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Market sentiment: a key factor of investors' imitative behaviour

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Abstract

The aim of this paper is to explore herding behaviour among investors to determine its rational and emotional component factors and identify relationships among them. We apply causality tests to evaluate the impact of return and market sentiment on herding intensity. The herding intensity is quantified using the measure developed by Patterson and Sharma (2006). The research was conducted during the period 1997–2003 in the Spanish stock market, where the presence of herding has been confirmed. The results reveal that the herding intensity depends on past returns and sentiment or subjective assessments and confirm the presence of both a rational and an emotional factor.

Key words: Behavioural finance; Herding; Sentiment; Stock market

JEL classification: G14, G11

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1. Introduction

Over the last few decades, there has been a growing interest in researching investor behaviour in capital markets, especially in relation to how and when the behavioural pattern may impact on stock prices and, thereby, on what is commonly considered to be market efficiency. The attention of the behavioural finance literature has been focused on the study of investor rationality and the implications of the cognitive processes involved in stock market investment

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decision-making (Fromlet, 2001). But certain reactions induced by innate psychological or behavioural traits may be compatible with rational decision-making, as in the case of investors engaging in loss avoidance (Kahnemann and Tversky, 1979; Tversky and Kahnemann, 1986). This type of investor will make a subjective assessment of historic data and current fundamental variables. In a context such as this, investor behaviour can cause price fluctuations that are not necessarily because of new information arrival, but to the emergence of collective phenomena such as herding behaviour (Thaler, 1991; Shefrin, 2000). The market might not be efficient in the strict traditional sense, but might rather be functioning within a limited rationality paradigm in which historic data acquires added value, either directly or indirectly through the formation of market sentiment and the intensity of investor herding behaviour.

Herding, that is imitation among investors, is said to appear in markets when, instead of following their own beliefs and private information, investors decide to imitate the decisions of other traders, who they perceive to be better informed. Numerous theories have been put forward to explain this kind of behaviour, and studies have been conducted to evaluate the presence of herding in capital markets, although the empirical results have been inconclusive. The explanations that have been given for herding include the way in which information is released (see Banerjee, 1992; Bikhchandani *et al*., 1992; Hirshleifer *et al*., 1994; Gompers and Metrick, 2001; or Puckett and Yan, 2007), reputation costs – under the agency theory and usually in developed markets – (see Scharfstein and Stein, 1990; Trueman, 1994) and compensation schemes, through which an investor will be compensated according to his performance relative to that of others, and therefore deviations from the market consensus might lead to an undesired cost (Roll, 1992; Brennan, 1993; Rajan, 1994; or Maug and Naik, 1996). In addition to these explanations, some authors (among others, Patterson and Sharma, 2006; hereafter PS; Demirer and Kutan, 2006; Henker *et al*., 2006; and Puckett and Yan, 2007) have recently considered other determinants of herding including the proportion of institutional traders, the quality of available information, dispersion of opinion or the presence of uninformed investors, among others.

Owing to the inconclusiveness of the empirical evidence of the presence of herding, and because there appear to be both theoretical and operational arguments to support its existence, recent years have seen the emergence of a variety of proposed measures and indicators designed to overcome the limitations of previous alternatives, either through modification of existing approaches or the proposal of new ones (Lakonishok *et al*., 1992; Wermers, 1999; Christie and Huang, 1995; Chang *et al*., 2000; Hwang and Salmon, 2004, 2005; PSY, 2006).

Following the line of reasoning used by Bikhchandani and Sharma (2001), herding could be segregated into sentiment-driven herding and herding driven by fundamentals. Also, Baddeley *et al*. (2007) argue that in the real world herding behaviour may be the outcome of interactions between instinctive or emotional and rational responses. This idea has drawn additional support from the world of practitioners. In this context, the focus of this paper is on exploring the components of herding behaviour and, more specifically, testing for the presence of both the sentiment and fundamental-driven factors just mentioned.

The component of emotional herding is usually identified with the emotional contagion phenomenon based on feelings and general subjective perceptions of investors. So, a proxy for emotional herding would be something similar to the so-called market sentiment measures. The second component arises from apparent rationality in analysing information flows arriving in the market and includes the so-called rational expectations drawn from the analysis of fundamentals. Thus, rational herding is approximated by the most recent past returns, which might be raising investors' expectations about future market fundamentals.

It is easy to appreciate the complexity of the relationships between investor behaviour at a given moment and the amount of objective and subjective variables considered by each investor, while also bearing in mind the possibility of feed-back or circular dependency between variables. Although analysing these components is no easy task, there is no excuse for avoiding it, despite our awareness of the limitations it may entail.

The paper sets out to study daily herding patterns using causality tests. Our first step is to determine the causal relations between each of the emotional and the rational components and the herding measure. Nevertheless, given the close interrelation between the objective and subjective variables that may be considered by agents participating in the market, we also test whether past returns drive herding behaviour indirectly through the formation of market sentiment and whether lagged sentiment drives herding effects by inducing returns that encourage mimetic decisions. To lend robustness to our findings, we perform the tests using three different indicators of market sentiment: two based on data from the derivatives market and a third one based on data from the spot market. Because the analysis requires a market in which the presence of herding has already been confirmed, the Spanish stock market[1] was considered ideal for the purpose. Based upon the results obtained, we constructed several models aimed at determining whether the (emotional and rational) components of herding can usefully inform predictions of future herding intensity. In other words, we aim to test whether the proxy variables for these factors have enough predictive power to limit the importance of other possible explanatory variables that cannot be so reasonably identified with proxy variables. The distinction of the different sources of herding might allow the anticipation of future herding episodes and information cascades, which would be useful not only for investors but also for the authorities, by enabling them to respond more rapidly to extreme market movements (Cuadro and Moreno, 2007).

This paper makes several contributions to the literature on herding behaviour among investors. Firstly, it furthers understanding of the phenomenon and

[1] Blasco and Ferreruela (2007, 2008), Lillo *et al.* (2008) and Blasco *et al.* (2011) present clear evidence for the presence of herding in this market.

advances the search for intensity determining factors. This is, as far as we are aware, the first paper to find empirical evidence to establish causal links between herding intensity and the proxies for its components and reach the point of identifying the sign of the relationships. The results obtained may be particularly relevant in providing a deeper understanding of market functioning. Secondly, we present an instrument to predict levels of herding based on the above-mentioned variables, which appears to be another novelty in the literature on the subject. In addition, we start out with an intraday herding measure, this being considered the optimal frequency of data for detecting herding behaviour. Finally, the sample period is long enough to dilute the bias produced by any market effects.

The paper is organised as follows: the second section presents the database used for the analysis together with some descriptive data for the Spanish stock market. Section 3 describes the methodology, the main findings and the implications of the causal links, in addition to several herding intensity prediction models. The paper concludes with Section 4 that gives a summary of the main findings deriving from the study.

2. The database

The sample period for this analysis runs from 1 January 1997 to 31 December 2003. The data used in the analysis were supplied by the Spanish Stock Exchange Association. They enabled us to compile an intraday data set for every stock listed in the market, recording the exact time of the trade in hours, minutes and seconds, the asset code, the trade price and volume traded in number of stocks for every trade made during the sample period. We were also provided with information about the Ibex-35 composition and the daily index return series data for the period considered. The Ibex-35 is the official index of the Spanish Continuous Market and records all movements of its 35 most liquid and actively traded stocks.

For the purpose of this analysis, all transactions that had taken place outside normal trading hours, that is, before market opening or after market closing were removed from the sample. Throughout the whole of 1997, the market trading hours were from 10 am to 5 pm, after which the trading day was gradually lengthened until in 2003 it was fixed from 9 am to 5.30 pm. The data used in this paper cover all trades executed on the stocks included in the Ibex-35 at any time during normal stock market trading hours.

We also used historical data relating to the options on the Ibex-35 at the derivatives market close of trading, supplied by MEFF, the Spanish Official Exchange for Financial Futures and Options. These data include the date of the trade, the stock underlying the contract (in our case the Ibex-35), whether it is a call option or a put option, the expiration date, the exercise price, daily trading volume, open interest and volatility at market closing.

It is worth noting that the securities comprising the Ibex-35 index account for 93.57 per cent of the total volume traded, and the average trading volume per security in the Ibex-35 is roughly four times higher than the average daily trading volume per security in the total market. These figures show the enormous importance of the Ibex-35 securities relative to the market as a whole.

3. Methodology

3.1. Herding intensity measure

One of the reasons why so little empirical evidence of herding has been found could be inadequate choice of data frequency. Radalj and McAleer (1993) note that the use of quarterly, or in some cases even annual, data would weaken the detection of herding behaviour if it happened to be taking place in a shorter time interval (monthly, weekly, daily or intradaily). The scarcity of the necessary data and the relative novelty of empirical analysis are further potential reasons for the real difficulty entailed in measuring the herding effect (Bikhchandani and Sharma, 2001).

To measure herding intensity in the market, this paper uses the measure proposed by PSY (2006), based on the information cascade models of Bikhchandani *et al.* (1992) that measure herding intensity in the market in both buyer-initiated and seller-initiated sequences. This measure presents a major advantage over other alternatives in that it is an intraday measure, that is, it provides a daily indicator but uses intraday data. It also suits our purposes better than other measures because it does not rest on the assumption that the level of herding will increase or decrease at extreme moments, and in addition it takes into account the whole market and not just a few institutional investors.

According to the Bikhchandani *et al.* (1992) model, market traders receive an imperfect signal G (a good news announcement that might trigger a price increase) or B (a bad news announcement that might trigger a price reduction) in the future value of an asset. Investors are aware of their own interpretation of the signal but can only infer how others have interpreted it by observing their investment decisions. In this model, investors make sequential investment decisions, and therefore observation of others' previous decisions can become crucial when pondering one's own. Information cascades occur when investors set such store by what they have observed in others that they ignore their own private information when making their decision.

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

PSY (2006) construct an indicator based on these theoretical foundations and suggest that at the empirical level, an information cascade will be observed in the presence of buyer-initiated or seller-initiated trading sequences of a longer duration than those that would be observed if there were no such cascade and each investor were to base his decision on his own information. The above-mentioned authors propose a statistic to establish the measure of herding intensity in the market by comparing the number of sequences. If investor behaviour is systematically imitative, the values of the statistic should be negative and statistically significant because the real number of initiated sequences will be lower than expected.

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

where r_i is the real number of sequences of type i (upward, downward or zero tick), n is the total number of trades executed in security j during the trading day t, ½ is a discontinuity adjustment parameter, and p_i is the probability of finding a sequence of type i. In asymptotic conditions, the statistic $x(i, j, t)$ follows a zero-mean normal distribution with variance

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

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

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

where i can take one of three different values according to whether the trade is buyer initiated, seller initiated or zero tick, which gives three series of H statistics. Ha is the statistic value series in upward (buyer-initiated) sequences, Hb represents the statistic values in downward (seller-initiated) sequences, and Hc is the statistic value series in zero tick sequences. As mentioned before, significantly negative values of the H statistic indicate that the number of real sequences is lower than expected and, therefore, support the presence of herding effects.

To obtain the herding measures required for our study, we began by ranking all trades executed during each trading day of the sample period (having once removed those executed outside official trading hours), sorting them by stock and then measuring the number of sequences (uptick, downtick or zero tick) that occurred on that day on each stock. We then proceeded to calculate the PSY (2006) statistic. We found Ha, Hb and Hc statistics for each day of the study period on all the stocks listed in the Ibex-35 and finally obtained average Ha, Hb and Hc statistic series for the Ibex-35.

Table 1 shows the descriptive data for the herding intensity measures. It can be seen that average herding intensity is negative and larger than the critical value of −1.96, and therefore, we find evidence in favour of herd behaviour at the 5 per cent of significance level across uptick, downtick and zero tick trading sequences.[2] There is, however, a notable difference between the first two types of sequence (−8.8169 and −8.7286, respectively) and the last (−4.0414), with herding intensity rising to much higher levels in the presence of price changes (upward and downward ticks) than in sequences of no price change (zero tick). In fact, if we observe the maximum values of the series, the highest value in the downward sequence is −1.5433, which is very close to significant. That is, investors showed a significant herding instinct towards Ibex-35 securities on practically every day of the study period, especially in seller-initiated sequences.[3]

[2] For long samples, $H(i,j,t)$ is normally distributed according to $N(0,1)$. Nevertheless, following the indications in PSY (2006), when the discretization of prices may modify the critical values, a bootstrap procedure can be used to assess the significance of the estimations. We have also designed a bootstrap procedure starting from the choice of an initial sample of Spanish stocks that do not show any evidence of herd behaviour according to the results in Blasco *et al.* (2009) and, therefore, properly represent the null hypothesis of absence of herding effect. By resampling 1000 bootstrap replicas, each one including about 1000 transactions, we calculate the number of sequences of each type and compare with the theoretical number $n.p_i.(1\text{-}p_i)$ and then compute the bootstrap distribution of H. Our results also indicate significant herding levels and are available upon request.

[3] However, it could be argued that larger sequences may also be attributed to other factors than imitative behaviour, such as splitting trading. If investors split large trades into several small trades with the aim of not artificially inducing price changes, their decisions should be reflected along zero-tick sequences. Nevertheless, sometimes the aim of avoiding unfavourable price variations is rather difficult. In order to examine the influence of splitting practices on our results, we look for those transactions that can be suspected of split decisions within our sample according to the following characteristics: trades initiated by the same broker for the same stock during a five second time interval, without any constraint about price changes. We find only a residual percentage for this type of operation (about 2 per cent of the transactions, both for seller-initiated trades or buyer-initiated trades) in non-zero-tick sequences. This result supports the convenience of independent consideration of the zero-tick sequences and justifies the use of the proposed herding measure.

Table 1
Descriptive data for the herding intensity measures

	Mean	Median	Standard deviation	Maximum	Minimum
Ha	−8.8169	−8.9000	2.1271	−1.0852	−14.3633
Hb	−8.7286	−8.7791	2.1485	−1.5433	−15.5900
Hc	−4.0414	−3.9792	1.3809	0.2202	−8.9243

The table shows the mean, median, standard deviation, maximum and minimum of the daily series of herding intensity measures in upward, downward and zero tick sequences affecting Ibex-35 stocks.

3.2. Components of herding

3.2.1. Emotional component

As explained in the introduction, emotional herding is related to market sentiment. In emotional herding, it is optimism, pessimism, hopes and fears that take control. Indeed, as argued by Brown and Cliff (2004), practically speaking one rarely sees or hears market news that is not accompanied by some analyst's comment on the market situation. Individual investors trading on sentiment is a common theme in the herding literature. Shiller (1984) and De Long *et al.* (1990), for example, posit that the influences of fad and fashion are likely to impact the investment decisions of individual investors. Market sentiment represents the expectations of participants in the market and is therefore a measure of investors' global subjective perception. Lakonishok *et al.* (1992) and Liao *et al.* (2010) conclude that market sentiment may be a key factor of herd behaviour. Also, Hwang and Salmon (2005, 2009) assume the existence of a relationship between market sentiment and herding to incorporate it into their measuring process.

Recent findings in psychology also support the importance of sentiment for decision-making. For instance, Schwarz (2002) suggests that the emotions experienced while making a decision are incorporated as information into choices. Consistent with Isen (1987), Au *et al.* (2003) found that financial market traders traded differently when in a good or bad incidental mood.

Stock market psychology is extremely varied and allows us to observe situations ranging from maximum confidence and optimism to others in which investors experience and transmit fear or absolute panic. There is a variety of formulas to test investor sentiment in markets, such as surveys of the investors, measures of investor′s humour, monetary flows towards investment funds, implied volatility, volume and return on the first day of an Initial Public Offering, derivatives market data or complex indexes such as the proposal in Baker and Wurgler (2006). Usually, these measures are computed at a monthly frequency because they are used to implement investment strategies based on the contrary opinion theory in which investors do not respond on a daily basis but on the perception of being in an upmarket or downmarket situation. However, if market sentiment is observed on a daily basis, we might then be dealing with market feeling or the sensation felt by investors at the close of trading every day rather than sentiment in the sense of a market situation, which could only be defined on the basis of longer-frequency data. This study uses daily data to achieve a more dynamic measure of the sentiment prevailing at the close of trading each day.

Following Wang *et al.* (2006), henceforth WKT (2006), this study uses three daily sentiment indicators based on market data, two for the derivatives market (the put-call trading volume ratio (PCV) and the put-call open interest ratio (PCO)) and a third calculated from spot market data (ARMS index).

The put-call trading volume ratio (henceforth PCV) is written as:

$$\mathrm{PCV} = \frac{V\mathrm{Put}_t}{V\mathrm{Call}_t} \tag{4}$$

that is, the ratio obtained by dividing the trading volume of put options by the trading volume of call options during a trading session. Given that the rest of the variables used in this study (herding intensity and stock returns) take the Ibex-35 as the base index, data for options on Ibex-35 stocks are used to calculate this ratio, which gives us a PCV daily sentiment indicator. Any increase (decrease) in the ratio implies a negative (positive) market sentiment.

If, instead of using the total volume of options traded, we use the open interest on these as our basis, we obtain the PCO, which is written as follows:

$$\mathrm{PCO} = \frac{O\mathrm{Put}_t}{O\mathrm{Call}_t}. \tag{5}$$

The open interest is used to describe positions that have not been closed by investors; they may be long or short depending on expected returns.

The third indicator of market sentiment used in this study is the ARMS index (Arms, 1989) which, unlike those just described, is constructed from stock market data. The ARMS index on day t is defined as the number of advancing issues scaled by the advancing volume, divided by the number of declining issues scaled by the declining volume. This index can be written as:

$$\mathrm{ARMS}_t = \frac{\mathrm{DV}_t/\#D_t}{\mathrm{AV}_t/\#A_t} \tag{6}$$

where DV_t is volume of declining issues traded (in number of shares), $\#D_t$ is the number of declining issues, AV_t is the volume of advancing issues traded (in number of shares), and $\#A_t$ is the number of advancing issues. An index value higher than 1 shows that the volume in declining issues is higher than in advancing issues, while an index value lower than 1 shows that the volume per advancing issue is higher than the volume per declining issue.[4]

Panel A of Table 2 shows the correlation coefficients among the three sentiment measures to determine, in the first instance, the possible redundancy of some of the ratios considered. Given that the ARMS index unveils stock market information that may differ, at least in intensity, from options market information, we consider it appropriate to use at least one derivatives market-based measure and one stock market-based measure for the purposes of comparison and robustness. With respect to derivatives market-based measures, while the traditional method of measuring sentiment via the PCV ratio is useful for indicating how meaningful the price movement in the market is, the whipsaw in its daily readings can make it less reliable for studying the underlying sentiment trend. In turn, open interest can help to determine whether there is unusually high or low volume for any particular option. An increasing open interest means that the market sentiment is supporting the current trend, whereas a decreasing open interest serves as a potential warning sign that the current price trend may be lacking real power, as no significant amount of money has entered the market.

Although all the correlation coefficients are low and we can infer that the three measures can be used independently as they report on different aspects of market sentiment, the relation between the option trading volume and the open interest will merit greater attention later in the analysis of the results.

Panel B of Table 2 gives some descriptive data of the three measures of market sentiment described earlier together with the series in first differences, in line with the literature that has used transformed series. We observe that all the series of indicators are extremely leptokurtic as well as skewed and that, at least on average, the market was biased towards pessimism.

3.2.2. *Rational component*

Most herding models suggest that investors follow some common signal. Nofsinger and Sias (1999) argue that feedback trading, a special case of herding, results when lag returns, or variables correlated with lag returns (e.g. earnings momentum, decisions of previous traders, changes in firm characteristics), act as the common signal. Thus, rational herding could be approximated by the most recent past returns, which might be raising investors' expectations about future market fundamentals.

Alternatively, Shefrin and Statman (1985) argue that individual investors tend to employ negative feedback trade strategies by selling past winners (the 'disposition effect'). Extant evidence also suggests that individual investors' herding is related to lag returns, that is, individual investors' feedback trade. Patel *et al.*

[4] In line with Richard Arms, creator of the contrary theory, who argues that if it is higher than 1 the market is oversold and generates an upward signal.

Table 2
Panel A: Correlation coefficients for the daily market sentiment indicators. Panel B: Descriptive data for the daily market sentiment indicators

Panel A

	PCV	PCO	ARMS
PCV	1	0.0767	0.0218
PCO		1	−0.0637
ARMS			1

Panel B

	Mean	Median	Standard deviation	Skewness	Kurtosis
PCV	1.2363	0.9155	1.5464	10.0547	154.7963
ΔPCV	0.0001	−0.0110	2.1151	−0.2349	90.7110
PCO	0.8074	0.7993	0.1129	0.4945	4.0935
ΔPCO	0.0002	0.0013	0.0294	−4.5489	55.4607
ARMS	3.0691	1.2109	5.4575	4.7410	35.7744
ΔARMS	0.0010	−0.0023	7.5894	−0.0866	20.3390

Panel A: This table shows the correlation coefficient for the daily market sentiment indicators: the put-call volume ratio (PCV), the put-call open interest ratio (PCO) and the ARMS index. Panel B: This table shows the descriptive data for the daily market sentiment indicators: the put-call volume ratio (PCV), the put-call open interest ratio (PCO) and the ARMS index. The changes of the series (preceded by the Δ symbol) are also shown.

(1991), for example, demonstrate that flows into mutual funds are an increasing function of recent market performance. Similarly, Sirri and Tufano (1998) present evidence that individual investors invest disproportionately in funds with strong prior performance. Also, consistent with the disposition effect, Odean (1998) presents evidence that individual investors are more likely to sell past winners than losers.

Other authors such as Grinblatt *et al.* (1995), Froot *et al.* (1998), Choe *et al.* (1999), Kim and Wei (2002a,b), within the context of momentum strategies, or Kremer (2010) within the context of institutional investment, show that herding is related to past returns, and this can be interpreted as evidence for herding.

Following these arguments, the return variable is considered as a proxy of the rational component of herding and is calculated, as usual in the financial literature, as $R_t = \mathrm{Ln}(P_t/P_{t-1})$, with P_t being the closing price of the Ibex-35 price on day t.

3.3. Causal linkages between herding intensity, stock returns and market sentiment

The first stage of the empirical analysis is aimed at testing for the presence of causal relationships between the herding intensity variables, market sentiment and stock returns and, if present, what direction they take. For this, an initial analysis is made to uncover any potential linear causal relationships using Granger's (1969) methodology, which is to test the variables pairwise.[5]

3.3.1. Herding and market sentiment

We begin by focusing on the relationship between the herding intensity variables and market sentiment. We do this by estimating a VAR model containing the two variables of interest, which in this case takes the following form:

$$
\begin{aligned}
H_{i,t} &= \alpha_1 + \sum_{j=1}^{n} \beta_j H_{i,t-j} + \sum_{j=1}^{n} \delta_j S_{k,t-j} + \varepsilon_{t1} \\
S_{k,t} &= \alpha_2 + \sum_{j=1}^{n} \phi_j H_{i,t-j} + \sum_{j=1}^{n} \gamma_j S_{k,t-j} + \varepsilon_{t2}
\end{aligned}
\tag{7}
$$

where H_i is the herding intensity measure calculated as described earlier, and i can take values of a, b or c, according to whether the herding sequence is upward, downward or zero tick; S_k denotes the market sentiment indicators and k can take three values, one for each of the indicators used, that is, PCV, PCO and ARMS. The number of lags included is determined on the basis of a likelihood test, starting the model with a high number of lags and reducing them until the optimal number is reached.[6] The causality test is based on the pairwise comparison of a restricted model and an unrestricted model and is χ^2 distributed with p degrees of freedom (the number of restricted coefficients).

The Granger causality test results obtained for the herding and market sentiment series are shown in Panel A of Table 3. The first two rows give the results for the different variables in levels and the last two rows show them in first differences. Overall, we are able to reject the hypothesis that sentiment does not cause herding; that is, the test reveals Granger causality running from market sentiment towards herding intensity, albeit with different levels of significance. In the opposite direction (herding does not cause sentiment), the null hypothesis can be rejected only in the case of *Ha* and *Hb* towards the ARMS index. The fact that we obtain feedback on this index and not on the other indicators may be because of the nature of the index that, like the herding measures, is derived from the spot market trading data. The PCV and PCO ratios can in fact be considered less noisy

[5] For further information on procedures for testing causality in the sense implied by Granger, see Geweke (1984) and Granger and Newbold (1986).

[6] The Schwartz Bayesian Criterion (SBC) instead of the Akaike Information Criterion (AIC) was used to determine the optimal number of lags, because the properties of the SBC are better suited to large samples. Nevertheless, a trial using the number of lags indicated by the AIC produced no change in the findings.

Table 3
Panel A: Results of the test for linear causality between herding intensity and market sentiment. Panel B: Results of the test for linear causality between herding intensity and PCO residual market sentiment (RPCO-PCV)

Panel A

	PCV			PCO			ARMS		
	Ha	*Hb*	*Hc*	*Ha*	*Hb*	*Hc*	*Ha*	*Hb*	*Hc*
H_0^{11}	17.1711 (0.0705)	16.9305 (0.0046)	13.0328 (0.0231)	16.8818 (0.0097)	11.5515 (0.0728)	11.1141 (0.0849)	23.6958 (0.0002)	10.3853 (0.0650)	11.6866 (0.0393)
H_0^{12}	4.1524 (0.5277)	2.9002 (0.7154)	1.5807 (0.9036)	6.5285 (0.3667)	8.6685 (0.1931)	8.2837 (0.2180)	13.0723 (0.0227)	15.1056 (0.0099)	6.7698 (0.2383)
H_0^{21}	9.5422 (0.0893)	16.4044 (0.0217)	13.5537 (0.0942)	14.6361 (0.0120)	12.9932 (0.0234)	12.9847 (0.0235)	27.3845 (0.0012)	3.2768 (0.8583)	13.8177 (0.0545)
H_0^{22}	3.3284 (0.6495)	5.1907 (0.6367)	2.3983 (0.9663)	2.4735 (0.7805)	5.2362 (0.3877)	5.5723 (0.3501)	9.3815 (0.4028)	7.8279 (0.3480)	3.2067 (0.8652)

Panel B

	RPCO-PCV		
	Ha	*Hb*	*Hc*
H_0^{11}	2.6762 (0.0457)	2.7796 (0.0398)	2.5244 (0.0392)
H_0^{12}	1.2382 (0.2943)	1.5554 (0.1983)	1.9238 (0.1039)
H_0^{21}	3.4833 (0.0153)	3.5056 (0.0148)	2.9146 (0.0331)
H_0^{22}	0.6614 (0.5757)	0.8996 (0.4406)	0.5142 (0.6725)

This tables shows the statistics together with their corresponding *P*-values in brackets, which under the null hypothesis are asymptotically chi-squared distributed. The number of lags included in the VAR models was determined by the Schwartz criterion. Panel A: H_0^{11} – Daily sentiment does not cause herding intensity. H_0^{12} – Herding intensity does not cause daily sentiment. H_0^{21} – Change in daily sentiment does not cause herding intensity. H_0^{22} – Herding intensity does not cause change in daily sentiment. Panel B: H_0^{11} – Daily PCO residual sentiment does not cause herding intensity. H_0^{12} – Herding intensity does not cause daily PCO residual sentiment. H_0^{21} – Change in daily PCO residual sentiment does not cause herding intensity. H_0^{22} – Herding intensity does not cause change in daily PCO residual sentiment. PCO, put-call open interest ratio; PCV, put-call trading volume ratio.

indicators when it comes to valuing sentiment, because what they capture is fundamentally expectations. The ARMS ratio, on the other hand, values reality at a given moment in time and is influenced by the real-time data arriving in the markets during a given trading day and therefore contains more than future expectations. This implies a higher degree of interaction between the herding intensity variables and the ARMS sentiment measure. As in the case of the variables in levels, we were able to conclude that changes in market sentiment do indeed have a causal effect on the level of herding intensity. The only case in which the result is non-significant is in the relationship between the change in the ARMS index and the herding measure in downward (seller-initiated)[7] sequences. Furthermore, we are unable to reject the hypothesis that herding intensity does not drive change in market sentiment, unanimously across all the sentiment indicators.

We find these results interesting in that the daily herding level may apparently be determined by the market sentiment that has arisen on the preceding days. In other words, daily market sentiment appears to be a key generating factor in herding behaviour. This is understandable if we consider that investors may be more inclined to herd if they feel the need to acknowledge the trading activity of a leader by mimicking his response to an overall view of market sentiment. For example, given a period of sustained pessimism, if the index starts to rise, herding investors wait to observe the position taken in the market by those they perceive to be better informed, which signals either change or continuity of the trend.

As mentioned earlier, the relation between the volume of options traded and the open interest deserves further attention to assess whether both the PCV and the PCO ratios are at least of equal interest from the point of view of explaining the causal relation between herd behaviour and market sentiment. To do this, we first run the regression of PCV as an explanatory variable of the PCO ratio. After confirming the statistical significance of the PCV ratio (*t*-statistic 3.21 at the 0 per cent significance level), we compute the regression residuals (RPCO-PCV) to obtain that part of the PCO ratio that is not explained either by the PCV ratio or the intercept. Then, we repeat the causality analysis between such residuals and the herding measure. Panel B of Table 3 shows the results. The conclusions remain unchanged, given that any of the derivatives-based ratios previously considered, as well as the PCO residuals, cause herd behaviour, indicating that all the proposed sentiment measures are equally important for our analysis.

3.3.2. Herding and returns

The next relationship to be analysed is the link between the herding intensity level and stock returns. The VAR model in this case is similar to the one above but substituting the variables:

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[7] As already mentioned, the nature of this index calls for caution when interpreting the results.

$$\begin{aligned} H_{i,t} &= \alpha_1 + \sum_{j=1}^{n} \beta_j H_{i,t-j} + \sum_{j=1}^{n} \delta_j R_{t-j} + \varepsilon_{t1} \\ R_t &= \alpha_2 + \sum_{j=1}^{n} \phi_j H_{i,t-j} + \sum_{j=1}^{n} \gamma_j R_{t-j} + \varepsilon_{t2} \end{aligned} \tag{8}$$

where H_i is the herding intensity measure, and i can take values of a, b or c, according to whether the herding takes place in an upward, downward or zero tick sequence and R_t denotes daily returns to the Ibex-35 index. The results of the causality tests are shown in Table 4. The causality revealed in this case runs from return performance to herding intensity in upward and downward sequences (but not in the zero tick sequences), although we cannot reject the absence of causality running from herding intensity (from *Ha*, *Hb* and *Hc*) to Ibex-35 stock returns. It would appear therefore that herding does not affect returns, whereas the past returns do influence herding behaviour among investors, allowing us to name past returns as a further component factor in herding intensity. In this respect, the use of momentum strategies, institutional investment or merely following a common signal on fundamentals might provide an explanation for the causal links between stock returns and herding.

3.3.3. Returns and sentiment

An important part of the literature on financial market sentiment deals with the analysis of the long-run sentiment–return relationship (Solt and Statman, 1988; Neal and Wheatley, 1998; Simon and Wiggins, 2001; Wang, 2001; Brown and Cliff, 2004; Baker and Wurgler, 2006; Kumar and Lee, 2006; Wang *et al.*, 2006; Baker *et al.*, 2009; and Chang *et al.*, 2009; are some examples).

Given that sentiment and stock returns are both factors in herding intensity, we now wish to test for a potential relationship between these variables within the same short-time horizon used for the analysis of the relation among herding and its components. To this end, we propose the following VAR model:

Table 4
Results of the test for linear causality between herding intensity and returns

	Ha	*Hb*	*Hc*
H_0^{31}: Returns do not cause herding intensity	25.2865 (0.0001)	15.3005 (0.0092)	5.0000 (0.5618)
H_0^{32}: Herding intensity does not cause returns	6.2109 (0.2862)	8.1493 (0.1482)	4.6971 (0.4540)

The table shows the statistics together with their respective *P*-values in brackets, which, under the null hypothesis, are distributed asymptotically as chi square. The number of lags included in the VAR models was determined by the Schwartz criterion.

$$\begin{aligned} R_t &= \alpha_1 + \sum_{j=1}^{n} \beta_j R_{t-j} + \sum_{j=1}^{n} \delta_j S_{k,t-j} + \varepsilon_{t1} \\ S_{k,t} &= \alpha_2 + \sum_{j=1}^{n} \phi_j R_{t-j} + \sum_{j=1}^{n} \gamma_j S_{k,t-j} + \varepsilon_{t2} \end{aligned} \tag{9}$$

where R_t is the daily return to the Ibex-35 and S_k denotes the daily market sentiment indicators, where k can take three values, one for each of the indicators used, that is, PCV, PCO and ARMS. The estimates are shown in Panel A of Table 5. In the case of PCO and ARMS, we reject the hypothesis of no impact of stock returns on either sentiment or changes in sentiment, whereas we confirm the absence of reverse causality. According to the PCV ratio, the causal link between these variables is feedback. Although in this case the results yielded by the various sentiment indicators fail to provide as clear an interpretation as in the previous relationships, we might say that past returns appear to drive daily sentiment. We have repeated the causality analysis between returns and PCO residual sentiment. The results in Panel B of Table 5 confirm that return causes PCO residual market sentiment, whereas the opposite causal relationship is not clear at all.

Table 5
Panel A: Results of the test for linear causality between returns and market sentiment. Panel B: Results of the test for linear causality between returns and PCO residual market sentiment (RPCO-PCV)

Panel A

	PCV	PCO	ARMS
H_0^{41}: Returns do not cause sentiment	18.1958 (0.0517)	15.4407 (0.0307)	4.3303 (0.0374)
H_0^{42}: Sentiment does not cause returns	26.4507 (0.0032)	3.0281 (0.8824)	1.2360 (0.2662)
H_0^{51}: Returns do not cause change in sentiment	17.7916 (0.0586)	13.5082 (0.0607)	56.1474 (0.0000)
H_0^{52}: Change in sentiment does not cause returns	28.8500 (0.0013)	4.3113 (0.7433)	6.7611 (0.3435)

Panel B

	RPCO-PCV
H_0^{41}: Returns do not cause daily PCO residual sentiment	2.0703 (0.0437)
H_0^{42}: Daily PCO residual sentiment does not cause returns	0.3488 (0.9312)
H_0^{51}: Returns do not cause change in daily PCO residual sentiment	1.8774 (0.0694)
H_0^{52}: Change in daily PCO residual sentiment does not cause returns	0.4281 (0.8851)

The table shows the statistics, together with their respective *P*-values in brackets, which, under the null hypothesis are asymptotically chi-squared distributed. The number of lags included in the VAR models was determined using the Schwartz criterion. PCV, put-call trading volume ratio.

These results merit close consideration as they provide evidence of an internal relationship between the two components of herding intensity, that is, stock returns and market sentiment, suggesting that stock returns may influence herding directly as well as indirectly through sentiment. Most of the research into this relationship finds causality running from sentiment to stock returns when using monthly or quarterly data, attributing it to noisy trading. Nevertheless, using a shorter horizon in which investor behaviour is measured by immediate events, it is reasonable to suppose that market behaviour may drive daily sentiment.[8,9]

3.4. The joint link between the level of herding intensity, stock returns and sentiment

Having detected that stock returns and market sentiment both have a linear cause–effect relationship with herding intensity, our next interest is to explore the directions of these relationships and discover whether the effect on herding is altered when the two are combined. For this, we propose an analysis in which we explain the herding level using lagged market sentiment and lagged returns.[10] As we can assume that the sentiment measures, although slightly correlated, are not redundant and can be used alternatively. The resulting model can be expressed as follows:

$$H_{i,t} = \alpha_1 + \sum_{j=1}^{n} \beta_j H_{i,t-j} + \sum_{j=1}^{n} \delta_j R_{t-j} + \sum_{j=1}^{n} \gamma_j S_{k,t-j} + \varepsilon_{t1} \tag{10}$$

where H_i, R_t and S_k denote the same as in Equations 7–9. As explained in the introduction, we could speak in terms of various herding components, taking these to be rational herding (approximated by past returns) and emotional herding (approximated by daily sentiment, either PCV, PCO or ARMS for robustness and comparison purposes). The models also contain the error term that represents that part of the herding measure that cannot be explained by the variables considered up to now.

The estimates of the above model are shown in Table 6, where Panel A gives the results for the regression using the PCV ratio as the daily sentiment indicator, Panel B displays the results for the regression using the PCO ratio and finally

[8] Solt and Statman (1988), Fisher and Statman (2000), Kumar and Lee (2006) and Wang *et al.* (2006) are some examples of these works. Brown and Cliff (2004), however, show that the relationship depends on the type of sentiment under analysis.

[9] We have tested for possible nonlinear causality between returns, sentiment and herding. The results do not provide evidence of nonlinear causal links among the variables analysed. Results are available upon request.

[10] In addition to the explanatory variables, five lags of the dependent variable are introduced in order to eliminate the autocorrelation noticeable in the series. The coefficients were estimated using White (1980) variance–covariance matrix.

Table 6
Results of the relationship between herding, returns and market sentiment

	Ha	*Hb*	*Hc*
Panel A			
Returns$_{t-1}$	−4.2677*** (0.0000)	2.1869** (0.0289)	−1.7106* (0.0873)
PCV$_{t-1}$	−2.0842** (0.0373)	−3.7004*** (0.0002)	−3.1098*** (0.0019)
Panel B			
Returns$_{t-1}$	−4.1771*** (0.0000)	2.3876** (0.0171)	−1.4555 (0.1457)
PCO$_{t-1}$	−0.2261 (0.8212)	−0.2266 (0.8208)	−1.0030 (0.3160)
Panel C			
Returns$_{t-1}$	−2.3571** (0.0185)	1.9509* (0.0512)	−0.4298 (0.6674)
ARMS$_{t-1}$	2.9742*** (0.0030)	−0.1503 (0.8805)	2.0288** (0.0426)
ARMS$_{t-2}$	−0.4169 (0.6768)	−2.3240** (0.0202)	−1.0086 (0.3133)

The table shows the *t*-statistics for the regression of the herding intensity measures on past returns and market sentiment. The regression included five lags of the dependent variable. The *P*-values are shown in brackets. PCO, put-call open interest ratio; PCV, put-call trading volume ratio. *** denotes significance at 1%, ** denotes significance at 5% and * denotes significance at 10%.

Panel C shows the results for the regression using the ARMS[11] index. The results for lagged returns are all significant, and the signs are the same in all cases. If the previous day's return goes up, the return increase raises the rational component of herding and we can therefore expect more herding of investors in buyer-initiated sequences, and less in seller-initiated sequences. In other words, positive (negative) past returns lead to a decline (increase) in the numerical value of the herding statistic in upward (downward) sequences, which implies higher (lower) herding levels in buyer (seller)-initiated sequences. When the previous day's returns are negative, the opposite effect will be observed; that is, investors will act more independently in bullish sequences while displaying herding behaviour in bearish sequences.

In any case, the data for daily market sentiment coincide in terms of their impact on herding levels, reminding us of the importance of the emotional component in herding behaviour, but the observed sign will depend on which sentiment indicator is considered. Thus, for the PCV ratio the sign of the coefficient of lagged sentiment is negative for all three types of sequence, therefore suggesting that pessimism increases the overall herding level. In other words, this indicator suggests that investors in these situations take more notice of both the buying and selling behaviour of other investors. The results for the PCO ratio, although negative, lack significance. Although the results in our previous analysis did not enable a decision to be made as to whether PCV and PCO was the better

[11] Unlike in the previous two cases, the table shows two market sentiment lags. This is because the second lag was found to be highly significant for *Hb*. It was omitted in the previous cases because tests showed that the second lag lacked statistical significance for these indicators.

derivatives-based sentiment measure, the joint analysis with the rational component suggests the usefulness of the PCV ratio as an explanatory variable.

The sentiment coefficients for the ARMS ratio are positive and statistically significant for *Ha* and *Hc* (the first lagged sentiment coefficient), whereas for *Hb*, the first lagged sentiment coefficient is not significant, but the second is. This suggests, firstly, that when the impact is on sales, investors are slower to react to sentiment and their memory is longer. By standard interpretation, the higher the ARMS index, the more bearish the market sentiment is. In regression terms, this means that the more bearish the sentiment, the more likely we are to find less herding in upward and zero tick sequences and more herding in downward sequences in the following period.

The choice between PCV and ARMS is not so easy, although both reveal their relevance in downwards sequences. Perhaps their different interactions with stock returns and their different origins may serve to explain the differences in the results.

Because the model presented is not deterministic but has an error term, there is a residual part of the herding measure that is not explained by the rational and emotional components. This random unexplained term can be associated with a different component that has not been sufficiently discussed in the empirical literature, namely neglect herding. This variable could be linked to certain characteristics of financial assets that can be considered as herding attractors such as firm size, trading volume, liquidity or the activity sector where they are included. In the particular case of a stock index, this term could be a common ingredient shared by all the assets included. It could also be related with a bearish or a bullish market or with some country characteristics (information availability, culture, type of investors, etc.) that could motivate herd behaviour. In spite of these considerations, the presence of investors with different motivations and trading strategies also influences the error term formation. It should be noted that it is very difficult to test the presence of all these factors in the error variable, specially in the index. However, we think that this error or neglect herding should be treated as playing a complementary role to the emotional and rational factors previously mentioned. This unmeasurable ingredient would encompass that part of the herd phenomenon that is because of sheer laziness or an innate tendency towards imitation.

Overall, these results show that both variables, stock returns and market sentiment, are key factors underlying the level of herding behaviour and also that they are interrelated. Therefore, investors' decision-making may be affected either by their return expectations, based on the analysis of key fundamentals, or by prevailing market sentiment and their herding instinct.

3.5. Predicting herding intensity

Finally, to provide an additional tool for the analysis of the components of investor herding, we aim to determine whether the rational and emotional components actually offer any clue as to the likelihood of future herding. With this idea in mind, we propose some potential models that might enable us to predict the intensity of future herding as a function of one or more of the proposed variables (stock returns or market sentiment, measured by one of the indicators considered, or a combination of the above). Initially, we start from a fifth-order autoregressive model (given that this is the number of lags that have been observed to be significant) in which the herding level is explained by its own lags. We then keep adding different variables to see whether they improve the power of the model to predict herding intensity. All the proposed models are given in Appendix I.

To obtain the prediction, the models are estimated for the period 1997–2002 and out-of-sample predictions, both static and dynamic, are calculated for the year 2003. Table 7 shows the error terms for each model and type of prediction. The first column shows the square root of the prediction error, column two contains the mean absolute error (MAE) and column three the mean absolute percentage error (MAPE). Given that investors will not attach the same importance to underestimation errors as to overestimation errors, we calculate two additional measures proposed by Brailsford and Faff (1996) called measure of underestimation error (MME(U)) and MME(O), respectively. The MME(U) measure, which penalises underestimation errors more heavily, is calculated as follows:

$$\mathrm{MME(U)} = \frac{1}{N}\left[\sum_{t=1}^{O}\sqrt{\left|\hat{H}_{i,t} - H_{i,t}\right|} + \sum_{t=1}^{U}\left|\hat{H}_{i,t} - H_{i,t}\right|\right] \tag{11}$$

where O is the number of predictions that underestimated the value of H, U is the number of predictions that overestimated the value of H, and N is the total number of predictions. The MME(O) measure, which penalises overestimation errors more heavily, is calculated as follows:

$$\mathrm{MME(O)} = \frac{1}{N}\left[\sum_{t=1}^{O}\left|\hat{H}_{i,t} - H_{i,t}\right| + \sum_{t=1}^{U}\sqrt{\left|\hat{H}_{i,t} - H_{i,t}\right|}\right]. \tag{12}$$

The results are similar in all cases. In the static *Ha* prediction, the lowest prediction errors were obtained with the return model and ARMS, while in the dynamic prediction the best model was that using lagged stock returns and the PCV ratio as the explanatory variables, except in the case of the MME error, which takes the model that used returns and changes in the PCO ratio. In the static *Hb* prediction, the square root of the error term selects the model that used only five lags and the PCV ratio, while the rest of the error measures select the one that used returns and the PCV ratio. In the dynamic prediction, the error measures select the five lag model with the ARMS index. In the case of *Hc*, in the static prediction, MAE and MAPE statistics show the ARMS model to be the best, while the square root of the error term and the MME would recommend the return and PCV model. In the case of the dynamic prediction, all the

Table 7
Prediction errors in the herding intensity models

	Static prediction					Dynamic prediction				
	√	*MAE*	MAPE%	MME(U)	MME(O)	√	MAE	MAPE%	MME(U)	MME(O)
Ha										
1	1.2250	0.9684	9.2154	0.9709	0.9042	2.2621	1.8881	16.8676	1.9178	1.2771
2	1.2135	0.9509	9.0622	0.9552	0.8908	2.2230	1.8650	16.6961	1.9022	1.2813
3	1.2266	0.9695	9.2252	0.9715	0.9048	2.3020	1.9271	17.2237	1.9649	1.3000
4	1.2256	0.9682	9.2136	0.9717	0.9073	2.2609	1.8871	16.8584	1.9115	1.2740
5	1.2248	0.9685	9.2183	0.9708	0.9050	2.2790	1.9037	17.0071	1.9315	1.2841
6	1.2288	0.9701	9.2329	0.9716	0.9065	2.2632	1.8895	16.8825	1.9366	1.2860
7	1.2082	0.9436	8.9788	0.9483	0.8849	2.3658	2.0163	18.1252	2.0738	1.3576
8	1.2191	0.9532	9.0614	0.9548	0.8889	2.2596	1.8870	18.1252	1.9171	1.2875
9	1.2140	0.9513	9.0635	0.9564	0.8919	2.2481	1.8891	16.9150	1.9359	1.2951
10	1.2130	0.9506	9.0595	0.9568	0.8925	2.2240	1.8659	16.7038	1.8770*	1.2716*
11	1.2105	0.9486	9.0380	0.9528	0.8892	2.2140*	1.8552*	16.6018*	1.8935	1.2777
12	1.2147	0.9520	9.0731	0.9558	0.8922	2.2240	1.8659	16.7038	1.9046	1.2821
13	1.2055*	0.9389*	8.9443*	0.9440*	0.8801*	2.3175	1.9721	17.7250	2.0258	1.3406
14	1.2118	0.9443	8.9912	0.9482	0.8834	2.2323	1.8725	16.7630	1.9093	1.2874
Hb										
1	1.3350	1.0014	9.3697	1.0016	0.9004	2.4365	2.0483	18.1930	2.0700	1.3481
2	1.3410	1.0012	9.3512	1.0049	0.8953	2.5090	2.1045	18.7376	2.1271	1.3646
3	1.3359	1.0013	9.3695	1.0017	0.8997	2.4595	2.0668	18.4137	2.0979	1.3585
4	1.3356	1.0013	9.3698	1.0005	0.9004	2.4284	2.0340	18.1112	2.0320	1.3332
5	1.3291*	0.9959	9.3160	0.9977	0.8968	2.4159	2.0106	17.8675	2.0415	1.3327
6	1.3330	0.9997	9.3566	1.0007	0.8983	2.4353	2.0426	18.1933	2.0766	1.3508
7	1.3358	0.9997	9.3476	1.0008	0.8964	2.4095*	2.0063*	17.8393*	2.0147*	1.3194*
8	1.3351	1.0016	9.3726	1.0024	0.8993	2.4361	2.0429	18.1946	2.0702	1.3482
9	1.3414	1.0013	9.3523	1.0049	0.8947	2.5159	2.1116	18.8025	2.1381	1.3689
10	1.3413	1.0013	9.3537	1.0022	0.8957	2.4983	2.0933	18.6342	2.0703	1.3435
11	1.3343	0.9954*	9.2944*	0.9973*	0.8927*	2.4706	2.0562	18.2685	2.0809	1.3437
12	1.3385	0.9987	9.3313	1.0015	0.8943	2.5060	2.1027	18.7232	2.1134	1.3600
13	1.3410	1.0010	9.3493	1.0036	0.8944	2.5041	2.0988	18.6837	2.1005	1.3519
14	1.3416	1.0009	9.3469	1.0046	0.8938	2.5156	2.1103	18.7900	2.1326	1.3669
Hc										
1	0.9326	0.6865	12.4059	0.7868	0.7365	1.8458	1.5442	26.2444	1.5659	1.1699
2	0.9310	0.6834	12.3575	0.7848	0.7349	1.8494	1.5513	26.3968	1.5733	1.1750
3	0.9328	0.6865	12.4123	0.7866	0.7368	1.8487	1.5477	26.3110	1.5754	1.1764
4	0.9327	0.6862	12.4023	0.7859	0.7359	1.8418	1.5401	26.1699	1.5627	1.1680*
5	0.9303	0.6859	12.4034	0.7864	0.7350	1.8449	1.5410	26.1746	1.5627	1.1683
6	0.9319	0.6869	12.4159	0.7878	0.7366	1.8455	1.5441	26.2427	1.5720	1.1729
7	0.9275	0.6796*	12.2811*	0.7851	0.7366	1.8586	1.5676	26.7319	1.5933	1.1858
8	0.9300	0.6810	12.3302	0.7854	0.7362	1.8442	1.5429	26.2231	1.5668	1.1708
9	0.9305	0.6831	12.3570	0.7843	0.7348	1.8432	1.5454	26.2915	1.5743	1.1762
10	0.9309	0.6831	12.3543	0.7835	0.7338	1.8435	1.5454	26.2909	1.5605	1.1685
11	0.9275*	0.6822	12.3418	0.7835*	0.7323*	1.8372*	1.5369*	26.1289*	1.5597*	1.1685

Table 7 (continued)

	Static prediction					Dynamic prediction				
	√	*MAE*	MAPE%	MME(U)	MME(O)	√	MAE	MAPE%	MME(U)	MME(O)
12	0.9299	0.6838	12.3721	0.7855	0.7342	1.8484	1.5508	26.3908	1.5701	1.1735
13	0.9280	0.6796	12.2836	0.7848	0.7361	1.8670	1.5766	26.8969	1.6009	1.1890
14	0.9299	0.6804	12.2939	0.7851	0.7360	1.8531	1.5536	26.4271	1.5777	1.1765

The table shows the prediction error estimates for each of the proposed models. √, square root of error; MAE, mean absolute error; MAPE, mean absolute percentage error; MME(U), measure of underestimation error; MME(O), measure of overestimation error. *Minimum error values.

error terms select the past return and PCV model, except MME(O), which selects the model that used changes in PCO.

In all cases, the inclusion of the return and/or sentiment variables can be seen to increase the predictive power of the model beyond that of the simple autoregressive model. The most predictive market sentiment measure is in fact the PCV ratio, followed by the ARMS ratio and changes in the PCO ratio, both on their own and in conjunction with returns. We are able to conclude that, in the proposed models, 'neglect herding', the innate tendency to herd, accounts for <20 per cent (9 per cent in static prediction and 17 per cent in dynamic prediction, according to the MAPE) of the herding intensity in either upward or downward sequences. These results reinforce our earlier comments to the effect that both returns and market sentiment appear to shape investor herding behaviour, and we must therefore stress the importance of these variables in herding prediction models. In fact, the models yield better herding intensity predictions when the most subjective component of this type of behaviour (that marked by sentiment) is considered.

4. Conclusions

This paper focuses on exploring the components of herding behaviour. Given the problems entailed in distinguishing how much of herding is caused by consensus on underlying fundamentals and how much is caused by emotional factors or the innate tendency to herd, the paper aims to explain the component factors of daily herding levels by performing causality tests on variables that we consider feasible proxies for the said components. Furthermore, given that there is strong interrelation between the objective and subjective variables and that this may be taken into account by the agents intervening in the market, we try to examine whether past returns are part of the source of herding behaviour, either directly or indirectly through the formation of market sentiment.

The herding intensity measure used in the paper is one based on information cascades and originally proposed by PSY (2006), which we calculate from intraday data on Ibex-35 stocks in the Spanish capital market during the period 1997–2003.

The results obtained support causality running from short-term sentiment to herding intensity. We also find evidence for the existence of a causal relationship running from returns to the intensity of herding in the market. These findings together with the existing relationship between returns and market sentiment lead us intuitively to believe these to be, whether directly or indirectly, key factors in investors' herding behaviour.

The confluence of these factors in a single model allows us to conclude that each one possesses its own separate capacity to explain the herding intensity level, while the herding instinct in itself (or neglect herding) can be determined from the model. An additional finding is that these variables are also useful in models for predicting herding intensity. By using models similar to those proposed, in combination with more sophisticated instruments, herding episodes and information cascades could be forecast, helping investors and authorities to speed up their response to extreme market movements.

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Appendix I

Prediction models used

$$(1)\quad H_{i,t} = \alpha_1 + \sum_{j=1}^{5} \beta_j H_{i,t-j} + \varepsilon_{t1}$$

$$(2)\quad H_{i,t} = \alpha_2 + \sum_{j=1}^{5} \beta_j H_{i,t-j} + \delta_1 R_{t-1} + \varepsilon_{t2}$$

$$(3)\quad H_{i,t} = \alpha_3 + \sum_{j=1}^{5} \beta_j H_{i,t-j} + \delta_2 \mathrm{PCO}_{t-1} + \varepsilon_{t3}$$

$$(4)\quad H_{i,t} = \alpha_4 + \sum_{j=1}^{5} \beta_j H_{i,t-j} + \delta_3 \Delta\mathrm{PCO}_{t-1} + \varepsilon_{t4}$$

$$(5)\quad H_{i,t} = \alpha_5 + \sum_{j=1}^{5} \beta_j H_{i,t-j} + \delta_4 \mathrm{PCV}_{t-1} + \varepsilon_{t5}$$

$$(6)\quad H_{i,t} = \alpha_6 + \sum_{j=1}^{5} \beta_j H_{i,t-j} + \delta_5 \Delta\mathrm{PCV}_{t-1} + \varepsilon_{t6}$$

$$(7) \quad H_{i,t} = \alpha_7 + \sum_{j=1}^{5} \beta_j H_{i,t-j} + \delta_6 \mathrm{ARMS}_{t-1} + \varepsilon_{t7}$$

$$(8) \quad H_{i,t} = \alpha_8 + \sum_{j=1}^{5} \beta_j H_{i,t-j} + \delta_7 \Delta\mathrm{ARMS}_{t-1} + \varepsilon_{t8}$$

$$(9) \quad H_{i,t} = \alpha_9 + \sum_{j=1}^{5} \beta_j H_{i,t-j} + \delta_8 \mathrm{PCO}_{t-1} + \tau_1 R_{t-1} + \varepsilon_{t9}$$

$$(10) \quad H_{i,t} = \alpha_{10} + \sum_{j=1}^{5} \beta_j H_{i,t-j} + \delta_9 \Delta\mathrm{PCO}_{t-1} + \tau_2 R_{t-1} + \varepsilon_{t10}$$

$$(11) \quad H_{i,t} = \alpha_{11} + \sum_{j=1}^{5} \beta_j H_{i,t-j} + \delta_{10} \mathrm{PCV}_{t-1} + \tau_3 R_{t-1} + \varepsilon_{t11}$$

$$(12) \quad H_{i,t} = \alpha_{12} + \sum_{j=1}^{5} \beta_j H_{i,t-j} + \delta_{11} \Delta\mathrm{PCV}_{t-1} + \tau_4 R_{t-1} + \varepsilon_{t12}$$

$$(13) \quad H_{i,t} = \alpha_{13} + \sum_{j=1}^{5} \beta_j H_{i,t-j} + \delta_{12} \mathrm{ARMS}_{t-1} + \tau_5 R_{t-1} + \varepsilon_{t13}$$

$$(14) \quad H_{i,t} = \alpha_{14} + \sum_{j=1}^{5} \beta_j H_{i,t-j} + \delta_{13} \Delta\mathrm{ARMS}_{t-1} + \tau_6 R_{t-1} + \varepsilon_{t14}.$$