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**Title:**

**DETECTING INTENTIONAL HERDING: WHAT LIES BENEATH  
INTRADAY DATA IN THE SPANISH STOCK MARKET.**

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INTRADAY DATA IN THE SPANISH STOCK MARKET.**

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**ABSTRACT:**

This paper examines the intentional herd behaviour of market participants, using Li's test to compare the probability distributions of the scaled cross-sectional deviation in returns in the intraday market with the cross-sectional deviation in returns in an "artificially created" market free of intentional herding effects. The analysis is carried out for both the overall market and a sample of the most representative stocks. Additionally, a bootstrap procedure is applied in order to gain a deeper understanding of the differences across the distributions under study. The results show that the Spanish market exhibits a significant intraday herding effect that is not detected using other traditional herding measures when familiar and heavily traded stocks are analysed. Furthermore, it is suggested that intentional herding is likely to be better revealed using intraday data, and that the use of a lower frequency data may obscure results revealing imitative behaviour in the market.

**Key words:** Behaviour, finance, time series.

**JELcodes:** G14, G11, G12, G15

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## 1- INTRODUCTION

Recent research in cognitive sciences and financial economics suggests that rationality and emotion are not antithetical but are in fact complementary in decision making. This notion tempers the traditional efficient markets hypothesis that price is a sufficient statistic and no other information is needed or relevant. More precisely, behavioural finance allows some emotional responses such as fear to be compatible with the optimizing behaviour of the economic agents (Elster [1998], Lo [1999], Loewenstein [2000], Peters and Slovic [2000]). In this context, Olsen (1997) suggests that the different perceptions of risk among investors depend on how investors are able to manage individual losses, and on their ability to control and reduce the probability of losses. Investors' preference for the avoidance of loss (Kahnemann and Tversky [1979], Tversky and Kahnemann [1986]) is a key element that may imply that significant fluctuations in prices are not necessarily related to the arrival of information on economic variables, but may also correspond to collective phenomena such as crowd effects or herd behaviour (Thaler [1991], Shefrin [2000]).

Herding arises when investors decide to imitate the observed decisions of other participants in the market, who are thought to be better informed, rather than follow their own beliefs and information. In developed markets, herding is usually explained within the context of the agency theory. There seems to be a compensation-reputation scheme rewarding imitation, so that an investor's compensation depends on how his performance compares to other investors' performance and on whether deviations from the consensus are potentially costly (Scharfstein and Stein [1990], Roll [1992], Brennan [1993], Rajan [1994], Trueman [1994] or Maug and Naik [1996] among the earlier references). In fact, mimetic behaviour is not new to stock markets. Index funds, for example, blindly replicate the movements of an index of a specific financial market in order to avoid underperforming portfolios and simply assuming a tracking error (see e.g. Meade and Salkin, 1989). Likewise, differences in factors such as the relative importance of institutional versus individual investors (Lakonishok, Shleifer and Vishny [1992], Grinblatt, Titman and Wermers [1995] and Wermers [1999]) or the level of sophistication of derivatives markets may also affect investors' decision to herd.

Nevertheless, in spite of the explanatory theoretical arguments and the opinion of market observers that herd behaviour exists, the results in the empirical literature do not lead to clear conclusions. From our viewpoint, the scarce evidence of herding found in previous studies may be explained by three key factors: the choice of the sample of

market participants (usually institutional investors); the frequency of the data used in the analysis; and the methodology used.

Most of the empirical studies focus their attention on institutional agents, due to their relative importance within the market (Nofsinger and Sias, [1999]). However, institutional investors are supposed to be better informed and more able to interpret the information available to them than other participants in the market and, consequently, they should have no clear incentive to herd intentionally. In this vein, Lakonishok et al, (1992), Grinblatt et al, (1995), Wermers (1999) or, more recently, Pirinsky (2002) and Sias (2004) do not find unanimous results. Therefore, results from institutional investors can not be easily applied in general terms to the market as a whole.

Therefore, it is appropriate to consider all market participants and to propose methodological alternatives that focus on titles rather than on investor type. Papers by Christie and Huang (1995) and Chang, Cheng and Khorana (2000) (henceforth referred to as CH and CCK, respectively) are often referenced in herding literature in connection with this idea. According to these authors, intentional herding implies a follow-the-leader relationship that might be statistically described by a lower cross-sectional deviation of returns, given that individual asset returns will not diverge substantially from the overall market return under volatile market conditions.

With respect to the frequency of data, it should be considered that a long time interval (usually quarterly in the case of institutional investors) does not permit herding to be detected if imitative behaviour occurs within much shorter periods (Radalj and McAleer [1993]). Furthermore, imitative behaviour is likely to be an intraday phenomenon. When news is released to the market at intraday levels, traders may have no time to apply complex analytical models to interpret news and predict future price movements and therefore their decisions may not be compatible with rational thinking (Orléan [1995]), but may spontaneously follow other market participants, particularly under extreme price conditions (Henker et al, [2006]). This intraday hypothesis is consistent with the theoretical models proposed by Bikhchandani et al, (1992), Banerjee (1992) and Avery and Zemsky (1998), among others.

Gleason et al, (2004) and Henker et al, (2006) apply CH and CCK using intraday data, and they find no evidence in favour of the existence of herd behaviour during periods of extreme market movements. In spite of the significant usefulness of both methodologies for describing and detecting herd behaviour, an unresolved question remains: how does the cross-sectional standard deviation of returns (henceforth CSSD)

behave in a market without intentional herding effects? Both CH and CCK set out results that would clearly be found in the presence of significant imitation, but we can not conclude that there is no herding effect in the absence of such results, given that we do not know how a theoretically “intentional herding-clean” market would function.

Intentional herd behaviour is a relative concept which may be difficult to test. Financial markets tend to function with moderate “intrinsic” herding levels. According to Forgas (1995), Prechter (2001), or Lowenstein et al, (2001), unconscious impulses to avoid losses spur herding behaviour, making rational independence extremely difficult to exercise in group settings and producing collective agreement in thought and action. These primitive impulses are not irrational if they have a purpose in a utility-maximising sense when knowledge is lacking or logic irrelevant, or if individuals merely have a certain level of intrinsic preference for conformity (Grinblatt and Keloharju [2000]). Nevertheless, we should differentiate them from intentional herding. Intentional dependence upon the behaviour of others is a rational decision when other participants are thought to be better informed, even at times when information is scarce, or when a strong market agreement is suspected. Rational pricing models are usually based on strict hypotheses of rational expectations that do not fully consider the evolution of financial markets, the possibility of contagion among markets or assets or, as mentioned, emotional responses or psychological factors characterizing market reality that may be complementary with rationality in decision making.

In this paper we propose an alternative less stringent approach for shedding light on these questions. The aim is to present a methodological approach, initially based on the measure proposed by CH and on a later adaptation by Blasco and Ferreruela (2008), to detect one aspect that, to our knowledge, has not been studied sufficiently, namely intentional herding in the intraday market. We apply this methodological proposal to the Spanish market in order to corroborate the results presented in Blasco and Ferreruela (2007) using alternative analytical tools. Our purpose is also thought-provoking and stimulating interest on a topic with noticeable potential value in the financial literature. The controversy about the meaning of herding and the difficulty in identifying or designing appropriate analytical tools should encourage researchers to overcome these problems.

The intuition underlying our approach permits a comparison of herding levels in relative terms. A stock market is said to intentionally herd if we can find significant

differences in the level of mimetic behaviour when compared with others that are assumed not to exhibit any significant herding effect (or at least no significant intentional herding effects), although they may exhibit other practical imperfections. A comparable market situation artificially created and reasonably identified as clean of intentional herding effects is constructed following the procedure set out in Blasco and Ferreruela (2008). The next question is to compare the herding-free market with the market under study. To do this, we first observe the discrepancies between the theoretical herding-free distribution and the actual distribution for the Spanish market using a global test for the null hypothesis of closeness of the distributions. It is from this that our contribution to the literature stems. Specifically, this paper uses Li's test (1996), which measures the distance between two unknown density functions using the integrated square error of these functions. The second step seeks to determine the main differences. For this purpose, we propose a significance test based on bootstrap methods. We apply this new empirical tool to the Spanish stock market using intraday data, our aim being to provide evidence of the usefulness of high frequency data for studying imitative behaviour. Finally, we attempt to corroborate previous results for the intraday Spanish market suggesting that imitative behaviour mainly affects heavily traded stocks.

The remainder of the paper is organized as follows. In section 2 we describe the methodology and data. In section 3, we provide a discussion of the empirical results and, finally, in section 4 we summarize our findings.

## **2- METHODOLOGY AND DATA DESCRIPTION**

According to CH, in the presence of intentional herd behaviour individuals are more likely to suppress their own beliefs in favour of the market consensus and, therefore, the returns on individual stocks cluster more tightly around the total market return. CH suggest that this phenomenon is particularly intense during periods of substantial volatility when markets are less discriminating of individual stocks and treat all stocks similarly. Nevertheless, investors may adopt strategies that imitate the general market movement at any given time when other participants are thought to be better informed, even at times when information is scarce.

Following the idea presented in CH, we propose to exploit the information held in the cross-sectional movements of the market (CSSD) to detect herd behaviour with

intraday data. In the presence of the herd effect, the cross-sectional dispersion at any given time should become smaller than when there is no herding, and prices may not correspond to their fundamental value during short time periods. The CSSD measure is defined in CH as

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

where  $R_{it}$  is the observed stock return on firm  $i$  at time  $t$  and  $R_{mt}$  is the aggregate market portfolio return at time  $t$ . What is relevant for our purpose is to determine the distribution of CSSD in the absence of intentional herd behaviour. That is, we should bring our “intentional herding-free” index as close as possible to the traditional definition of market efficiency and, therefore, we should construct it with a number of individual assets that basically respond to their own information and whose trading is mainly justified by their own attributes. This “herding-clean” distribution will be the reference in order to test the relevance of mimetic actions in any other market at any time.

Orl an (1995), in a framework inspired by the Ising model<sup>1</sup>, suggests that a market in which agents do not interact with each other would tend to give rise to a Gaussian distribution for market fluctuations when the imitation is weak. We use Orl an’s suggestions in order to construct our “intentional herding-free” index but allowing some intrinsic tendency towards conformity and mimetic behaviour as well as other responses or psychological factors characterizing market reality. A stock market is said to intentionally herd if we can find significant differences in the level of mimetic behaviour when compared with others that are assumed not to exhibit any significant herding effect or, at least, not significant intentional herding effects, although they may exhibit other practical imperfections (e.g. spurious autocorrelation or other noisy statistical inferences that could be present in any stock market, even in an “intentional herding-free” market).

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<sup>1</sup> This proposal has been used to model diverse phenomena in which bits of information, interacting in pairs, produce collective effects. Although this model is usually acknowledged to usefully explain statistical mechanics, Schneidman et al, (2006) show that the Ising model is useful for any model of neural function. They find that collective behaviour is described quantitatively by models that capture the observed pairwise correlations and predict that larger networks are completely dominated by correlation effects

To proceed with the CSSD replication, we initially take the methodological approach suggested in Blasco and Ferreruela (2008). The procedure may be summed up as follows: we first generate a fictitious equally-weighted stock index as the average of 28 real (and very diverse) international stock indexes (henceforth  $NMI_t$ ). Correlations are generally lower between international than domestic markets which implies, by construction, the lowest likely intentional herding levels. Second, we select the ten least correlated international indexes ( $LCI_j$  with  $j=1\dots 10$ ) and identify them with non-intentionally imitative individual behaviour, that is, individual financial assets whose evolution depends very significantly on the information available in its own domestic market. This proposal pretends to minimize the outcomes of imitative collective behaviour following the findings in Schneidman et al, (2006). Third, we calculate the empirical CSSD distribution of these ten indexes with respect to the fictitious equally-weighted stock index and thus determine a proxy distribution for CSSD in the absence of intentional imitating behaviour. More precisely, we calculate the empirical time series of CSSD in the absence of herding ( $CSSD_{NH}$ ) as follows:

$$CSSD_{NHt} = \sqrt{\frac{\sum_{j=1}^n (RLCI_{jt} - RNMI_t)^2}{n-1}}$$

where  $RLCI_{jt}$  is the observed stock return on  $LCI_j$  at time  $t$  with  $j=1\dots 10$ , and  $RNMI_t$  is the aggregate return in the notional stock market at time  $t$ .

The results and conclusions of a number of papers such as Sornette and Johansen (1997), King and Wadhvani (1990), King et al, (1994), Groenen and Franses (2000) or Heaney et al, (2000) support the use of real international market data rather than artificially generated time series to provide a better basis for the analysis of intrinsic herding. By averaging international indexes as if they were individual assets, we can re-create a market by statistical analogy free of intentional herding but exhibiting an intrinsic tendency to herd in which there are groups of assets sharing more characteristics than others. At this point we use daily averaged returns of the above-mentioned 28 international stock indexes over the period January 1998-April 2004<sup>2</sup>.

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<sup>2</sup> As mentioned before, under the assumption of, at most, weak imitation, the return time series of the notional index should behave as a Gaussian distribution. The value of the Kolmogorov-Smirnov (K-S) test (Chakravarti et al, 1967) is 0.0327 with a p-value of 10.88%, indicating that we can not strongly reject the normality of the return distribution.

This methodological approach starts from the advantageous availability of daily data belonging to very different international stock markets. Nevertheless, its replica with intraday data becomes extremely difficult due to the scarce availability of high frequency data in so many diverse international markets. Hence, we must propose some practical changes for applying the suggested procedure to an intraday database. In order to provide a more homogeneous comparison avoiding proportional differences among daily and intraday differences in cross-sectional deviations and returns, we first scale cross-sectional deviations with their corresponding aggregated return. This is the first modification of the initial approach in Blasco and Ferreruela (2008).

Then, we compare the scaled CSSD distribution of the market under study ( $CSSD_S$ ) with that computed in the absence of intentional herding effect ( $CSSD_{SNH}$ ). In the presence of intentional herd behaviour (where individuals ignore their own beliefs and base their investment decisions on the aggregate behaviour of the market), individual returns will not deviate significantly from the overall market return and, therefore, this behaviour will lead to a scaled CSSD distribution highly concentrated around zero, which implies a scaled CSSD distribution with a significant kurtosis compared to the scaled CSSD distribution of a market free of intentional herding behaviour.

The following step involves carrying out a significance test in order to assess the observed discrepancy, if any, between the  $CSSD_S$  distribution of the Spanish market and the  $CSSD_{SNH}$  distribution, the latter corresponding to the null hypothesis of no intentional herding effect. In this case, the distribution of the computed differences between both probability distributions is not properly supported by a well-known theoretical formula that permits an accurate assessment of their significance. In order to address this weakness, we use the consistent nonparametric Li's test (1996) of closeness between two CSSDs distributions under quite mild conditions. This test provides us with a global measure of the difference between distributions. This is the second significant change with respect to Blasco and Ferreruela (2008). Li's measure can be generally defined as:

$$I(f, g) = \int_x (f(x) - g(x))^2 dx$$

Where  $f$  and  $g$  are estimated using kernel methods, such that:

$$\hat{f}(x) = \frac{1}{n_1 h} \sum_{j=1}^{n_1} K\left(\frac{x_j - x}{h}\right)$$

$$\hat{g}(x) = \frac{1}{n_2 h} \sum_{j=1}^{n_2} K\left(\frac{y_j - x}{h}\right)$$

Where  $K(\cdot)$  is the kernel function and  $h$  is the smoothing parameter. A feasible estimator of  $I$  can be obtained by

$$I = \frac{1}{h} \left\{ \sum_{i=1}^{n_1} \sum_{j \neq i, j=1}^{n_1} \frac{1}{n_1(n_1-1)} K\left(\frac{x_i - x_j}{h}\right) + \sum_{i=1}^{n_2} \sum_{j \neq i, j=1}^{n_2} \frac{1}{n_2(n_2-1)} K\left(\frac{y_i - y_j}{h}\right) \right\} \\ - \frac{1}{h} \left\{ \sum_{i=1}^{n_1} \sum_{j \neq i, j=1}^{n_2} \frac{1}{n_1(n_2-1)} K\left(\frac{x_i - y_j}{h}\right) + \sum_{i=1}^{n_2} \sum_{j \neq i, j=1}^{n_1} \frac{1}{n_1(n_2-1)} K\left(\frac{y_i - x_j}{h}\right) \right\}$$

Let  $\lambda_n = n_1 / n_2$ , assume  $\lambda_n \rightarrow \lambda$  as  $n_1 \rightarrow \infty$ ,  $\lambda$  is a constant, then we have

$$J = \frac{n_1 h^{1/2} I}{\sqrt{\hat{\sigma}_\lambda^2}} \rightarrow N(0,1)$$

where

$$\hat{\sigma}_\lambda^2 = 2 \left\{ \sum_{i=1}^{n_1} \sum_{j=1}^{n_1} \frac{1}{n_1^2} K\left(\frac{x_i - x_j}{h}\right) + \sum_{i=1}^{n_2} \sum_{j=1}^{n_2} \frac{\lambda_n^2}{n_2^2} K\left(\frac{y_i - y_j}{h}\right) \right\} \\ + 2 \left\{ \sum_{i=1}^{n_1} \sum_{j=1}^{n_2} \frac{\lambda_n}{n_1 n_2} K\left(\frac{x_i - y_j}{h}\right) + \sum_{i=1}^{n_2} \sum_{j=1}^{n_1} \frac{\lambda_n}{n_1 n_2} K\left(\frac{y_i - x_j}{h}\right) \right\} \left[ \int K^2(u) du \right]$$

Once we have tested the overall discrepancy between the distributions, we need to look for those sample intervals along which the differences are likely to be interestingly significant. For this purpose we propose a bootstrap method. This is the third significant change with respect to the initial proposal in Blasco and Ferreruela (2008). Re-sampling methods are not new to significance testing (see, among others, Lei and Smith [2003], Chou [2004] or Güttler [2004]). The bootstrap-based procedure applied in this paper is very simple, although computer-intensive. According to the nature of significance tests, in order to calculate the significance of the differences in probability under the null hypothesis, we must re-sample with replacement from  $CSSD_{SNH}$  the same number of observations as in our raw data set. We construct 5000 bootstrapped data sets to guarantee the accuracy of the analysis.

If we denote  $FCSSD_{SNH}^{booti}$  with  $i=1, \dots, 5000$ , the bootstrapped data set  $i$  from  $CSSD_{SNH}$ , the differences in the probability of landing in the same interval between the  $CSSD_{SNH}$  distribution ( $FCSSD_{SNH}$ ) corresponding to the null hypothesis and every bootstrapped distribution and between  $FCSSD_{SNH}$  and the raw distribution are computed for 102 intervals in which we divide the whole range of scaled CSSD values. For each interval  $j=1 \dots 102$ , with lower and upper limits  $l_j$  and  $l_{j+1}$ , respectively, the differences in the probability can be expressed as follows:

$$\begin{aligned} \Pr(l_j \leq x < l_{j+1} | FCSSD_{SNH}) - \Pr(l_j \leq x < l_{j+1} | FCSSD_{SNH}^{booti}) &= Dj_{NH}^{booti} \\ \Pr(l_j \leq x < l_{j+1} | FCSSD_{SNH}) - \Pr(l_j \leq x < l_{j+1} | FCSSD^{raw}) &= Dj^{raw} \end{aligned}$$

for  $i=1, \dots, 5000$ , and  $l_1=-50$ ,  $l_{102}=50$ , with  $FCSSD^{raw}$  being the raw distribution of the scaled CSSD ( $CSSD_S$ ). The computed differences  $Dj_{NH}^{booti}$  with  $i=1, \dots, 5000$  are used to generate the bootstrap p-values for interval  $j$  as

$$p_j^{boot} = \Pr(Dj_{NH}^{boot} \geq Dj^{raw}) \quad \text{when } Dj^{raw} > 0$$

or

$$p_j^{boot} = \Pr(Dj_{HF}^{boot} \leq Dj^{raw}) \quad \text{when } Dj^{raw} < 0$$

The above equations calculate the p-value for finding the same (or higher in absolute value) bootstrapped differences in probability compared to the difference between the scaled CSSD distribution corresponding to the null hypothesis and the raw distribution without implying the true presence of an intentional herding effect.

Our empirical test focuses on intraday data, the raw database consisting of information about all intraday trades carried out from January 1996 to December 2003. For each trade in a trading session we know the exact time (hour, minutes and seconds) in which the transaction takes place, the stock denomination, the transaction price, the number of titles being traded, as well as the broker codes corresponding to the stock buyer and seller.

In order to properly apply our tests, we have eliminated from the database those trades occurring before and after the open and close of formal trading sessions. In spite

of this elimination, the number of transactions during an ordinary session fluctuates between approximately 20,000 and 100,000, implying highly complex computational treatment if all data and all trading sessions are analytically involved. The number of transactions progressively increases over time, particularly from 1999 onwards, due to the longer trading time in a daily session and to the number of brokers participating in the market. For this reason, following the suggestions in Patterson and Sharma (2006) we have selected 100 trading sessions randomly but taking into account every month over the eight years considered in the complete database. To compute the series of CSSD, we determine half-hour time intervals within each trading session, usually between nine o'clock in the morning and half past five in the afternoon.

At this point it should not be difficult to accept that stock assessment depends on individual perceptions. Shefrin and Statman (1999) or Ganzach (2000) offer results indicating that analysts evaluate stocks not only discounting the proper information but also in terms of global attitudes toward them. Among other factors, familiarity is shown to affect preference in the financial analysis. Furthermore, for familiar assets, participants directly access relevant information and, from our viewpoint, whenever they decide to imitate each other, the intentionality may be stronger. For this reason, it seems to be important to consider familiarity of financial assets in analysing issues such as herd behaviour and we repeat the analysis carried out for the overall market using only the 10% most heavily traded stocks.

Additionally, and in order to provide evidence about the particular usefulness of intraday data for studying herding effects, we repeat the analysis using daily data of the 10% most heavily traded stocks. In this case, although the time interval is the same that we use with intraday data (January 1996 to December 2003), we have not selected a random sub-sample and all daily returns are considered in the analysis.

### **3- RESULTS**

Table 1 Panel A shows some averaged descriptive statistics about trading activity in the Spanish stock market calculated from the 100 days taken as a database in the first analysis of this paper. It should be pointed out that trading volume increased significantly (about 900%) during the period under study. The trading volume (both in titles and in euros) of some noticeable stocks such as Telefónica, BSCH (or its previous constituents Banco Santander and Central Hispano), BBVA (or its previous constituents

BBV and Argentaria), Repsol, Endesa and Iberdrola is remarkably high. Table 1 Panel B reports statistics of the CSSD series for the overall market with intraday data and for the most traded stocks both with intraday and daily data, as well as for the market free of herding effects. The results indicate that the dispersion measure is lower when calculated with intraday data. The mean values of the CSSD series corresponding to our Spanish raw data are, in all cases, lower than those corresponding to the market clean of herding. These summary statistics invite a deeper analysis of the imitative behaviour.

For purposes of comparison, before implementing the methodological proposal, Table 2 gives the results of the traditional CH test using intraday and daily data. CH use one or five percent of the observations in the upper and lower tail of the market return distribution to define extreme price movement days. As an intermediate alternative, we propose 3% of the observations in the upper and lower tail. This table includes both the results for the overall market and for the sample of stocks with high trading volume. In both cases (intraday and daily data) the coefficients of the dummy variables  $D^L$  and  $D^U$  are positive and significant at the 1% significance level, indicating that dispersion increases under extreme market price conditions. Hence, following the traditional methodology, the results suggest no evidence of intraday herding effect in the Spanish market either in the overall market or in the selected heavily traded stocks. Nevertheless, the estimated values of  $\beta^L$  and  $\beta^U$  provide additional information if considered individually. For the overall market, these coefficients are not remarkably different. However, the coefficients estimated from the sub-samples of heavily traded stocks indicate that the dispersion increases more rapidly with extreme downward price changes than with upward movements. This finding agrees with the suggestion in Henker et al, (2006) questioning the assertion of Chang et al, (2000) that there is an increased likelihood that herding will occur during periods of down-market stress.

As far as we know, there are not many papers offering results for the purposes of comparison. Gleason et al, (2004) apply CH and CCK using intraday data for sector Exchange Traded Funds traded on the American Stock Exchange and Henker et al, (2006) apply the same methodology to Australian stocks. As in our case, their results support the conclusion that investors do not herd during periods of extreme market movements.

Table 3 and Figures 1 and 2 show the results obtained with the proposed methodology. Table 3 offers the results of Li's test when comparing the density function of the scaled CSSDs in a herding-free market with the three samples taken for

examination from the Spanish markets: the overall sample using intraday data, the most familiar stocks with intraday data and the most familiar stocks with daily data. Specifically, the table shows the results using the Epanechnikov kernel, which seems to be one of the most efficient for a wide range of density estimation purposes, and the choice of the data-based automatic relation  $h=0.009kn^{-1.5}\min(\sigma,\pi/1.34)$ , where  $n$  is the number of observations,  $\sigma$  is the standard deviation,  $\pi$  is the inter-quartile range of the series, and  $k$  is a canonical bandwidth-transformation that differs across kernel functions, so that the bandwidth is adjusted for the automatic density estimates to have roughly the same amount of smoothness across various kernel functions. All the results are significant and robust to the choice of the smoothing parameter and the kernel function<sup>3</sup>. We can conclude that there are significant differences among the distributions under study and the distribution in the absence of intentional herding effect. These results support the presence of an imitation effect in the Spanish stock market. Figure 1 enables the visualization of the scaled cross-sectional deviations for the fictitious herding-free market and the distributions calculated using intraday data. Figure 2 additionally presents the scaled cross-sectional deviations for the daily data. The graphs support the numerical results and suggest that the main differences among distributions are concentrated around zero, that is, around the midpoint of the scale.

Table 4 summarizes the results of the bootstrap procedure used to test the statistical significance of the main differences in probability when we analyze different intervals of scaled CSSD values<sup>4</sup>. The presence of herd behaviour in the Spanish market appear to be associated with a high probability of finding low values of its scaled CSSD statistics, indicating that the dispersion values around aggregate returns are low relative to those for  $FCSSD_{SNH}$ . As can be seen in Table 4, when the overall sample is considered, the differences in probability when the distributions of scaled CSSD values are compared ( $FCSSD_{SNH} - FCSSD^{raw}$ ) indicate that our raw sample is more likely to determine larger dispersion values than a free of intentional herding market, given that such differences are basically negative except in central values around zero. However,

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<sup>3</sup> We have used either the Epanechnikov and the Gaussian kernels. We have also used several bandwidth parameters. We first follow the Silverman option that suggest a data-based automatic relation  $h_1=0.9kn^{-1.5}\min(\sigma,\pi/1.34)$ , Then we used lower values up to  $h_2= h_1/100$ . The larger the bandwidth, the smoother the estimate. We always choose the lower  $h$  value for each couple of density functions. The results do not vary significantly, and are available upon request.

<sup>4</sup> For clarity, the table only captures the central range of interval limits, as we consider them the most relevant in our analysis. Further details on additional intervals can be provided by the authors upon request.

when heavily traded stocks are selected, scaled CSSD values significantly concentrate around zero, more precisely within the interval  $(-1, 1]$ , suggesting that those financial assets tend to move co-ordinately even though they respond to different individual information and belong to different activity sectors.

Finally, Table 4 also shows the results using daily data for heavily traded stocks. Our findings confirm the results provided by intraday data and suggest the robustness of the methodology when applied to different data frequency. There are significant negative differences in probability in central values around zero, indicating the noticeable weight of reduced dispersion values around the aggregated return in the Spanish market when compared to  $FCSSD_{SNH}$ . Scaled daily CSSD values significantly concentrate around zero, once again within the interval  $(-1, 1]$ , suggesting that the selected financial assets tend to move co-ordinately. Nevertheless, the differences in probability, although significant, are not so great as in the case of intraday data<sup>5</sup>. We interpret these estimations as evidence in favour of high frequency data in order to better reveal the existence of herding effects. These results are clearly reflected in Figures 1 and 2. It is worth noting the shape of the distributions of scaled CSSD which show a marked depression in the middle of the distribution, in all but the intraday data for heavily traded stocks. This depression is explained by the definition of the test being applied. The figures represent the probability of finding a range of scaled CSSD values. Small dispersions are more prone to identify stock co-movements and herd behaviour, especially if the low values are associated with high returns, whereas large dispersions are more likely to indicate the absence of imitation effects. In the absence of herd behaviour, high returns are usually accompanied by larger dispersions, indicating that stocks do not tend to move co-ordinately.

However, the lack of clear guidelines for assessing herding intensity in absolute terms makes the relative comparison valuable. Like other tests in the literature, this statistical test result should only be interpreted in one sense: that there is a higher probability of small deviations per return unit than in the herding-free market. A higher probability of wide cross-sectional deviation than specified for the herding-free market should be interpreted as differences of interpretation and information processing, whether in specialisation, information diffusion, broker rewards or risk levels in the market. The graphs represent the natural consequences of our empirical results: scaled

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<sup>5</sup> The analysis has been repeated changing the interval width (both 0.5 and 2 units). The results do not change significantly and are available upon request.

CSSD values for the intraday heavily-traded stock sample indicate intense herd behaviour, whereas this effect is less noticeable when the two other distributions are studied, particularly in the case of the overall sample with intraday data, where we find no significant evidence of mimetic behaviour.

These results are consistent, on the one hand, with the findings documented by Blasco et al, (2005). In the Spanish market, stocks tend to react more quickly and strongly to macroeconomic or general information (especially bad news) rather than to firm-specific information. This indicates that prices may respond to factors and effects other than particular items of information. When firm-specific news is released, investors may not be sure of what to expect and may need additional time to analyse the information flow in order to make appropriate inferences. They consequently take short-term decisions following other market participants, favouring the market consensus. The significant levels of intentional herding behaviour could be due to the way in which Spanish investment professionals rely heavily on reasoning by analogy, so that their decision procedures may become more intuitive as complexity increases. They are "satisfiers", not optimizers. Their primary aim is to make an acceptable choice.

Furthermore, these results also agree with those documented in Blasco and Ferreruela (2008), where a proposed daily CSSD measure is notably lower in the Spanish market over the whole market return range when some familiar stocks are analyzed in the international context, and with those documented in Blasco and Ferreruela (2007), where imitative behaviour is found in the intraday dynamic of the Spanish market using some alternative methodologies as those proposed in Patterson and Sharma (2006). In this sense, we think our work contributes to the empirical literature by proposing a methodological alternative that appears to be more powerful than the measure first presented in CH and corroborates the results yielded by other analytical tools, suggesting that further analysis in this line of research is worth encouraging.

#### **4- CONCLUSIONS**

In this paper we present an empirical test for detecting intentional herding, even to a moderate degree, using a variant of the methodology first presented by Christie and Huang (1995) that may be usefully applied to intraday data. Our empirical proposal consists of a comparison of scaled cross-sectional standard deviation measures in a particular market with those calculated in an artificially created market which is

assumed to be free of intentional imitative behaviour. We first use Li's test to examine the overall closeness of the scaled cross-sectional standard deviation density functions and then determine the significant discrepancy intervals using bootstrap procedures that have proven useful and robust in significance testing.

We apply this methodological procedure to a database covering a wide time horizon (1997-2003) that permits general results to be obtained independently of specific market situations. We propose two different comparative analyses: first, the application both to the overall market and to a selection of large trading volume stocks and second, the application to heavily traded stocks using both intraday and daily data, our purpose being to obtain additional information on the herding effect characteristics.

Heavily traded stocks are useful in the analysis given that if investors can easily access relevant information about these titles, their decision to herd is consistent with an intentional preference for following the decision of other participants. Our results lead to the general conclusion that the Spanish market, particularly in heavily traded stocks, exhibits a tendency towards imitation.

To sum up, in addition to the robustness of the methodology, our results show the key importance of heavily traded stocks for studying mimetic behaviour as well as the key importance of intraday data. The use of overall market data and lower frequency data may obscure the existence of intentional herding if imitative attitudes take place only on a sub-sample of titles or over a shorter time interval.

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**Table 1 Panel A. Averaged descriptive statistics of the overall sample.**

Averaged daily trading volume (in euros)	1,102,659,483
Averaged daily trading volume (in euros) for one title	3,291,521
Averaged daily trading volume (in titles)	89,925,689
Averaged daily trading volume (in titles) for one title	268,435
Averaged daily number of transactions	42,869
Averaged daily number of transactions for one title	124
Averaged daily trading volume (in titles) in one transaction	2,098
Averaged daily trading volume (in euros) in one transaction	25,722

**Table 1 Panel B. Descriptive statistics of the daily and intraday CSSD**

	<i>Overall intraday sample</i>	<i>Heavily traded stocks. Intraday data.</i>	<i>Heavily traded stocks. Daily data.</i>	<i>Herding-free market</i>
Mean	1.436	0.006	2.655	3.333
Std. Deviation	96.470	0.128	114.612	119.842
Max.	2153.591	3.296	4596.433	1900.526
Min.	-1129.293	-0.557	-1059.505	-2456.440

**Table 2. CH Regression results of the intraday and daily CSSD.**

<i>Overall market. Intraday data</i>				
		<i>Coefficients</i>	<i>t-Statistic</i>	<i>P-value</i>
	Intercept	0.00761345	2.74840052	0.00606666
	Variable $D_t^L$	0.12842556	8.13068343	9.4057E-16
	Variable $D_t^U$	0.11485873	8.07997141	1.4006E-15
<i>Heavily traded stocks. Intraday data.</i>				
		<i>Coefficients</i>	<i>t-Statistic</i>	<i>P-value</i>
	Intercept	1.581E-05	0.0081625	0.9934885
	Variable $D_t^L$	0.09233908	9.24331095	8.786E-20
	Variable $D_t^U$	0.03124289	3.1574038	0.0016263
<i>Heavily traded stocks. Daily data.</i>				
		<i>Coefficients</i>	<i>t-Statistic</i>	<i>P-value</i>
	Intercept	0.0197931	22.3117338	3.2097E-97
	Variable $D_t^L$	0.12739446	25.4310679	1.268E-121
	Variable $D_t^U$	0.02269866	4.73313447	2.3891E-06

Reports the estimated coefficients of the following regression model:

$$CSSD_t = \alpha + \beta^L D_t^L + \beta^U D_t^U + \varepsilon_t$$

$D_t^L=1$ , if the market return on day  $t$  lies in the extreme *lower* tail of the distribution; and equal to zero otherwise, and

$D_t^U=1$ , if the market return on day  $t$  lies in the extreme *upper* tail of the distribution; and equal to zero otherwise.

The percentage of observations in the upper and lower tails of the market return distribution used to define price movements is the 3%.

**Table 3.** Results of the Li's test of closeness between  $FCSSD_{SNH}$  and  $FCSSD^{raw}$

FCSSD <sup>raw</sup>	Overall sample. Intraday data (h=0.007)	Heavily traded stocks sample. Intraday data (h=0.00026)	Heavily traded stocks sample. Daily data (h=0.006)
J statistic (p-value).	21,36 (0.00)	135.42 (0.00)	10.13 (0.00)

$$J = \frac{n_1 h^{1/2} I}{\sqrt{\hat{\sigma}_\lambda^2}} \rightarrow N(\mathbf{0}, \mathbf{1}), \text{ where}$$

$$I = \frac{1}{h} \left\{ \sum_{i=1}^{n_1} \sum_{j \neq i, j=1}^{n_1} \frac{1}{n_1(n_1-1)} K\left(\frac{x_i - x_j}{h}\right) + \sum_{i=1}^{n_2} \sum_{j \neq i, j=1}^{n_2} \frac{1}{n_2(n_2-1)} K\left(\frac{y_i - y_j}{h}\right) \right\}$$

$$- \frac{1}{h} \left\{ \sum_{i=1}^{n_1} \sum_{j \neq i, j=1}^{n_2} \frac{1}{n_1(n_2-1)} K\left(\frac{x_i - y_j}{h}\right) + \sum_{i=1}^{n_2} \sum_{j \neq i, j=1}^{n_1} \frac{1}{n_1(n_2-1)} K\left(\frac{y_i - x_j}{h}\right) \right\}, \quad \lambda_n = n_1 / n_2, \quad \lambda_n \rightarrow \lambda \text{ as } n_1 \rightarrow \infty,$$

$$\text{and } \hat{\sigma}_\lambda^2 = 2 \left\{ \sum_{i=1}^{n_1} \sum_{j=1}^{n_1} \frac{1}{n_1^2} K\left(\frac{x_i - x_j}{h}\right) + \sum_{i=1}^{n_2} \sum_{j=1}^{n_2} \frac{\lambda_n^2}{n_2^2} K\left(\frac{y_i - y_j}{h}\right) \right\}$$

$$+ 2 \left\{ \sum_{i=1}^{n_1} \sum_{j=1}^{n_2} \frac{\lambda_n}{n_1 n_2} K\left(\frac{x_i - y_j}{h}\right) + \sum_{i=1}^{n_2} \sum_{j=1}^{n_1} \frac{\lambda_n}{n_1 n_2} K\left(\frac{y_i - x_j}{h}\right) \right\} \left[ \int K^2(u) du \right]$$

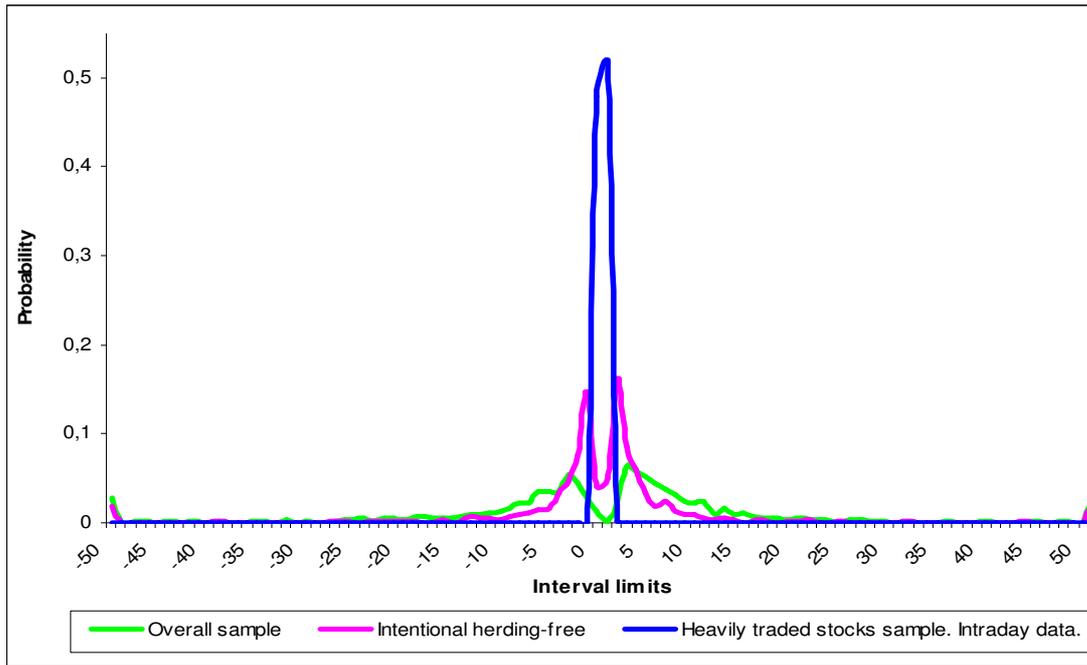
K represents the Epanechnikov kernel

**Table 4.** Differences in probability and their significance.

Overall sample. Intraday data			Heavily traded stocks sample. Intraday data.			Heavily traded stocks sample. Daily data.		
Interval limits	Differences in probability	Signif. level	Interval limits	Differences in probability	Signif. level	Interval limits	Differences in probability	Signif. level
And hitherto	-0.200%		And hitherto	0.114%		And hitherto	0.012%	
-15	-0.577%	0%	-15	0.074%	NS	-15	-0.098%	NS
-14	-0.576%	0%	-14	0.148%	NS	-14	0.034%	NS
-13	-0.275%	NS	-13	0.666%	0%	-13	0.265%	NS
-12	-0.349%	4.963%	-12	0.592%	0%	-12	0.248%	NS
-11	-0.640%	0%	-11	0.518%	0.124%	-11	0.175%	NS
-10	-0.860%	0%	-10	0.370%	0.124%	-10	-0.031%	NS
-9	-0.851%	0%	-9	0.814%	0%	-9	0.184%	NS
-8	-1.356%	0%	-8	0.815%	0%	-8	0.029%	NS
-7	-0.987%	0.124%	-7	1.183%	0%	-7	-0.247%	NS
-6	-1.920%	0%	-6	1.553%	0%	-6	-0.163%	NS
-5	-1.843%	0%	-5	1.775%	0%	-5	0.231%	NS
-4	-0.290%	NS	-4	3.328%	0%	-4	-0.104%	NS
-3	-0.840%	NS	-3	4.587%	0%	-3	-0.375%	NS
-2	3.132%	0%	-2	7.546%	0%	-2	0.696%	NS
-1	11.969%	0%	-1	14.719%	0%	-1	0.875%	NS
0	2.912%	0%	0	-43.788%	0%	0	-3.181%	0.00%
1	4.811%	0%	1	-46.606%	0%	1	-1.909%	0.00%
2	13.810%	0%	2	16.053%	0%	2	-0.392%	NS
3	2.211%	0.124%	3	8.506%	0%	3	0.440%	NS
4	0.128%	NS	4	5.845%	0%	4	1.054%	4.84%
5	-1.734%	0%	5	3.476%	0%	5	0.616%	NS
6	-2.711%	0%	6	1.775%	0%	6	-0.056%	NS
7	-1.396%	0%	7	2.367%	0%	7	0.593%	NS
8	-1.780%	0%	8	1.331%	0%	8	0.073%	NS
9	-1.425%	0%	9	1.036%	0%	9	0.177%	NS
10	-1.356%	0%	10	0.888%	0%	10	0.144%	NS
11	-1.868%	0%	11	0.592%	0%	11	0.191%	NS
12	-0.645%	0%	12	0.296%	1.241%	12	-0.162%	NS
13	-1.219%	0%	13	0.518%	0%	13	0.175%	NS
14	-0.498%	0%	14	0.370%	0.248%	14	-0.145%	NS
15	-1.011%	0%	15	0.074%	NS	15	-0.441%	0.00%
16	-0.574%	0%	16	0.222%	NS	16	0.050%	NS
And thereafter	-0.138%		And thereafter	0.127%		And thereafter	0.019%	NS

The differences in probability (Probability in intentional herding-free distribution - Probability in raw distribution) for each of the 102 intervals for the scaled CSSD values are computed as well as the bootstrapped significance level for positive and negative differences.

**Figure1.** Probability distributions of standardized CSSD



**Figure 2.** Probability distributions of standardized CSSD. Heavily traded stocks with daily data included.

