	0.0249	0.0248	0.0254	0.0463	-0.0083	-0.1494
	Standard deviation	1.40%	1.32%	1.50%	1.43%	1.47%	3.90%	3.22%	9.72%
	Mean p-value	0.0000	0.0007	0.0032	0.0003	0.0001	0.1772	0.2536	0.0000
	%of 10% sig. estim.	100%	100%	100%	100%	100%	52%	37%	100%
Quintile 4	Mean estimate	0.0225	0.0209	0.0213	0.0208	0.0213	-0.0212	-0.0032	-0.1091
	Standard deviation	2.01%	1.90%	1.85%	1.85%	1.92%	5.75%	4.09%	9.73%
	Mean p-value	0.1049	0.1080	0.0021	0.0826	0.0989	0.1354	0.3320	0.0000
	%of 10% sig. estim.	89%	89%	100%	89%	89%	66%	23%	100%
Small Quintile 5	Mean estimate	0.0070	0.0070	0.0064	0.0065	0.0067	-0.0859	-0.0240	-0.0402
	Standard deviation	0.59%	0.61%	0.62%	0.59%	0.58%	9.17%	3.31%	3.02%
	Mean p-value	0.1807	0.1895	0.1602	0.1587	0.2457	0.0026	0.3963	0.1485
	%of 10% sig. estim.	69%	74%	69%	81%	69%	100%	34%	74%

Table IV. -Results of the volatility model estimation according to ACG06.
Stocks are ranked by capitalization. For clarity, only the results for the first three lagged variables u $_{i,t}$ are presented.

$$|u_{i,t}| = \Phi_i + \Psi_i M_t + \sum_{k=1}^{3} \rho_{i,k} |u_{i,t-k}| + c_i NT_{i,t} + \left[d_{i,0} + \underbrace{d_{i,1} \frac{NS_{i,t-1}}{NT_{i,t-1}} (u_{i,t-1} \geq 0)}_{Contrarian} + \underbrace{d_{i,2} \frac{NS_{i,t-1}}{NT_{i,t-1}} (u_{i,t-1} < 0)}_{Mimetic} \right] u_{i,t-1} + \eta_{i,t}$$

Capitalization		Φ	Ψ	ρ_1	ρ_2	ρ_3	c	d_0	d_1	d_2
Large Quintile 1	Mean estimate	-0.0013	0.0022	-0.0598	0.0631	0.0727	1.2E-06	0.0010	0.3885	-0.7138
	Stand. dev.	0.39%	0.21%	22.29%	3.30%	1.20%	0.00%	14.97%	147.14%	291.91%
	Mean p-value	0.0869	0.1477	0.2058	0.2098	0.0368	0.0000	0.2136	0.1853	0.0131
	%. of 10% sig.	73%	79%	71%	66%	74%	100%	48%	71%	92%
Quintile 2	Mean estimate	0.0025	0.0005	-0.0279	0.0755	0.0368	3.1E-06	-0.0050	1.3479	-1.0888
	Stand. dev.	0.25%	0.11%	10.78%	3.03%	4.24%	0.00%	9.44%	124.85%	107.18%
	Mean p-value	0.0052	0.4543	0.2760	0.0932	0.0597	0.0001	0.3263	0.2091	0.3617
	%. of 10% sig.	100%	16%	54%	84%	94%	100%	20%	38%	58%
Quintile 3	Mean estimate	0.0023	0.0008	0.0128	0.0901	0.0605	1.0E-05	-0.0249	0.9166	-0.3994
	Stand. dev.	0.26%	0.09%	14.00%	5.58%	1.35%	0.00%	14.70%	153.49%	134.97%
	Mean p-value	0.1339	0.4320	0.1797	0.0967	0.0466	0.0000	0.4629	0.0471	0.1589
	%. of 10% sig.	74%	25%	65%	85%	85%	100%	24%	91%	46%
Quintile 4	Mean estimate	0.0012	0.0016	0.1944	0.0863	0.0486	5.6E-05	0.0082	-0.5490	0.1892
	Stand. dev.	0.25%	0.19%	11.21%	6.07%	6.64%	0.01%	10.87%	62.42%	126.20%
	Mean p-value	0.3931	0.2072	0.1368	0.1365	0.1603	0.0000	0.2187	0.3198	0.1218
	%. of 10% sig.	48%	36%	69%	79%	65%	100%	24%	33%	75%
Small Quintile 5	Mean estimate	0.0054	0.0010	0.1038	0.0564	0.0356	9.4E-05	-0.0142	0.1123	-0.4082
	Stand. dev.	0.20%	0.10%	10.11%	2.88%	2.22%	0.01%	4.31%	35.13%	49.75%
	Mean p-value	0.0000	0.2925	0.1158	0.0332	0.2568	0.0000	0.4446	0.5402	0.2282
	%. of 10% sig.	100%	64%	76%	94%	66%	100%	31%	29%	63%

Table V. Results of the volatility model estimation using the PIN variable.
Stocks are ranked by capitalization. For clarity, only the results for the first three lagged variables u $_{i,t}$ are presented.

Panel A. Results of the volatility model for the period 1997-2010.

$$|u_{it}| = \phi_i + \sum_{k=1}^{3} \rho_{ik} |u_{i,t-k}| + \gamma_i NT_{it} + \varphi_{i1}\left(\frac{NS_{it} + NB_{it}}{NT_{it}} PIN_{it} - \frac{NS_{it-1} + NB_{it-1}}{NT_{it-1}} PIN_{it-1} \right) + \zeta_{it}$$

Capitalization		ϕ	ρ1	ρ2	ρ3	γ	φ	φ	
	Mean estimate	0.0031	0.0967	0.1207	0.1373	1.1E-06	-0.2869	% negative. estim.	100%
Large	Standard deviation	0.15%	6.07%	4.56%	2.22%	0.00%	19.93%	signif.neg.estim.	100%
Quintile 1	Mean p-value	0.1386	0.1180	0.0300	0.0002	0.0000	0.0151	signif.pos.estim.	0%
	Percent. of 10% signif. estim.	74%	78%	100%	100%	100%	100%		
	Mean estimate	0.0046	0.1808	0.0937	0.0939	2.8E-06	-0.0830	% negative. estim.	89%
	Standard deviation	0.20%	15.32%	6.48%	4.83%	0.00%	7.27%	signif.neg.estim.	100%
	Mean p-value	0.0028	0.0406	0.1149	0.0385	0.0171	0.0729	signif.pos.estim.	0%
Quintile 2	Percent. of 10% signif. estim.	100%	84%	77%	94%	94%	89%		
	Mean estimate	0.0046	0.1501	0.1163	0.0906	1.0E-05	-0.0151	% negative. estim.	46%
	Standard deviation	0.26%	6.92%	5.65%	2.82%	0.00%	4.30%	signif.neg.estim.	80%
	Mean p-value	0.0439	0.0356	0.1431	0.0529	0.0002	0.4204	signif.pos.estim.	7%
Quintile 3	Percent. of 10% signif. estim.	85%	85%	85%	85%	100%	44%		
	Mean estimate	0.0036	0.1579	0.1015	0.0717	5.6E-05	0.0240	% negative. estim.	0%
	Standard deviation	0.24%	5.86%	6.34%	6.52%	0.01%	2.06%	signif.neg.estim.	0%
Quintile 4	Mean p-value	0.0407	0.0133	0.1369	0.1282	0.0000	0.5299	signif.pos.estim.	0%
	Percent. of 10% signif. estim.	84%	100%	84%	73%	100%	0%		
	Mean estimate	0.0070	0.1558	0.0669	0.0523	8.9E-05	-0.0205	% negative. estim.	65%
Small	Standard deviation	0.24%	5.15%	2.81%	2.64%	0.01%	3.78%	signif.neg.estim.	45%
Quintile 5	Mean p-value	0.0000	0.0000	0.0129	0.1183	0.0000	0.3661	signif.pos.estim.	32%
	Percent. of 10% signif. estim.	100%	100%	94%	71%	100%	40%		

Panel B. Results of the φ estimation in the volatility model for the period 2008-2010

	Mean estimation φ	Mean p-value	% negative estimates	%10% significant negative estimates
Large Quintile 1	-0.2587	0.0560	91%	86%
Quintile 2	-0.1097	0.3150	100%	28%
Quintile 3	0.0117	0.5439	29%	0%
Quintile 4	0.0258	0.5046	9%	0%
Quintile 5 Small	-0.0004	0.3596	48%	0%

Table VI.- Results of the estimation of the GARCH model. Stocks are ranked by capitalization.

$$R_{it} = \sum_{k=1}^{5} a_{ik} D_{kt} + \sum_{k=1}^{2} b_{ik} R_{it-k} + c_i \left(\frac{NS_{it} + NB_{it}}{NT_{it}} PIN_{it} - \frac{NS_{it-1} + NB_{it-1}}{NT_{it-1}} PIN_{it-1} \right) + u_{it}$$

$$\sigma^2_{it} = \theta_i + \beta_i u^2_{it-1} + \varpi_i \sigma^2_{it-1} + \varphi_i NT_{it} + \nu_i \left(\frac{NS_{it} + NB_{it}}{NT_{it}} PIN_{it} - \frac{NS_{it-1} + NB_{it-1}}{NT_{it-1}} PIN_{it-1} \right)$$

		Equation of the mean								Equation of the variance						
Capitalization		a_1	a_2	a_3	a_4	a_5	b_1	b_2	c	θ	β	ϖ	φ	ν	ν	
Large Q1	Mean estimate	0.0002	-0.0004	0.0007	0.0001	0.0000	0.0251	-0.0282	-0.1591	0.0000	0.1473	0.6731	2.0E-08	-0.0016	% neg.estim.	88%
	Stand. deviat.	0.09%	0.14%	0.06%	0.11%	0.13%	5.41%	1.91%	30.08%	0.00%	6.61%	29.32%	0.00%	0.32%	sig.neg.estim.	100%
	Mean p-value	0.5077	0.4709	0.4890	0.3768	0.4653	0.2119	0.3523	0.1306	0.3621	0.0002	0.1029	0.0915	0.0772	sig.pos.estim.	0%
	%. of 10% signif.	9%	0%	35%	44%	21%	65%	53%	92%	43%	100%	92%	78%	88%		
Q2	Mean estimate	0.0009	0.0007	0.0008	0.0028	0.0000	-0.0640	-0.0356	-0.0061	0.0000	0.1385	0.6294	1.8E-08	-0.0004	% neg.estim.	45%
	Stand. deviat.	0.13%	0.25%	0.11%	0.48%	0.32%	13.19%	8.27%	8.64%	0.01%	9.15%	33.55%	0.00%	0.27%	sig.neg.estim.	100%
	Mean p-value	0.1455	0.3365	0.4248	0.2467	0.2430	0.1712	0.4427	0.2868	0.1529	0.0000	0.0004	0.0773	0.0759	sig.pos.estim.	49%
	%. of 10% signif.	50%	33%	32%	57%	33%	70%	30%	45%	57%	100%	100%	81%	72%		
Q3	Mean estimate	0.0001	-0.0001	0.0005	-0.0001	0.0008	0.0023	-0.0060	-0.0006	0.0000	0.1615	0.5541	2.7E-07	-0.0008	% neg.estim.	61%
	Stand. deviat.	0.07%	0.11%	0.07%	0.15%	0.07%	4.00%	2.14%	8.21%	0.01%	8.01%	38.39%	0.00%	0.17%	sig.neg.estim.	75%
	Mean p-value	0.6241	0.3248	0.4948	0.4143	0.3319	0.4101	0.5714	0.3033	0.0114	0.0307	0.0006	0.0000	0.1229	sig.pos.estim.	61%
	%. of 10% signif.	0%	0%	11%	7%	36%	20%	0%	52%	89%	85%	100%	100%	70%		
Q4	Mean estimate	0.0003	0.0000	0.0012	-0.0001	0.0005	-0.0459	-0.0344	-0.0074	0.0000	0.2332	0.4221	9.3E-07	0.0010	% neg.estim.	0%
	Stand. deviat.	0.13%	0.10%	0.19%	0.15%	0.14%	7.86%	3.00%	4.11%	0.01%	9.85%	30.78%	0.00%	0.12%	sig.neg.estim.	0%
	Mean p-value	0.3857	0.3931	0.2997	0.3755	0.4813	0.2142	0.2529	0.5281	0.1629	0.0000	0.0673	0.0600	0.2333	sig.pos.estim.	43%
	%. of 10% signif.	25%	21%	22%	0%	0%	46%	9%	11%	75%	100%	83%	89%	43%		
Small Q5	Mean estimate	-0.0008	-0.0008	-0.0012	-0.0005	-0.0007	-0.1705	-0.0584	-0.0046	0.0001	0.2458	0.3160	3.2E-06	0.0003	% neg.estim.	48%
	Stand. deviat.	0.08%	0.10%	0.13%	0.15%	0.10%	11.01%	4.76%	0.71%	0.01%	8.31%	29.08%	0.00%	0.08%	sig.neg.estim.	100%
	Mean p-value	0.3201	0.2247	0.1345	0.2889	0.3072	0.1366	0.2323	0.3556	0.0000	0.0000	0.0792	0.0000	0.0114	sig.pos.estim.	100%
	%. of 10% signif.	25.00%	25.00%	62.50%	50.00%	37.50%	87.50%	62.50%	12.50%	100.00%	100.00%	75.00%	100.00%	100.00%		