Laboratoire
de Recherche
en Gestion
& Economie

Working Paper
2011-03

What drives the herding behavior of individual investors?

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July 2011

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What drives the herding behavior of individual investors?*

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June 2012

Abstract

We introduce a new measure of herding that allows for tracking dynamics of individual herding. Using a database of over 8 million trades by 87,373 retail investors between 1999 and 2006, we show in an original way that individual herding is persistent over time and that past performance and the level of sophistication influence this behavior. We are also able to answer a question that was previously unaddressed in the literature: is herding profitable for investors? We demonstrate, as a primary result, that the investors trading against the crowd tend to exhibit more extreme returns and poorer risk-adjusted performance than the herders.

*We are grateful to the brokerage firm that provided us with the data for this study. We thank Raphaëlle Bellando, Patrice Fontaine, Sonia Jimenez-Garces, Achim Mattes, Andrey Ukhov and Russ Wermers, as well as seminar participants at the 2011 Academy of Behavioral Finance and Economics, 2012 Annual Meeting of the Midwest Finance Association, 2012 EFM Symposium on Asset Management, 2012 AFFI Conference, Grenoble University and Strasbourg University, for comments and suggestions. The second author gratefully acknowledges a PhD scholarship from Région Rhône-Alpes.

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1 Introduction

Herding behavior, defined in a broad way as an investor's imitation of the actions of others, has been widely documented for institutional investors but less studied for individual investors. In this paper, we characterize the herding behavior of individual investors using the trading records of 87,373 investors at a major European brokerage house over the 1999-2006 period. We address three research questions. 1) Do poor past portfolio returns lead investors to subsequently follow the crowd? 2) Do sophisticated investors herd more than others? 3) Does herding hurt or boost individual performance?

To answer these questions, we introduce an original investor-specific herding measure that estimates the herding intensity of a given investor at any moment in time. This new measure leads us to evaluate the influence of individual attributes (especially sophistication) on herding behavior. Furthermore, we elucidate the strong links between the herding level, the past portfolio returns and the future portfolio performance.

Imitating other agents could be rational or irrational. The latter type of herding is extremely difficult to capture empirically because it is driven by fashion and fads. In our empirical study, we essentially focus on the former type, namely rational herding. Devenow and Welch (1996), in a literature survey emphasize three reasons for rational herding. The first reason is payoff externalities (the outcome of an action is increasing in the number of agents undertaking it). These payoff externalities generate trading patterns that are caused by liquidity issues. It has been documented that investors tend to trade at the same time to benefit from a deeper liquidity (Admati and Pfeiderer, 1988; Dow, 2005).

Reputational effects are the second reason for rational herding. These effects are particularly important in the principal-agent models. It can be said that a manager hides in the herd. The idea behind this metaphor is that the performance of an institutional trader is very often considered relative to a benchmark (the average performance of other managers or the performance of a market/industry index). By closely following the benchmark, the manager sacrifices the potential to perform better than average but hedges himself against a poor relative performance. Models of herding caused by reputational concerns can be found in Scharfstein and Stein (1990), Rajan (1994) or Graham (1994).

Finally, the third explanation for rational herding is informational externalities. In Bikhchandani *et al.* (1992) and Welch (1992), investors acquire (noisy) information by observing the actions of other agents. Information externalities can be so strong that an investor can decide to completely ignore his own signal. In an extreme case of information externalities, individuals do not carry information anymore because their actions result only from the imitation of others. In that case, an informational cascade occurs.

Early studies such as Lakonishok *et al.* (1992) investigate a method to empirically measure correlated trading across groups of investors. The idea underlying the measure proposed by the authors (the LSV measure, hereafter) is to quantify the buying pressure on a given asset for a homogeneous subgroup (pension funds, mutual funds, individual investors). For the market as a whole, each purchase is balanced by a sale. However, for a given subgroup of investors and a given asset, there can be an excess of purchases or sales, indicating that the investors in the subgroup herd. After the seminal work of Lakonishok *et al.* (1992), herding among investors has been the subject of a number of empirical studies, which are divided in two categories. The first category primarily addresses institutional investors and the second category addresses individual investors. The present paper belongs to this second stream of the literature.

The mimetic behavior of U.S. mutual funds and institutional investors has been scrutinized (Lakonishok *et al.*, 1992; Grinblatt *et al.*, 1995; Wermers, 1999). Similar studies have been performed outside of the U.S., in particular in Germany (Oehler, 1998; Frey *et al.*, 2007; Kremer et Nautz, 2011), the United Kingdom (Wylie, 2005), Portugal (Loboa and Serra, 2002) and Poland (Voronkova and Bohl, 2005).

In the second category of studies, targeting individual investors, the number of studies is lower. These studies have been performed in the U.S. (Barber *et al.*, 2009), Germany (Dorn *et al.*, 2008), Israel (Venezia *et al.*, 2010) and China (Feng and Seasholes, 2004). Briefly speaking, all of these studies demonstrate that the trades of individuals are significantly correlated. The herding behavior is clearly stronger for individuals than for fund managers and exhibits a strong persistence over time (Barber *et al.*, 2009). This behavior is positively and significantly correlated with the volatility of the market returns (Venezia *et al.*, 2010). Addressing the drivers of these findings, Barber *et al.* (2009) show that psychological biases contribute to herding behavior. These biases, for instance, lead investors to buy stocks with strong recent performance or with an abnormally high trading volume. In an original way, Feng and Seasholes (2004) demonstrate a positive relationship between the herding behavior of Chinese investors and their trading location.

Even if the LSV measure has been widely used to study the herding behavior of investors (and, particularly, the influence of stock characteristics), this measure suffers from some drawbacks. In particular, it does not permit for an evaluation of the herding level of a given investor, and thus, fails to evaluate herding persistence over time at the investor level. Furthermore, the drivers of the individual herding behavior cannot be deeply studied.

Our first contribution is a new measure of individual herding behavior. Our measure (the Individual Herding Measure, denoted IHM in the following) overcomes this drawback and is in the spirit of the measure proposed by Grinblatt *et al.* (1995). We evaluate the individual herding in a given quarter by the weighted sum of the signed LSV measures of the assets for which changes in holdings for the quarter under consideration occur. Over the entire eight-year period under study, our results demonstrate a strong persistence of the herding behavior over time at the investor level. The average first-order autocorrelation of our IHM is equal to 12.43%. Our preliminary analysis of the herding behavior at the asset level, using the LSV and Frey *et al.*'s (2007) measures, already notes the persistence of herding and provides results that are consistent with Barber *et al.* (2009). One of the main advantages of our individual measure lies in the potential for investigating the individual heterogeneity of the herding behavior. The study of the individual heterogeneity of this behavior is the second contribution of our paper. We demonstrate that a poor past performance increases the propensity to herd in the next quarter. By using direct and indirect measures of sophistication (derivatives trading or portfolio value, for example), we show that sophisticated investors are less prone to herd after a poor past performance.

However, the main contribution of the paper is to show that, contrary to the other individual investors, those trading against the crowd earn an abnormal return by doing so. Unfortunately, this premium is not sufficient to compensate for the higher risk that they bear. Consequently, they perform poorly, compared to the average investor.

This paper is structured as follows. Section 2 is dedicated to the data. Section 3 is dedicated to the estimation of herding at the stock level. In section 4, we describe the individual herding measure and examine the factors that affect individual herding. The last section concludes the paper.

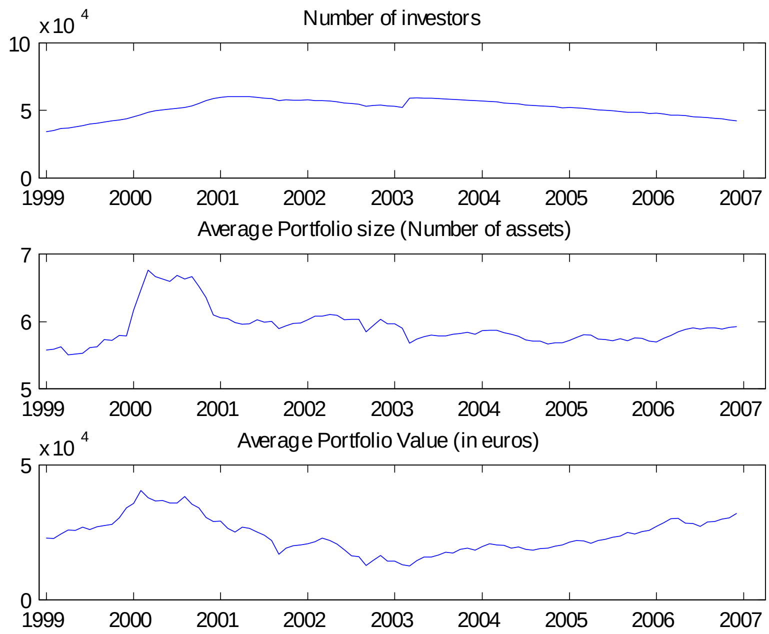
2 Data and descriptive statistics

The primary data set used in this study is a record of the daily transactions of 87,373 French investors at a major European brokerage house. From this record, we computed the daily stock portfolio of each investor for the January 1999-December 2006 period. We are therefore able to calculate the daily realized returns. To calculate these returns, we extracted the closing prices (adjusted for splits and dividends) of the traded securities from Bloomberg (1,180 stocks) and Eurofidai[1] (1,311 stocks). A little over one thousand securities were ignored because of missing data. However, these securities accounted only for 1.51% of the total number of transactions. Of the 2,491 stocks under consideration, there are 1,190 French stocks. The remaining are from the U.S. (1,020), Great Britain (62), Canada (35), the Netherlands (34), Germany (31), Italy (15) and others (104). It should be noted that the trading volume across the different countries is not homogeneous: French stocks represent over 90% of the trading volume while U.S. stocks account for under 1%.

To compute the LSV herding measure, we consider the portfolios at the beginning of each quarter (January, April, July and October) for the years 1999 to 2006. For a given quarter, we exclude the investors that have no investment in stocks. On average, there are 51,266 investors with at least one position. The average number of stocks held by investors is 5.9, the median is 4 and the maximum is 503. The average Herfindahl index of diversification is 0.4836. The average portfolio value is 23,896 €, and the median is 6,454 €. It appears that the sample of investors contains a few very wealthy individuals. Figure 1 below shows the evolution, from January 1999 to December 2006, of the number of investors, the average number of assets, and the average portfolio value. To gain a deeper look into the structure of the data, we present in Table 1 the distribution of portfolio values conditioned on the number of assets held, at three points in time.

[1] European Financial Data Institute

Figure 1: Summary Statistics



3 Herding behavior at the asset level

3.1 The LSV measure and extensions

One of the first herding measures was introduced by Lakonishok *et al.* (1992). This measure aims to evaluate the herding behavior among pension funds. The underlying idea is that herding can be measured as the tendency for traders to accumulate on the same side of the market for a given stock and during a given period. To determine on which side (buy or sell) of the market the investor is, we observe the difference between the number of shares held at time t and at time $t-1$[2]. We note $n_{i,j,t}$, the number of shares of asset j held by investor i at time t. If the difference $n_{i,j,t} - n_{i,j,t-1}$ is positive (respectively, negative), investor i increased (decreased) her holdings and thus is on the buy (sell) side. For a given asset j, the purchase intensity $p_{j,t}$ is defined as the number of investors that increased their holdings divided by the number of investors that traded the asset. We write

[2]We stress the fact that the variations in holdings between $t-1$ and t correspond to the variations in the number of shares and not in weight because price variations would incur artificial increases or decreases. It is also important to point out that corporate actions such as splits, new issues, etc., must be taken into account.

$$p_{j,t} = \frac{\sum_{i=1}^{I_{j,t}} b_{i,j,t}}{\sum_{i=1}^{I_{j,t}} \left(b_{i,j,t} + s_{i,j,t}\right)} = \frac{1}{I_{j,t}} \sum_{i=1}^{I_{j,t}} b_{i,j,t}, \tag{1}$$

where $I_{j,t}$ is the number of active traders over the period $[t-1;t]$ and $b_{i,j,t}$ $(s_{i,j,t})$ is a binary variable that takes the value 1 if the investor i increased (decreased) her holdings of asset j between $t-1$ and t and takes the value 0 otherwise.

It follows that it is possible to compute the purchase intensity, and thus the LSV measure, only for a subgroup of investors,because for the whole universe of investors, the number of purchases equals the number of sales. Formally, the LSV herding measure of asset j at time t is written as

$$LSV_{j,t} = |p_{j,t} - p_t| - AF_{j,t}, \tag{2}$$

where p_t is the purchase intensity across all stocks and $AF_{j,t}$ is an adjustment factor[3] due to the absolute value in the definition of $LSV_{j,t}$ and the fact that the number of traders $I_{j,t}$ varies across stocks and over time.

The quantity p_t is subtracted to account for liquidity shocks. To illustrate this point, let us assume that for the majority of assets, the individual investors aggregate on the buy side. This aggregation does not necessarily mean that they herd: it can be the result of a new fiscal disposition that favors investments in the stock market rather than traditional saving accounts. The aggregation results in high buying pressure among the individual investors as they withdraw their money from the saving accounts and invest it in the stock

[3] In order to obtain an unbiased measure in the case of no herding, the adjustment coefficient needs to satisfy $AF_{j,t} = E\left[|\varepsilon_{j,t}|\right]$. We thus write

$$\begin{aligned} AF_{j,t} &= E\left[\left|\frac{\sum_{i=1}^{I_{j,t}} b_{i,j,t}}{I_{j,t}} - p_t\right|\right] = \frac{1}{I_{j,t}} E\left[\left|\sum_{i=1}^{I_{j,t}} b_{i,j,t} - p_t I_{j,t}\right|\right] \\ &= \sum_{k=0}^{I_{j,t}} \binom{I_{j,t}}{k} (p_t)^k (1-p_t)^{I_{j,t}-k} \left|\frac{k}{I_{j,t}} - p_t\right|. \end{aligned} \tag{3}$$

market. By subtracting p_t, we take into consideration the aggregate shifts in and out of the stock market and separate them from the herding behavior.

As mentioned before, the LSV measure suffers from a few drawbacks and has therefore been exposed to a certain number of criticisms. The LSV measure does not allow us to observe the intertemporal herding behavior of investors. We are able to follow how investors herd over time on a given asset, but we cannot observe the persistence in herding of a given investor. The second part of this paper will address this issue by introducing an investor-specific herding measure. Among the other criticisms addressed to the measure, Bikhchandani and Sharma (2001) first note that the LSV measure captures both intentional and unintentional (or spurious) herding. According to their definition, an investor is said to herd intentionally if, by observing the other investors' actions, he prevents himself from making an investment he would have made otherwise (or conversely, he undertakes an investment that he would not have undertaken otherwise). In other words, intentional herding corresponds to a deliberate imitation of others' actions. Alternatively, spurious herding occurs when investors with similar preference sets are provided with the same information. Separating these two types of herding is important because the latter is an efficient outcome whereas the former can destabilize markets and increase volatility. A second issue discussed by Bikhchandani and Sharma (2001) is that the LSV measure considers only the number of traders and ignores the amount that is bought or sold. Oehler (1998) and Wermers (1999) propose derived measures that aim to remedy this problem. This issue has important consequences when studying the impact of herding on the market. However, because we adopt a more behavioral approach and focus on the drivers of the herding behavior, this issue does not have important consequences for our results.

Finally, Frey *et al.* (2007) show that under the alternative hypothesis of herding, the measure is biased downward. Therefore, because the adjustment factor does not depend on the herding level, the LSV measure is biased downward and this bias increases with the herding level. These authors also prove that the bias declines with the number of active traders $I_{j,t}$. We will see in the empirical results that the level of herding rises when we impose a minimum number of active traders. This observation has crucial consequences for the interpretation of the empirical results. For example, Dorn *et al.* (2008) establish a link between differences in opinion (proxied by trading activity) and herding behavior because they observe a very important positive correlation between trading activity and herding. It appears that the properties of the adjustment factor might explain part of the observed correlation. Indeed, the higher the trading activity, the lower the bias and the higher the herding measure. Even if trading activity and herding behavior were independent, a positive correlation would appear.

To remedy this problem, Frey *et al.* (2007) propose using square values instead of absolute values in the expression of the LSV measure. Formally, their new measure is defined as:

$$FHW_{j,t}^{2} = \left((p_{j,t} - p_t)^2 - E\left[(p_{j,t} - p_t)^2 \right] \right) \frac{I_{j,t}}{I_{j,t} - 1}, \tag{4}$$

where the notations are the same as in the previous equations.

For a given time period t and a universe of J stocks, the average FHW measure is computed as:

$$\overline{FHW} = \sqrt{\frac{1}{J} \sum_{j=1}^{J} FHW_{j,t}^{2}}. \tag{5}$$

Monte-Carlo simulations show that this new measure does not suffer from the bias that exists for the LSV measure. Frey *et al.* (2007) show that for varying values for the number of active traders and/or for the level of herding, their measure is unbiased and possesses good statistical properties.

However, Bellando (2010) shows that the measure is unbiased only in the particular setting considered by Frey *et al.* (2007). As soon as the probability of no herding is not null or when some asymmetry is introduced, the measure is biased upward. However, it is possible to show that the true value of herding lies between the LSV and the FHW values.

3.2 General results

Table 2 provides the values of the semiannually, quarterly and monthly LSV and FHW measures for all stocks (line 1) for the entire period. These measures are also calculated with respect to, for each stock, a level of capitalization (Large, Medium, Small), a level of volume of trading (High, Medium, Low) and, finally, an industry classification (based on the ICB industry classification). Table 3 shows the results for the two measures for each quarter between 1999 and 2006.

At a general level, the monthly average value of the LSV measure for all stocks is 0.126. Briefly speaking, this level means that for a given stock during a given month, approximately 13% more investors are on the same side than would be predicted if decisions were randomly taken. This result supports the previous findings that individual investors herd more than institutional investors. For instance, in the U.S. market, Lakonishok *et al.* (1992) provide an average value for institutional investors of 0.02 and Wermers (1999) reports a value of 0.036. More recently, Venezia *et al.* (2011) calculate an average herding measure of 0.058 for the Israeli market.

Our findings indicate that French individual investors exhibit a high degree of herding. Our results are consistent with the findings for U.S. individual investors (Barber *et al.*, 2009) but are slightly higher than those of Dorn *et al.* (2008) for Germany. More precisely, the monthly average value of the LSV measure for all stocks is 0.1279 in the US against 0.064 in Germany. As in Dorn *et al.* (2008), the results highlight correlated trading across all horizons and all industries and the correlation is higher for the longer observation intervals. Concerning the impact of the capitalization, our results, using the LSV measure, confirm the findings of Dorn *et al.* (2008) and contrast with those of Barber *et al.* (2009) and of previous studies of institutional investors that demonstrate that investors herd more on small firm stocks (Wermers, 1999, for example). In fact, we find that correlated trading is higher for larger capitalizations. Note that this result is not obtained for all quarters (23/31 quarters, see Table 3, Column "Market capitalization"). However, this result is not robust when using the FHW measure. Indeed, with this last measure, we find that for 18/31 quarters, herding is more pronounced for smaller capitalizations.

Finally, the LSV measure takes a higher value for the stocks ranked in the "high volume of trading" category. Even if further investigations are needed, this result could be due to a concentration of purchases in attention-grabbing stocks (Barber and Odean, 2008; Barber *et al.*, 2009) or to informational signals. Note that this result is effective for 21/31 quarters (see Table 3, Columns "Volume of trading"). Once again, this result is not robust when we use the FHW measure instead (only 8/31 quarters where the herding is higher for the "high volume of trading" category). Considering these findings, it is natural to wonder how the downward bias of the LSV measure (see the previous section) could impact our results. Comparing the level of the two measures (Tables 2 and 3), it is apparent that the value of the FHW is sharply higher whatever the category (or the quarters) under study. At a general level, the monthly average value of the FHW measure for all stocks is 21.70%. The herding behavior is also 1.72 times stronger when this last measure is implemented. Note that this difference is stable when the observation intervals are modified (6 months or 3 months). Finally, for monthly observation intervals, we can conclude that the true value of herding for French individual investors is high and takes a value between 12.63% and 21.70%.

To go one step further, in the next section we conduct some tests in the spirit of Barber *et al.* (2009) to analyze the persistence of herding behavior over time.

3.3 Persistence in herding

In this section, we adopt another approach (following the methodology used by Barber *et al.*, 2009) to test whether investors' trading decisions are correlated. We also analyze the persistence, at the asset level, of the herding behavior. The herding behavior is said to be persistent if the autocorrelation of the purchase intensity $p_{j,t}$ is high: a high (respectively low) level of purchase intensity at time t is followed by a high (low) level in the consecutive periods.

For each month, we divide the population of investors into two equally sized random groups. We then calculate the assets' monthly purchase intensity $p_{j,t}^{G_1}$ (respectively, $p_{j,t}^{G_2}$) resulting from the transactions of group 1 (group 2). If the investors' trading decisions are independent, we should observe no correlation between the purchases intensities $p_{j,t}^{G_1}$ and $p_{j,t}^{G_2}$. The transaction records span over 8 years, resulting in a time-series of 96 contemporaneous correlations between purchases intensities. We then compute the average correlation and employ a t-test to check whether the average correlation is significantly different from 0. As explained by Barber *et al.* (2009), the null hypothesis of no correlation is similar to the null hypothesis of no herding in the LSV and FHW herding measures. As in the previous analysis, it is not possible to distinguish between spurious and intentional herding. The rejection of the null hypothesis only indicates that trading decisions are correlated, but it does not allow us to verify whether the investors intentionally herd.

Once we show that investors engage into correlated trading, we aim to see if they tend to herd on the same assets over time. A high persistence in the herding behavior would indicate that herding is influenced by characteristics that do not change much over time such as industry classification, index membership and market capitalization. On the contrary, a low persistence might indicate that herding is dynamic and is a direct reaction to new information, new market conditions or new trading strategies.

To measure the persistence of herding, we first compute for each month the correlation between stock purchase intensities at time t and time $t + \tau$ with $\tau = 0, ..., 36$. For $\tau = 1$, we measure the correlation between the purchase intensities between month t and the consecutive month. We thus obtain a time series of 95 correlations that we average to obtain the general persistence for a horizon equal to 1. It follows that we have a time-series of 94 correlations for $\tau = 2$, ..., and a time-series of 60 correlations for $\tau = 36$. We first compute these correlations for the entire set of investors. In a second calculation, we compute this persistence for two random groups of investors (in the fashion of the analysis for contemporaneous correlations which is actually the particular case where $\tau = 0$). That is, we compute the correlation between the purchase intensities obtained from the transactions of group 1 at time t, and the purchases intensities obtained from the transactions of group 2 at time $t + \tau$.

Table 4 presents contemporaneous and time-series correlations of the purchase intensities. The first row ($\tau = 0$) indicates the contemporaneous correlation of purchase intensities between groups 1 and 2. We observe that the average correlation is very strong (a little over 85%), indicating that the investors' trading decisions are highly correlated. Our correlation is 10 points higher than the correlation found by Barber *et al.* (2009). This finding is coherent with the fact that we also obtain slightly higher values for the LSV measure. It follows that by knowing the purchase intensities associated with one group, we are able to explain over 2/3 of the variations in purchase intensities of the second group. The rest of the table presents the correlations between the purchase intensities at time t and time $t+\tau$ where $\tau = 1, ..., 36$. The persistence between two consecutive months is expressed by an average correlation of 30.27%. The average correlations are all significantly different from zero up to a horizon of $\tau = 15$. In comparison to Barber *et al.* (2009), the correlations are slightly lower (30.27% instead of 46.7% for a horizon of one month) and the persistence fades at a faster rate (the correlation at a 6 month horizon is 9.10% in our study compared to 16.4% in Barber *et al.*, 2009).

4 Measuring herding at the investor level

4.1 The Investor Herding Measure (IHM)

One of the drawbacks of the LSV measure is that it is not possible to compute an investor-specific measure. Thus, we cannot determine whether only some of the investors herd and whether some investor-specific characteristics influence the herding behavior, nor can we observe the persistence in the herding of investors. To analyze the tendency of individual investors to herd, we first need to discriminate between buy herding ($p_{j,t} > p_t$) and sell herding ($p_{j,t} < p_t$). Following Grinblatt *et al.* (1995) and Wermers (1999), we consider the signed herding measure defined by:

$$SLSV_{j,t} = \begin{cases} LSV_{j,t} \mid p_{j,t} > p_t \\ -LSV_{j,t} \mid p_{j,t} < p_t \end{cases} = \begin{cases} p_{j,t} - p_t - AF_{j,t} \\ p_{j,t} - p_t + AF_{j,t} \end{cases}. \tag{6}$$

Grinblatt *et al.* (1995) introduced the Fund Herding Measure (FHM) defined as:

$$FHM_{i,t} = \sum_{j=1}^{J} (\omega_{i,j,t} - \omega_{i,j,t-1})\, SLSV_{j,t} \tag{7}$$

where $\omega_{i,j,t}$ is the weight of asset j in the portfolio of the i^{-th} fund at time t.

This measure is quite appealing, but it poses the problem that an investor can be seen as herding on an asset that he does not trade. Indeed, a transaction on one asset only causes the weights of all of the other assets in the portfolio to change.

We propose introducing a new measure, the Investor Herding Measure (IHM), that considers herding only for the assets that are actually traded by the investor. For a given transaction, there are six possible scenarios represented below:

	Purchase	**Sale**
SLSV > 0	Herding	Anti-Herding
SLSV < 0	Anti-Herding	Herding
SLSV = 0	No Herding	No Herding

If an investor trades only one asset, her herding value will be equal to the signed LSV measure of the asset if the transaction is a purchase (the investor increases her holdings in this asset) and to minus the signed LSV measure otherwise. When trading several assets, it is less obvious how to compute the individual herding value. A first approach would be to sum the signed herding measures of every asset purchased and to subtract those of the assets that were sold. This solution has two drawbacks. First, it does not consider the size of the transactions. Second, this measure is not bounded (in the sense that it is not independent with the number of assets traded by the investor). As a consequence, the first drawback is that the zero-herding assets are not taken into consideration (a situation where an investor substantially increased her holdings on her zero-herding assets and only slightly on a high buy-herding asset will result in a high individual herding measure). To illustrate the second drawback, let us consider an investor who makes only one purchase of asset 0 with a signed herding measure equal to $SLSV_0 > 0$. As stated above, her individual herding measure will be equal to $SLSV_0$. Now, let us consider another investor who purchases assets $1, ..., n$ with equal herding measures $SLSV_1, ..., SLSV_n = SLSV_0$. The second investor will achieve an individual herding measure of $n \times SLSV_0$, that is, n-times the herding measure of the first investor. We adopt a solution that resolves both of these problems: the herding value of an asset is weighted by the size of its transaction and the sum of the weighted herding measure is then divided by the total sum of the transactions of the investor over the period. Formally, we write

$$IHM_{i,t} = \frac{\sum_{j=1}^{J} \left(n_{i,j,t} - n_{i,j,t-1}\right) \overline{P}_{j,t} SLSV_{jt}}{\sum_{j=1}^{J} \left|n_{i,j,t} - n_{i,j,t-1}\right| \overline{P}_{j,t}}, \tag{8}$$

where $n_{i,j,t}$ is the number (adjusted for corporate actions) of the shares of asset j held by investor i at time t, and $\overline{P}_{j,t}$ is the average price of asset j over the period $[t-1; t]$. It follows that $\left(n_{i,j,t} - n_{i,j,t-1}\right) \overline{P}_{j,t}$ is the average value of the asset j transaction and the denominator in the formula is the total value of all of the transactions[4] made by investor i in the considered period.

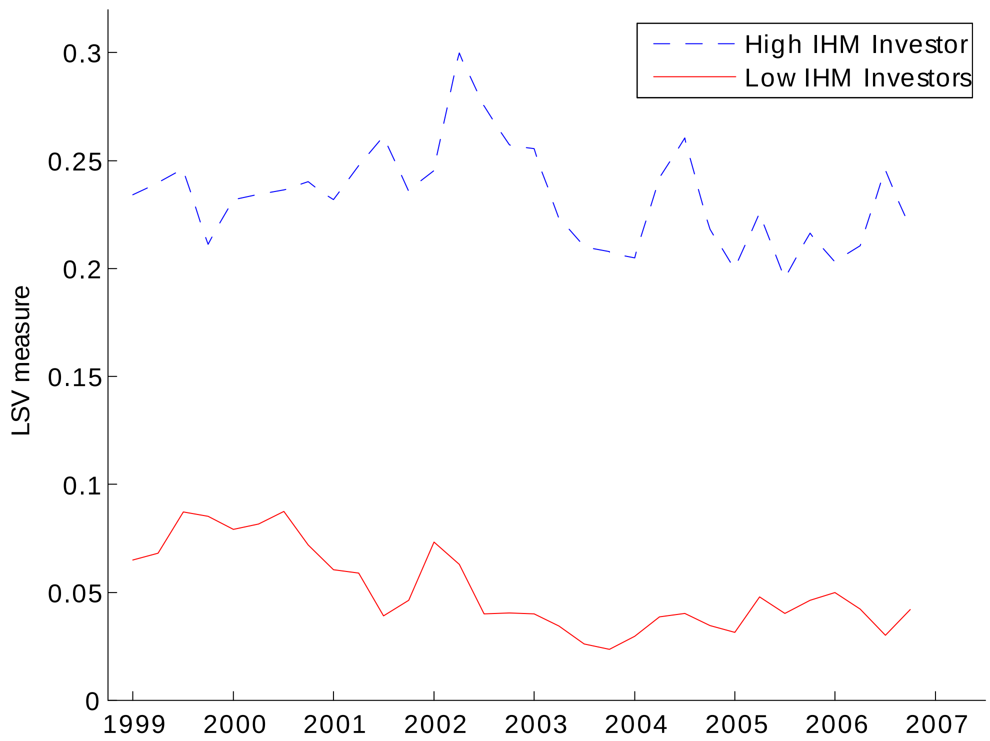
In this way, we account for the herding coefficient of assets only for those that are traded during the quarter, and we weight them by the size (euros-volume) of the transactions.

[4] We only observe the number of shares at time t and $t-1$ but not the sequence of transactions during the period under study. Hence, we chose to use the average price to evaluate the value by which the investor increased or decreased her holdings.

The IHM measure indicates that investor i is herding if it takes a positive value and that he is going against the herd if the value is negative.

A first confirmation of the validity of this measure is to separate the population of investors into two equally sized subgroups: low and high IHM investors. We then compute the standard LSV measure for both subgroups. We observe in Figure 2 that the difference between the two subgroups is quite important and highly significant[5], which appears to support the validity of our measure to evaluate herding at the individual level.

Figure 2: LSV measure for high IHM investors and low IHM investors



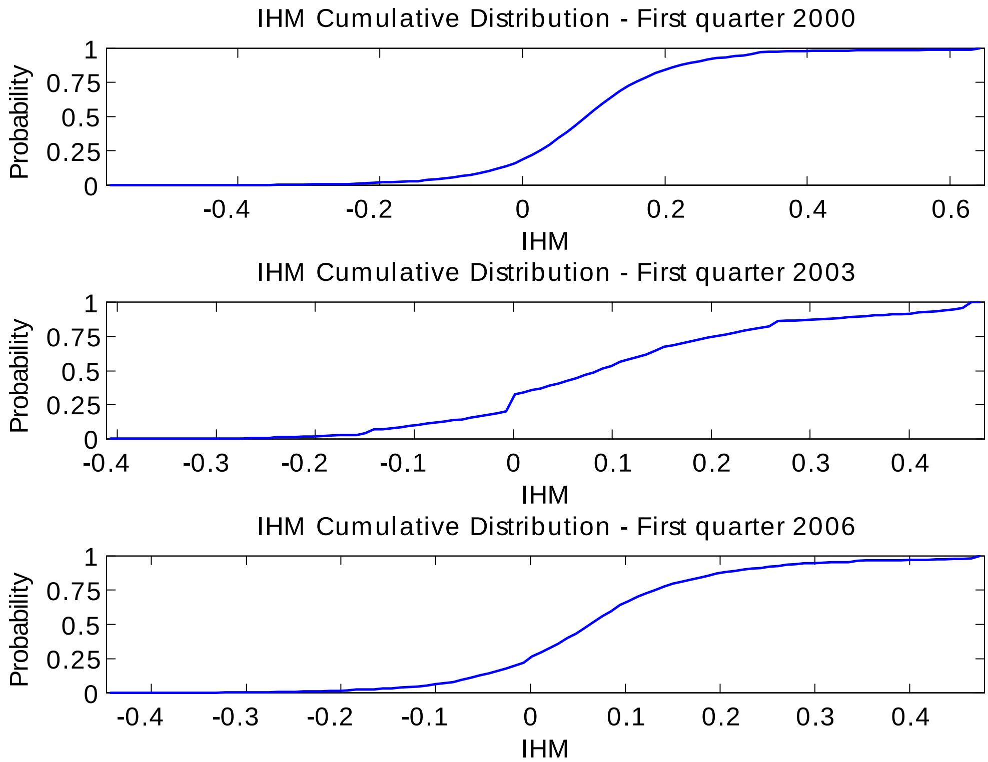
4.2 General results and persistence

We first provide a brief overview of the computed IHM values. Figure 3 gives the distribution of the IHM at three time points (first quarter of 2000, 2003 and 2006). Not

[5]Significance tests were done using Monte-Carlo simulations. The results are not reported here.

surprisingly, we observe that most individuals have a positive IHM value. The average IHM value is equal to 0.1003 for the first quarter of 2000, 0.1078 for the first quarter of 2003 and 0.0770 for the first quarter of 2006. The medians are, respectively, 0.0954, 0.0887 and 0.0675. In the first part of the article, we showed that the LSV and FHW values were much higher in the beginning of the sample period. The computed IHM values are coherent with these initial results.

Figure 3: Empirical cumulative distribution of IHM



Using the same methodology as that employed to measure the persistence at the asset level, we check whether there is significant autocorrelation in the investor herding behavior. That is, we verify if a high herding (anti-herding) behavior at a quarter t is followed by high herding (anti-herding) in the subsequent quarters. The presence of a strong autocorrelation would tend to indicate that some investors are more prone to herd, regardless of the time-period considered. The results in Table 5 give an average correlation of 12.43% between the IHM values of two consecutive quarters. The correlations appear to be significant for a horizon up to four years with a minimum of 4.74%. It follows that the herding behavior shows some signs of persistence. However, this persistence is relatively weak and these results call for a deeper investigation of the components of the individual herding behavior.

4.3 Performance, investor attributes and the Investor Herding Measure

4.3.1 The relationship between sophistication and herding

In this section, we focus on whether the investor's profile determines part of the observed herding behavior. The baseline assumption is that some investors might be more prone to herd than others (regardless of the market conditions or other time-varying variables). We test different characteristics such as gender, sophistication and the wealthiness of individuals. The gender differences in investment behavior are well-documented. For instance, Barber and Odean (2001) investigate overconfidence by using a "gender approach" and show that men are more overconfident than women, leading them to trade 45% more than women. This behavior consequently hurts portfolio performance and reduces net returns. It follows that it is a natural choice to test whether the herding intensity differs between women and men. Our second hypothesis is that more sophisticated investors herd less on average. A number of researchers have documented the role played by sophistication on trading behavior. For instance, the individual differences in the disposition effect - which describes the tendency of investors to more readily sell winning stocks than losers - are significantly related to financial sophistication (Feng and Seasholes, 2005; Dhar and Zhu, 2006). Because sophisticated investors have a better ability to obtain and manage information (or, at least, they have the impression that they do), the need to rely on others' information is less pronounced.

In this paper, sophistication is proxied by three variables. The first proxy is the investor's total number of transactions made over the sample period. The second proxy is a dummy variable that is equal to one if the investor is trading warrants in addition to common stocks and zero otherwise. Compared to "traditional" instruments, trading warrants requires familiarity with option-like payoffs. The third proxy is the investor average portfolio value. It accounts for the wealth of the individuals. Of course, this proxy is imperfect and only partially reflects the real wealth (or the individual income) of the investor. These three measures are valid under the assumption that the investors' attributes are relatively stable over time. From a methodological point of view, the fact that we use data from $t+\tau$ to discriminate investors at time t can appear startling or even wrong. However, under the assumption that characteristics do not change radically over the sample period, these measures provide us with proxies that do not vary over time and that carry little noise. A change of behavior (for exogenous reasons) in one unique quarter has a negligible impact on the measures that we use to capture the investors' profiles.

The results are presented in Table 6. We first report the average IHM values for male and female investors. The warrant characteristic discriminates investors between those that trade warrants and those that do not. For the third attribute, we distinguish between investors who execute fewer than 100 trades and those who trade over 200 times. For the average portfolio value, the first subgroup contains investors with an average portfolio value below 5000 €. The second subgroup is formed by the investors whose value is above 100,000 €.

Because we do not know the theoretical distribution of the difference between two average IHM values, we use Monte-Carlo simulations to estimate the empirical distribution. The methodology that we apply to compute the p-values associated with the test of no difference between two average IHM values is the following. For a given attribute and a given quarter, we compute the average IHM of the two subgroups that we denote as $\overline{IHM}_1$ and $\overline{IHM}_2$. $\overline{IHM}_1$ (respectively, $\overline{IHM}_2$) is the average of the n_1 (n_2) IHM values of the investors that belong to the first (second) subgroup. To estimate the empirical distribution of the difference, we randomly divide the population of investors into two subgroups of size n_1 and n_2. We compute the average IHM for each subgroup and calculate the absolute value of the difference, which we denote as $\left|\overline{IHM}_1^* - \overline{IHM}_2^*\right|$ This step is then repeated 10000 times. The p-value ξ associated with the test of no difference is then equal to

$$\xi = \frac{1}{10000} \sum_{k=1}^{10000} 1_{\left\{\left|\overline{IHM}_1 - \overline{IHM}_2\right| < \left|\overline{IHM}_{1,k}^* - \overline{IHM}_{2,k}^*\right|\right\}}, \tag{9}$$

where $\overline{IHM}_1$ ($\overline{IHM}_2$) is the average IHM value of the investors that belong to the first (second) subgroup and $\overline{IHM}_{1,k}^*$ ($\overline{IHM}_{2,k}^*$) is the average IHM value associated with the first subgroup of n_1 (n_2) investors obtained by randomly dividing the sample for draw k.

The quarterly results are provided in Table 6. It appears that, on average, women herd more than men. The average IHM value for men is 0.1051 compared to a value of 0.1094 for women. However, the reported p-values indicate that, for most quarters, the difference is not significant. The results for sophistication reveal that the investors who trade warrants have, on average, a lower herding intensity than the investors who do not. The individuals with a low number of transactions tend to herd more than the investors who trade frequently. For both sophistication attributes, the differences are highly significant. In particular, when considering the number of transactions, we observe a very high magnitude (up to 8 points) difference between the two subgroups' average IHM values. The average IHM value for the subgroup associated with a low number of transactions is 0.1150, whereas the value for the subgroup associated with a high number of transactions is only 0.0870. Finally, we observe differences between the two subgroups when discriminating by the portfolio's average value. Although these differences are significant for most quarters, their sign varies over the different quarters and prevents us from drawing any clear conclusion.

4.3.2 Relationship between past performance and herding

To go deeper in our analysis, we evaluate the influence of the investors' past performance on herding. We use the investors' quarterly gross returns, computed from their daily positions. The portfolio returns are estimated using total returns (*i.e.*, dividends are included) calculated using Eurofidai and Bloomberg data. We deliberately ignore the intraday movements and assume that the transactions are evaluated using day closing quotes. The gross quarterly return $R_{i,t}$ for investor i and quarter t is therefore calculated as

$$R_{i,t} = \prod_{\tau=1}^{n_t} \left(1 + \sum_{j=1}^{N_{i\tau}} \omega_{j,\tau} r_{j,\tau} \right) - 1, \tag{10}$$

where n_t is the number of days in quarter t; $N_{i\tau}$ is the number of stocks composing the portfolio of investor i for day τ of quarter t; $\omega_{j,\tau}$ is the weight of stock j and $r_{j,\tau}$ is its daily return.

In our first analysis, we compute the Spearman rank correlation between investor's IHM and the four moments of the investors' portfolio past returns for each quarter. The results in Table 7 indicate that there exists a strong rank correlation between the past average returns and the investors' herding (all but four coefficients are significant at a 1% level). However, the sign of these coefficients varies over time without any clear pattern. The coefficients for the Spearman correlation between the IHM and the portfolio's standard deviation are all significant and negative. This result means that the less risky investors are those that herd the most. The results for skewness[6] are less clear because only 20/28

[6] Mitton and Vorkink (2007) show that individual investors have a heterogeneous preference for skewness. This heterogeneity helps explain why individual investors are underdiversified.

of the coefficients are significant at a 1% level and the sign changes over time.

So far, we are not able to determine precisely how an investor's own past performance influences her herding behavior. However, it appears clear that a relationship exists. We now wish to exploit both the cross-section and the time dimensions of our database. For each quarter, we compute the investors' IHM value, past performance, level of diversification, and portfolio value. We then have unbalanced panel data[7]. We aim to test the influence of past performances that vary across individuals and over time. We thus run a panel data regression. The results of the Hausman test lead us to reject the null hypothesis of random effects. We therefore choose to include both the investor and the time fixed effects. We estimate the past performances by using the risk-adjusted past return, that is, the return of the portfolio divided by its standard deviation. The formulation of the regression is the following:

$$\begin{aligned} IHM_{i,t} &= \gamma_0 IHM_{i,t-1} + \gamma_1 IHM_{i,t-2} + \sum_{\tau=1}^{2} \beta_\tau RAR_{i,t-\tau} \\ &\quad + \theta EXP_{i,t} + \alpha_1 IFE_i + \alpha_2 TFE_t + \varepsilon_{i,t}, \end{aligned} \tag{11}$$

where $IHM_{i,t}$ is the herding value of investor i in quarter t, $RAR_{i,t-\tau}$ is the performance of investor i in the quarter $t-\tau$ and $EXP_{i,t}$ is the investor experience, proxied by the cumulative number of trades made up to quarter t by investor i. IFE_i are the individual fixed effects and TFE_t are the time fixed effects.

We do not add any lag for the experience EXP because the individual investors in our sample do not trade frequently and thus the experience is not expected to change significantly from one quarter to another. By incorporating several lags, we would include multicollinearity in the regression. Additionally, we include two lags for IHM because more lags would too dramatically reduce the size of our sample. Thus, we consider the observations that correspond only to investors trading 3 quarters consecutively. The results are presented in Table 8 (IFE and TFE not reported). The lags of the herding measure appear to be significant and negatively correlated with the herding measure. The estimates of the coefficients are -0.0614 for lag 1 and -0.0312 for lag 2. The coefficients for the performance over the preceding quarter and the quarter before that take the negative values -0.0165 and -0.0208 and are significant. This result confirms our hypothesis that poor past performance creates incentives to herd. Additionally, we note that the variable EXP

[7] The panel is unbalanced because investors are excluded from the quarters where they do not trade.

is significant and negative. This finding indicates that, as investors acquire experience on the stock market (and therefore knowledge), they tend to rely more on their private information.

In models 2 to 4, we condition the performance RAR to the realization of a sophistication variable. The new variable is equal to the risk-adjusted return if the characteristic is realized and 0 otherwise. The sophistication characteristics are the same as those used in the previous section. We find that trading warrants has an impact on the coefficient of the performance variable. Indeed, the coefficient for RAR_{t-1} is not significantly different from 0 for the investors that trade warrants, while it is negative and highly significant for the others. When considering the second lag ($t-2$), both coefficients are negative and significant, but the effect is lower for the sophisticated investors. In Model 3, we use the total number of transactions as the sophistication variable. For the first lag, the performance is significant and negative for investors with fewer than 200 trades while it is not significant for the investors associated with a high number of transactions. For the second lag, although the coefficient is significant and negative for the active investors (over 200 transactions), it is much lower than the coefficients for the investors that do not trade frequently. In Model 4, the sophistication is proxied by the Average Portfolio Value. The results are consistent with Models 3 and 4. We observe that the effect of past performance is weaker for sophisticated investors (*i.e.*, investors with a high Average Portfolio Value).

4.4 Payoff externalities

A question that was not yet addressed in the literature is whether there are payoffs externalities associated with the herding behavior. In other words, we want to check whether there is a rational motivation for this behavior that can be expressed in terms of increased performance. At an aggregate level, some concerns are that herding could increase volatility and destabilize markets (Bikhchandani and Sharma, 2001). However, the literature is nearly non-existent on the consequences of herding on the investors' performance. A simple reason for this dearth of information is the lack of herding measures at the individual level. We remedied this problem by introducing the Individual Herding Measure (IHM) in the previous section.

A preliminary analysis consists in computing the Spearman correlation between the IHM values and the investors' average return, standard deviation, skewness and kurtosis for each quarter. The results in Table 9 appear to indicate that a relationship exists between herding and returns. The correlation between the IHM and the average return is significant for nearly all quarters. However, the sign does not remain the same for every quarter. We thus cannot yet determine the relationship between the two variables. The results for the standard deviation are easier to interpret. All of the coefficients are negative and significant at a 1% level indicating that herders hold less risky portfolios. The interpretation of the coefficients for skewness and kurtosis is not straightforward because they change signs and are not all significant.

To extend our analysis on the influence of herding on performance, we build four average investors for whom we compute performance measures. First, we consider an average investor who is representative of the entire population. His return is calculated as

$$R_t^{AV} = \frac{1}{I_t} \sum_{i=1}^{I_t} R_{i,t}, \tag{12}$$

where I_t is the number of investors for quarter t.

We then form, for each quarter, an average investor for each herding category, whom we designate as an anti-herder, an independent trader and a herder. These three average investors correspond, respectively, to investors trading against the crowd (determined by an IHM value below -0.05), investors trading independently of others (defined by $-0.05 \leq IHM \leq 0.05$) and investors engaging in a herding behavior ($IHM > 0.05$)[8]. The anti-herder quarterly return R_t^{AH} is estimated to be:

$$R_t^{AH} = \frac{1}{I_t^{AH}} \sum_{i=1}^{I_t} R_{i,t} 1_{\{IHM_i < -0.05\}}, \tag{13}$$

where I_t is the number of investors who trade at least once during quarter t and I_t^{AH} is the number of investors with IHM values below -0.05.

The independent trader return R_t^{IT} is computed as

$$R_t^{IT} = \frac{1}{I_t^{IT}} \sum_{i=1}^{I_t} R_{i,t} 1_{\{-0.05 \leq IHM_i \leq 0.05\}}, \tag{14}$$

[8]The limit of 0.05 is arbitrary determined. However, our results do not change if we impose different bounds (in the neighborhood).

where I_t^{IT} is the number of investors with IHM values between -0.05 and 0.05.

Finally, the herder return R_t^H is

$$R_t^H = \frac{1}{I_t^H} \sum_{i=1}^{I_t} R_{i,t} 1_{\{IHM_i > 0.05\}}, \tag{15}$$

where I_t^H is the number of investors with IHM values above 0.05.

We follow the approach of Barber and Odean (2000) when choosing the performance measures. First, we compute the own-benchmark abnormal return. For a given quarter, this return is simply the return that would have been obtained by the beginning-of-quarter portfolio if no transactions had been made. For each quarter and each individual, the abnormal return is thus computed as the difference between the realized return (computed from daily returns) and the own-benchmark return. Our second benchmark is the quarterly market-adjusted return. This return is simply the difference between the investors' realized return and the market return. Our third benchmark is the intercept obtained from Carhart's (1997) four-factor model. The intercept is obtained by estimating the following time-series regression:

$$R_{i,t} - R_{f,t} = \alpha + \beta \left(R_{m,t} - R_{f,t} \right) + \theta SMB_t + \lambda HML_t + \eta MOM_t + \varepsilon_{i,t},$$

where $R_{f,t}$ is the EURIBOR 3-month rate, $R_{m,t}$ is the quarterly return on the French CAC All-Tradable index[9], SMB_t and HML_t are the two additional Fama-French (1993) factors, respectively the quarterly return on a zero-investment size portfolio and the quarterly return on a zero-investment book-to-market portfolio. The last coefficient MOM_t is the momentum factor (Jegadeesh and Titman, 1993), which is the quarterly return on a zero-investment momentum portfolio[10].

The results for the four average investors (the investor representative of the whole population, the anti-herder, the independent trader and the herder) are presented in Table 10. We obtain a negative and significant (as in Barber and Odean, 2000) coefficient of -0.23% for the own-benchmark abnormal return. This result means that the investors would earn an additional 0.23 point by keeping their portfolio unchanged. More interestingly, we observe a clear negative relationship between the own-benchmark abnormal return and

[9] This index (also called SBF250) is composed of the 250 largest capitalizations on the French market.
[10] The index and the Carhart (1997) factors are provided by Eurofidai (www.eurofidai.org).

the Individual Herding Measure (IHM). It appears that the investors who trade against the crowd dramatically increase their performance by trading contrary to the rest of the population. This finding suggests that the trades made by anti-herders are motivated by information. The results for the market-adjusted return and the intercept from the Carhart (1997) four-factor model are not significant. This finding is not surprising because the under-diversification and the particularities of the individual investors make these benchmarks unfit. It is worth noting however, that the anti-herders and independent traders hold much more aggressive portfolios than herders. The market betas for these investors are, respectively, 1.3734 and 1.3859 compared to 1.2976 for herders. The tilt toward small stocks is relatively strong for independent traders (the SMB coefficient takes the value 0.5016). Because the probability of trading with the other investors in the sample is lower for smaller capitalizations, the investors who invest mainly in small capitalizations tend to have an IHM value close to zero (because the LSV value of the stocks they trade is zero).

To go one step further in our analysis, we choose another approach that evaluates investors' returns, conditional on their herding behavior, relative to the rest of the sample. That is, we want to evaluate whether an investor that herds has better performance than the rest of the investors in the sample and, more generally, if there exists a relationship of dependence between performance and herding.

For each quarter, we build a 10×3 contingency table where the quarterly returns are divided into ten deciles and investors are split in three categories (anti-herders, independent traders and herders defined as before). The generic element α_{ij} of the table is the number of investors in decile i and category j. To test the null hypothesis of independence between herding and returns, we use a χ^2 test. The advantage of this test is that nothing is assumed about the type of relationship between the two variables (returns and IHM); in particular, does not need to be linear. The component of the chi-square CS_{ij} for decile i and category j is calculated as

$$CS_{ij} = \frac{\left(\alpha_{ij} - \alpha_{ij}^{*}\right)^2}{\alpha_{ij}^{*}}, \tag{16}$$

where α_{ij} is the observed number of investors for decile i and category j and α_{ij}^{*} is the theoretical number of investors that should be observed under the null hypothesis of independence.

The global chi-square value GCS is simply equal to:

$$GCS = \sum_{i=1}^{10}\sum_{j=1}^{3} CS_{ij} \rightsquigarrow \chi^2\left((10-1)(3-1)\right). \qquad (17)$$

The chi-square values for the 32 quarters from January 1999 to December 2006 range from 59.90 to 520.64 (unreported). With a critical value of 28.87 for 18 degrees of freedom, these results indicate the existence of a relationship between herding and returns. We then perform the same analysis with Sharpe ratios instead of returns. We obtain chi-square values ranging from 22.56 to 230.90. We then reject the null hypothesis of independence between the IHM and the Sharpe ratios for nearly all quarters.

The limitation of the chi-square test is that while we are able to show that a relationship exists between herding and performance, we cannot distinguish whether the herders perform better or worse than the other investors. To make this distinction, we build, for each quarter, a new contingency table where the generic element α_{ij} corresponds to the ratio of the observed number of investors for decile i and category j over the theoretical number that would be observed for this decile and this category if the IHM and performance were independent[11]. If the generic element α_{ij} is greater than one, it means that there are more investors for this decile and this category than should be observed if there was independence between herding and performance.

Because we do not know the theoretical distribution of the number of investors for a given decile and a given category, we need to estimate it. The process that is used is similar to the one for Table 6. Each decile (category) contains $d_{i,\ i=1,\ldots,10}$ $(c_{j,\ j=1,\ldots,3})$ investors. For a given quarter, we randomly separate the investors in the sample into ten categories (corresponding to the deciles) of sizes $d_{i,\ i=1,\ldots,10}$ and in three categories of sizes $c_{j,\ j=1,\ldots,3}$. We then compute the number of investors $\overline{I_{ij}}$ for each decile and category. We repeat this step 10000 times. The p-value ξ_{ij} associated with the test of no difference between the observed number of investors and the theoretical one is then

$$\xi_{ij} = \frac{1}{10000}\sum_{k=1}^{10000} 1_{\left\{\left|I_{ij}-I^*_{ij}\right|<\left|\overline{I_{ijk}}-I^*_{ij}\right|\right\}}, \qquad (18)$$

where I_{ij} is the observed number of investors for decile i and category j, I^*_{ij} is the theoretical number of investors that should be observed under the null hypothesis of independence

[11] The theoretical number of investors for decile i and category j is equal to the number of investors in decile i times the number of investors in category j divided by the total number of investors.

and $\overline{I_{ijk}}$ corresponds to the number of investors observed at draw k (where the sample is randomly divided).

Table 11 shows, for each decile i and category j, the average of the generic elements α_{ij} of the 32 contingency tables computed for each quarter from January 1999 to December 2006. The numbers in brackets indicate the number of quarters for which the observed number of investors is significantly different than the theoretical number at a 5% level (using p-values computed with Monte-Carlo simulations as explained previously). In addition, we estimate the statistical significance of the coefficients by applying a t-test on the 32 values obtained.

We observe that the anti-herders have a higher probability of exhibiting extreme returns. For the lowest (highest) return decile, this category contains 27% (15%) more investors than it would contain under independence. On the contrary, the values taken for deciles 4 through 8 range from 0.8866 to 0.9255. The result for the herders is the complete opposite. We find that the herders are underrepresented in the lowest and highest deciles while there are more investors than would be expected under independence in the intermediate ones. The lowest (highest) decile contains 7% (5.5%) fewer investors than would be observed if the herding behavior had no impact on performance.

The results for Panel B (using Sharpe ratios instead of returns) are even more striking. For the anti-herders, the proportion of the observed number of investors on the theoretical number is 1.1772 for the first decile, and it decreases monotonically to reach 0.9341 by decile 9. This trend appears to indicate that the portfolios of the investors who trade against the crowd perform poorly. The results for the herders category show that these investors concentrates in the intermediate deciles.

To conclude, on the one hand, investors who invest against the crowd improve their performance by trading. On the other hand, the portfolios of these same investors exhibit lower Sharpe ratios. One possible explanation for these results is that, by trading against the crowd, they earn a liquidity premium. However, the consequence of this behavior is that they hold stocks that are more risky and that perform relatively poorly (hence the lower Sharpe ratios).

5 Conclusion

Most studies focus on stock characteristics to explain the herding behavior of individual or institutional investors. By introducing a new individual measure that allows the herding behavior of a given investor to be evaluated through time, this article investigates whether the herding behavior can be explained by some investor attributes. In addition, this is the first study to analyze the relationship between individual performance and herding.

Our primary findings are the following. First, by studying a unique sample of 87,373 French individual investors, we demonstrate the importance and the persistence of herding behavior. Our results confirm, at an individual level, the observation made in previous studies that herding is much more pronounced for individual investors than for institutional ones. Second, we were able to show that sophisticated investors are less prone to herding. Additionally, we found an interesting link between past performance and mimetic behavior. It appears that an adverse performance decreases the incentives to gather information. When faced with negative performance, investors (and, in particular, unsophisticated ones) tend to herd in the next period. Finally, we provide original insights on the relationship between herding and performance. It appears that the investors who invest against the crowd improve their performance by reallocating their portfolio. However, we also found that these investors exhibit more extreme results and that they have lower Sharpe ratios than the rest of the population.

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Table 1: Descriptive Statistics

The dataset consists of the transaction records of 87373 investors at a major European broker for the period January 1999 to December 2006. Investors' portfolios are sorted with respect to the number of stocks held at three points in time (January 2000, January 2003 and January 2006). The first (second) column gives the number of stocks in portfolio (investors). The four remaining columns indicate the mean, the 25^{th} percentile, the median and the 75^{th} percentile of portfolio values in euros, conditional on the number of stocks held.

		Portfolio Value (€)			
Portfolio Size	Nb. of Observations	Mean	25^{th} percentile	Median	75^{th} percentile
Panel A: Portfolios as of January 2000					
1	9109	6973	740	1640	3930
2	6797	9717	2038	3782	7755
3	5321	15479	3623	6265	12067
4	4046	19734	5366	9038	16888
5	3131	24223	7262	12184	21318
6-9	7640	41694	11263	18797	35279
10+	7593	105255	27578	48552	91609
All	43637	34039	3179	9317	26336
Panel B: Portfolios as of January 2003					
1	11421	2154	218	502	1329
2	7925	3738	700	1417	3115
3	6087	6377	1330	2532	5304
4	4793	7585	2040	3750	7561
5	3692	10275	3002	5254	10061
6-9	9256	16380	4969	8714	16297
10+	9866	44771	13471	24499	46293
All	53040	14341	1160	4027	12572
Panel C: Portfolios as of January 2006					
1	11221	4216	381	993	2487
2	7349	7878	1243	2769	6250
3	5468	11025	2456	4796	10190
4	4131	16214	3772	7104	14428
5	3344	20720	5189	9537	19292
6-9	8073	31114	8856	16137	31167
10+	8065	83783	23769	44358	87414
All	47651	25784	1923	6831	21720

Table 2: LSV and FHW measures

The LSV measure for stock j in period t is computed as $LSV_{jt} = |p_{jt} - p_t| - E[|p_{jt} - p_t|]$, where p_{jt} is the purchase intensity for stock j, p_t is the purchase intensity across all stocks, and $E[|p_{jt} - p_t|]$ is an adjustment factor. With the same notations, the FHW measure for stock j is computed as, $FHW_{jt} = ((p_{jt} - p_t)^2 - E[(p_{jt} - p_t)^2])\frac{I_{jt}}{(I_{jt}-1)}$ where I_{jt} is the number of active traders and $E[(p_{jt} - p_t)^2]$ is an adjustment factor. We consider a minimum number of 10 active traders per stock. Stocks with less than 10 active traders in period t are excluded from the analysis for this period. Average semiannually, quarterly and monthly LSV and FHW measures are calculated for all stocks over the period 1999-2006. The LSV and FHW measures are calculated for 3 levels of stock capitalization ("Market capitalization"). Large (small) capitalizations correspond to the 30 % top (bottom) capitalizations. The medium category contains the remaining observations. The LSV and FHW measures are computed for 3 levels of trading volume in euros ("Volume of trading"). High trading volume (low trading volume) corresponds to the 30 % top (bottom) volume. The medium category contains the remaining observations. The herding measures of the different industries ("Industry") are the average herding measures of stocks that belong to the industry (using the Industry Classification Benchmark, ICB). Results are expressed in percentages

	Semiannualy		Quaterly		Monthly	
	LSV	FHW	LSV	FHW	LSV	FHW
All stocks	13.90	22.93	13.10	22.00	12.63	21.70
Market capitalization						
Large capitalization	14.79	22.10	13.97	21.16	13.86	21.28
Medium capitalization	12.42	21.00	11.88	20.48	11.44	20.32
Small capitalization	12.54	22.54	12.09	21.97	12.04	22.16
Volume of trading						
High volume of trading	14.58	21.13	13.68	20.13	13.35	20.16
Medium volume of trading	11.98	20.49	11.56	20.18	11.09	19.90
Low volume of trading	13.29	23.94	12.75	23.16	12.88	23.50
Industry						
Oil & Gas	12.87	20.20	12.77	19.33	12.74	19.75
Basic Materials	14.20	23.33	13.36	22.17	13.67	22.71
Industrials	13.84	23.04	12.81	21.88	12.42	21.47
Consumer Goods	13.78	22.78	13.10	22.15	12.96	22.08
Health Care	13.14	21.93	11.89	20.63	11.86	20.84
Consumer Services	13.79	22.43	13.42	21.96	12.84	21.48
Telecommunications	18.24	27.67	16.33	24.83	14.51	22.50
Utilities	15.68	22.82	14.28	20.49	12.70	18.67
Financials	15.26	24.54	14.17	23.14	13.40	22.54
Technology	13.18	21.75	12.55	21.12	11.90	20.79

Table 3: The LSV measure for stock j in period t is computed as $LSV_{j,t} = |p_{j,t} - p_t| - AF_{j,t}$, where $p_{j,t}$ is the purchase intensity for the stock j, p_t is the purchase intensity across all stocks and $AF_{j,t}$ is an adjustment factor. With the same notations, the FHW measure is computed as, $FHW^2_{j,t} = \left((p_{j,t} - p_t)^2 - E\left[(p_{j,t} - p_t)^2\right]\right) \frac{I_{j,t}}{I_{j,t-1}}$, where $I_{j,t}$ is the number of active traders. We consider a minimum number of 10 active traders per stock. Stocks with less than 10 active traders in period t are excluded of the analysis for this period. Quarterly measures are calulated for all stocks over the period 1990-2006. The LSV and FHW measures are calculated for 3 levels of stock capitalization ("Market capitalization"). Large (small) capitalizations correspond to the 30 % top (bottom) capitalizations. The medium category contains the remaining observations. The LSV and FHW measures are computed for 3 levels of trading volume in euros ("Volume of trading"). High trading volume (low trading volume) corresponds to the 30 % top (bottom) volume. The medium category contains the remaining observations. The results are expressed in percentages

				Market Capitalization						Volume of trading					
		All stocks		Small		Medium		Large		Low		Medium		High	
		LSV	FHW	LSV	FHW	LSV	FHW	LSV	FHW	LSV	FHW	LSV	FHW	LSV	FHW
1999	Q1	-	-	-	-	-	-	-	-	-	-	-	-	-	-
	Q2	14.02	22.63	12.39	22.12	12.35	20.41	13.56	19.47	12.23	22.09	11.98	19.96	14.37	20.17
	Q3	13.28	21.81	9.47	18.79	13.13	22.12	15.99	22.56	9.41	18.74	12.85	21.87	16.58	23.08
	Q4	13.35	21.87	8.84	17.75	11.94	20.02	16.38	23.09	9.44	19.19	11.14	19.43	16.29	21.98
2000	Q1	15.69	24.67	12.41	21.68	17.24	26.58	15.93	24.35	13.58	23.80	15.97	25.15	16.14	23.77
	Q2	14.82	24.07	10.56	20.99	12.54	21.04	18.06	24.86	12.49	23.44	11.80	20.41	16.46	22.57
	Q3	15.26	24.61	11.80	22.44	13.76	22.72	18.67	26.58	12.20	23.30	14.17	23.52	16.87	23.98
	Q4	13.84	22.45	9.07	18.32	11.83	20.19	18.78	25.50	10.41	20.29	11.27	19.56	17.79	24.28
2001	Q1	13.23	21.97	9.20	19.06	12.05	20.40	17.10	24.23	9.68	19.85	11.64	20.24	16.76	23.29
	Q2	13.96	22.96	11.63	21.56	12.86	21.70	15.13	22.64	12.20	22.55	12.65	21.66	14.40	21.01
	Q3	13.29	21.93	14.28	23.96	12.37	20.79	13.00	20.25	13.40	23.47	11.93	20.38	14.39	21.18
	Q4	13.13	22.35	12.79	22.62	11.79	20.89	14.46	22.59	13.48	23.74	11.41	20.75	14.48	21.76
2002	Q1	13.49	23.15	10.12	20.79	12.42	22.21	17.21	24.96	11.70	23.21	12.06	21.72	16.31	23.57
	Q2	16.09	24.91	17.44	27.60	14.29	23.34	16.24	22.87	17.80	28.65	13.61	22.51	17.07	23.09
	Q3	15.48	24.59	20.43	29.72	13.45	22.91	12.80	19.73	21.09	30.75	11.96	20.83	14.66	21.83
	Q4	13.61	23.59	17.60	28.09	11.19	21.13	13.28	22.57	17.87	29.01	11.64	21.66	12.94	21.26
2003	Q1	13.70	22.88	16.97	27.59	10.49	18.96	13.37	20.75	16.77	27.49	11.92	20.84	12.02	18.62
	Q2	11.96	21.35	14.39	24.39	10.43	19.85	11.58	20.32	15.28	25.87	10.67	20.35	9.93	16.77
	Q3	11.75	20.92	12.49	23.35	10.90	19.77	11.54	18.66	13.49	24.86	10.86	19.99	10.99	17.03
	Q4	11.36	20.18	10.57	20.89	10.76	19.59	12.36	19.46	11.28	22.06	11.57	20.28	10.74	17.13
2004	Q1	11.02	19.44	9.50	19.13	10.40	18.81	13.05	20.15	10.10	20.35	10.80	19.34	11.85	17.88
	Q2	12.08	20.78	13.38	23.81	10.39	18.30	12.15	19.25	12.46	23.22	11.76	20.34	10.85	16.38
	Q3	11.95	20.75	12.76	23.25	9.56	17.55	12.72	19.28	13.88	24.39	9.03	17.22	12.60	18.55
	Q4	12.41	21.44	14.10	24.21	11.02	19.48	11.08	18.41	13.36	23.83	11.46	20.13	11.23	17.92
2005	Q1	11.66	19.91	10.08	19.02	11.81	20.30	11.84	18.68	12.62	22.79	9.78	17.59	12.05	18.14
	Q2	12.34	21.17	12.49	22.53	11.24	19.58	11.26	18.20	12.49	23.01	10.32	18.46	12.15	18.54
	Q3	11.87	20.50	10.20	20.03	11.14	19.20	12.31	18.92	10.94	20.90	10.45	18.47	12.38	18.61
	Q4	12.52	21.46	10.09	20.29	11.48	19.71	13.46	20.67	11.61	22.31	10.71	19.25	13.23	19.37
2006	Q1	12.30	20.52	10.41	19.16	10.30	17.60	13.41	20.03	11.44	21.20	10.35	17.35	11.96	17.68
	Q2	12.18	21.19	9.82	19.45	12.17	20.60	11.29	18.39	12.29	23.02	10.14	17.94	11.67	18.12
	Q3	12.11	20.41	9.43	18.85	12.26	20.21	13.45	20.41	9.57	19.78	11.48	19.12	14.15	20.49
	Q4	12.30	21.40	10.05	19.64	10.68	18.80	11.73	18.20	10.66	20.75	11.02	19.39	10.74	16.05

Table 4: Mean contemporaneous and time-series correlation of percentage buys by individual investors

Results are based on trades data from a large European broker house for the period January 1999 to December 2006. For each stock in each month, we compute the proportion of all trades that are purchases. The second column of the table represents the correlations between percentage buys at month t and month $t+\tau$ where $\tau = 1, ..., 36$. The third column gives the correlation between the percentage buys by group 1 at time t with the percentages buys by group 2 at time $t+\tau$. The first element of this column is the mean contemporaneous correlation across groups. T-statistics are based on the mean and standard deviation of the calculated correlations. Results are expressed in percentages.

Horizon (τ)	Correlation of % buys in month t with % buys in months t+L		t-Statistics	
	Whole set of investors	Group 1 with group 2	Whole set of investors	Group 1 with group 2
0	100.00	85.09	n.a.	2330.93***
1	30.27	31.59	22.64***	215.61***
2	19.51	19.82	16.31***	148.91***
3	15.11	14.49	13.74***	118.87***
4	10.95	10.88	10.52***	89.85***
5	11.22	11.14	10.77***	90.53***
6	9.10	8.21	8.94***	71.03***
7	6.48	5.88	6.61***	53.10***
8	6.09	6.52	6.98***	64.20***
9	3.96	3.39	4.00***	29.47***
10	2.74	2.52	2.76***	22.32***
11	3.66	3.55	3.47***	29.91***
12	5.44	5.49	4.97***	43.35***
13	2.96	1.83	2.79***	15.80***
14	1.85	1.66	1.96*	14.88***
15	2.56	0.58	2.60**	5.13***
16	1.29	0.19	1.21	1.58
17	1.95	0.56	1.76*	4.32***
18	2.12	1.97	1.88*	14.95***
19	2.17	2.07	2.47**	18.32***
20	1.42	2.68	1.25	19.69***
21	0.43	−0.45	0.38	−3.37***
22	1.62	1.72	1.40	13.42***
23	2.68	3.24	2.73***	26.06***
24	3.18	2.86	3.07***	21.89***
25	1.34	1.45	1.33	11.37***
26	1.02	−1.14	1.02	−9.09***
27	−0.72	−1.31	−0.72	−9.58***
28	−2.12	−2.55	−1.76*	−16.88***
29	−3.31	−3.68	−2.95***	−28.01***
30	−1.50	−1.15	−1.40	−8.56***
31	−0.18	−0.45	−0.17	−3.18***
32	0.25	−0.97	0.22	−6.66***
33	−0.49	−1.11	−0.44	−8.29***
34	−1.84	−1.56	−1.92*	−12.64***
35	−0.67	0.51	−0.57	3.40***
36	−0.19	0.41	−0.17	2.99***

Table 5: Mean contemporaneous and time-series correlation of individual investors herding measure

Results are based on IHM values computed from trades data from a large European broker for the period January 1999 to December 2006. The second column of the table represents the correlation between IHM values at quarter t and quarter $t+\tau$ where τ=0,...,16. T-statistics are based on the mean and standard deviation of the calculated correlations.

Horizon (τ)	Correlation of % buys in month t with % buys in months $t+\tau$	t-Statistics
	Whole set of investors	Whole set of investors
0	100.00	n.a.
1	12.43	12.19***
2	11.22	12.80***
3	10.23	12.73***
4	10.96	12.62***
5	9.71	16.79***
6	8.68	13.91***
7	7.98	12.49***
8	7.51	10.38***
9	7.13	9.75***
10	6.94	9.82***
11	6.73	9.21***
12	5.90	8.59***
13	5.36	9.08***
14	4.74	7.08***
15	4.74	7.13***
16	5.59	4.98***

Table 6: This table reports average IHM values using various subsamples of investors. Four characteristics are considered: the gender, whether the investor trades warrants during the sample period, the total number of transactions and the average portfolio value. For each characteristic and each quarter, we compare the average IHM values of the two subsamples of investors. Reported P-values (computed with Monte-Carlo simulations) correspond to the test of no difference between the average IHM values of the two subsamples of investors.

		Gender			Warrants			Number of transactions			Average Portfolio Value		
		Male	Female	P-value	Yes	No	P-value	< 100	> 200	P-value	< 5000	> 100000	P-value
1999	Q1	0.1097	0.1094	0.9216	0.1135	0.1086	0.0566	0.1071	0.1134	0.0026	0.1058	0.1183	0.0000
	Q2	0.1263	0.1188	0.0066	0.1166	0.1273	0.0000	0.1331	0.1077	0.0000	0.1351	0.1186	0.0000
	Q3	0.1574	0.1590	0.5294	0.1408	0.1621	0.0000	0.1719	0.1309	0.0000	0.1763	0.1361	0.0000
	Q4	0.1332	0.1373	0.0742	0.1269	0.1358	0.0000	0.1393	0.1240	0.0000	0.1342	0.1456	0.0000
2000	Q1	0.1011	0.0972	0.0370	0.1040	0.0994	0.0099	0.1032	0.0978	0.0008	0.1040	0.1006	0.0371
	Q2	0.1336	0.1384	0.0343	0.1299	0.1358	0.0046	0.1349	0.1330	0.2826	0.1225	0.1518	0.0000
	Q3	0.1499	0.1569	0.0029	0.1229	0.1581	0.0000	0.1677	0.1170	0.0000	0.1531	0.1573	0.0424
	Q4	0.1233	0.1290	0.0072	0.1158	0.1265	0.0000	0.1309	0.1076	0.0000	0.1200	0.1242	0.0280
2001	Q1	0.1132	0.1214	0.0002	0.1073	0.1165	0.0001	0.1187	0.1016	0.0000	0.0988	0.1138	0.0000
	Q2	0.1100	0.1135	0.1486	0.1035	0.1124	0.0003	0.1174	0.0913	0.0000	0.0969	0.1219	0.0000
	Q3	0.0875	0.0888	0.5852	0.0837	0.0887	0.0298	0.0941	0.0698	0.0000	0.0763	0.0884	0.0000
	Q4	0.1093	0.1142	0.0623	0.1016	0.1123	0.0000	0.1184	0.0882	0.0000	0.0927	0.1072	0.0000
2002	Q1	0.1566	0.1569	0.9114	0.1465	0.1590	0.0000	0.1617	0.1401	0.0000	0.1256	0.1662	0.0000
	Q2	0.1129	0.1190	0.0204	0.1162	0.1136	0.3396	0.1154	0.1024	0.0000	0.0791	0.1163	0.0000
	Q3	0.0799	0.0823	0.2552	0.0767	0.0812	0.0477	0.0828	0.0673	0.0000	0.0603	0.0825	0.0000
	Q4	0.0953	0.1010	0.0291	0.0857	0.0988	0.0000	0.1087	0.0704	0.0000	0.0898	0.0768	0.0000
2003	Q1	0.1062	0.1143	0.0053	0.0974	0.1102	0.0000	0.1168	0.0885	0.0000	0.1055	0.1130	0.0033
	Q2	0.1225	0.1432	0.0000	0.0982	0.1328	0.0000	0.1503	0.0771	0.0000	0.1158	0.0915	0.0000
	Q3	0.0812	0.0927	0.0001	0.0732	0.0858	0.0000	0.0932	0.0663	0.0000	0.0687	0.0791	0.0000
	Q4	0.0599	0.0613	0.5366	0.0506	0.0624	0.0000	0.0673	0.0483	0.0000	0.0502	0.0542	0.0656
2004	Q1	0.0608	0.0640	0.1471	0.0533	0.0633	0.0000	0.0687	0.0495	0.0000	0.0567	0.0552	0.4841
	Q2	0.0906	0.1005	0.0005	0.0822	0.0950	0.0000	0.1017	0.0745	0.0000	0.0858	0.0811	0.0869
	Q3	0.1328	0.1410	0.0157	0.1026	0.1417	0.0000	0.1641	0.0853	0.0000	0.1450	0.0847	0.0000
	Q4	0.0982	0.0992	0.7272	0.0896	0.1006	0.0000	0.1104	0.0764	0.0000	0.0967	0.0689	0.0000
2005	Q1	0.0723	0.0785	0.0100	0.0731	0.0736	0.8490	0.0774	0.0646	0.0000	0.0549	0.0668	0.0000
	Q2	0.1126	0.1158	0.2837	0.1084	0.1145	0.0395	0.1302	0.0827	0.0000	0.1101	0.0906	0.0000
	Q3	0.1093	0.1144	0.0708	0.0929	0.1142	0.0000	0.1253	0.0850	0.0000	0.0998	0.0894	0.0002
	Q4	0.0993	0.1046	0.0479	0.0905	0.1025	0.0000	0.1142	0.0748	0.0000	0.1114	0.0787	0.0000
2006	Q1	0.0764	0.0794	0.1589	0.0682	0.0789	0.0000	0.0854	0.0589	0.0000	0.0771	0.0577	0.0000
	Q2	0.0786	0.0852	0.0059	0.0672	0.0827	0.0000	0.0965	0.0511	0.0000	0.0866	0.0611	0.0000
	Q3	0.0839	0.0849	0.7015	0.0767	0.0858	0.0010	0.0889	0.0729	0.0000	0.0640	0.0841	0.0000
	Q4	0.0793	0.0793	0.9763	0.0766	0.0799	0.1499	0.0859	0.0657	0.0000	0.0740	0.0677	0.0040

Table 7: Quarterly returns are based on investors daily portfolios from January 1999 to December 2006. This table presents the coefficients of the Spearman correlation between investors' IHM and, respectively, the previous quarter portfolios' average return, standard deviation, skewness and kurtosis. *** corresponds to a p-value of 0.01, ** to a p-value of 0.05 and * to a p-value of 0.1.

		Spearman correlation with IHM			
		Average Return	Standard Deviation	Skewness	Kurtosis
2000	Q1	−0.1388***	−0.0896***	0.0235***	−0.0197***
	Q2	−0.1138***	−0.2387***	0.1085***	0.0054
	Q3	0.0582***	−0.1320***	−0.0049	−0.0331***
	Q4	0.0203***	−0.1458***	−0.0265***	0.0187***
2001	Q1	0.1269***	−0.1659***	−0.0265***	0.0015
	Q2	0.1231***	−0.1447***	−0.0293***	0.0232***
	Q3	−0.0288***	−0.0615***	−0.0261***	−0.0119*
	Q4	0.0657***	−0.1061***	−0.0352***	0.0826***
2002	Q1	0.0040	−0.0996***	0.0067	−0.0785***
	Q2	−0.0108*	−0.0552***	0.0327***	0.0094
	Q3	0.0281***	−0.0882***	−0.0188***	−0.0378***
	Q4	0.0649***	−0.1033***	−0.0051	−0.0518***
2003	Q1	−0.0087	−0.1450***	−0.0252***	−0.0654***
	Q2	0.1011***	−0.2723***	0.0139**	−0.0386***
	Q3	−0.1097***	−0.1938***	−0.1117***	0.0178**
	Q4	0.0361***	−0.0884***	0.0141**	0.0130*
2004	Q1	0.0256***	−0.1425***	0.0129*	0.0122*
	Q2	−0.0293***	−0.0851***	0.0150**	−0.0241***
	Q3	0.0621***	−0.1209***	−0.1453***	0.0131*
	Q4	0.0446***	−0.0938***	−0.0513***	−0.0033
2005	Q1	−0.0342***	−0.0686***	−0.0321***	−0.0253***
	Q2	0.0206***	−0.1005***	0.0556***	0.0301***
	Q3	−0.0928***	−0.1228***	−0.0327***	−0.0080
	Q4	−0.0739***	−0.0756***	−0.0393***	−0.0231***
2006	Q1	−0.0027	−0.1170***	−0.0340***	0.0112*
	Q2	−0.0873***	−0.1333***	−0.0263***	−0.0260***
	Q3	0.0990***	−0.1624***	−0.0543***	−0.0847***
	Q4	0.0799***	−0.0923***	0.0028	−0.0460***

Table 8: This table presents the results of the panel regression estimated by $IHM_{i,t} = \gamma_0 IHM_{i,t-1} + \gamma_1 IHM_{i,t-2} + \sum_{\tau=1}^{2} \beta_\tau RAR_{i,t-\tau} + \theta EXP_{i,t} + \alpha_1 IFE_i + \alpha_2 TFE_t + \varepsilon_{i,t}$. The independent variable is the Investor Herding Measure (IHM) for quarter t. We include two lagged values of IHM (quarters $t-1$ and $t-2$) in order to account for autocorrelation. RAR_t is the investor's portfolio Risk Adjusted Return for quarter t, defined as the ratio of the average return on the standard deviation. WRT is a dummy variable that takes the value 1 if the investor trades warrants at any moment during the sample period and 0 else. NT is the investor's total number of transactions and APV is the investor's average portfolio value. $Experience_t$ represents the number of transactions accomplished by the investor up to quarter t. Models 1 to 4 incorporate individual- and time-fixed effects. Returns are windsorised at the 1^{st} and 99^{th} percentiles. Coefficients are standardized.

	Model 1	Model 2	Model 3	Model 4
Explanatory Variable	Coefficients	Coefficients	Coefficients	Coefficients
$(IHM)_{t-1}$	-0.0614*** (-33.2600)	-0.0614*** (-33.2800)	-0.0617*** (-33.4100)	-0.0614*** (-33.2800)
$(IHM)_{t-2}$	-0.0312*** (-16.9000)	-0.0311*** (-16.8700)	-0.0310*** (-16.8100)	-0.0312*** (-16.8900)
$(RAR)_{t-1}$	-0.0165*** (-6.3300)			
$(RAR)_{t-2}$	-0.0208*** (-8.0800)			
$(RAR)_{t-1}\|(WRT=1)$		0.0020 (0.5300)		
$(RAR)_{t-1}\|(WRT=0)$		-0.0239*** (-8.4600)		
$(RAR)_{t-2}\|(WRT=1)$		-0.0150*** (-4.0200)		
$(RAR)_{t-2}\|(WRT=0)$		-0.0234*** (-8.3700)		
$(RAR)_{t-1}\|(NT<100)$			-0.0363*** (-10.2100)	
$(RAR)_{t-1}\|(100 \leq NT \leq 200)$			-0.0247*** (-6.1500)	
$(RAR)_{t-1}\|(NT>200)$			0.0016 (0.5000)	
$(RAR)_{t-2}\|(NT<100)$			-0.0356*** (-10.1400)	
$(RAR)_{t-2}\|(100 \leq NT \leq 200)$			-0.0231*** (-5.8300)	
$(RAR)_{t-2}\|(NT>200)$			-0.0099*** (-3.0900)	
$(RAR)_{t-1}\|(APV<5000)$				-0.0144*** (-2.6200)
$(RAR)_{t-1}\|(5000 \leq APV \leq 100000)$				-0.0192*** (-6.9200)
$(RAR)_{t-1}\|(APV>100000)$				-0.0004 (-0.0800)
$(RAR)_{t-2}\|(APV<5000)$				-0.0243*** (-4.5300)
$(RAR)_{t-2}\|(5000 \leq APV \leq 100000)$				-0.0215*** (-7.8300)
$(RAR)_{t-2}\|(APV>100000)$				-0.0123** (-2.2400)
$(Experience)_t$	-0.0187*** (-5.7200)	-0.0189*** (-5.7600)	-0.0190*** (-5.7900)	-0.0190*** (-5.8100)
Number of Observations	332154	332154	332154	332154
R-squared	0.2466	0.2467	0.2469	0.2466

Table 9: Quarterly returns are based on investors daily portfolios from January 1999 to December 2006. This table presents the coefficients of the Spearman correlation between investors' IHM and, respectively, the portfolios' contemporary average return, standard deviation, skewness and kurtosis. *** corresponds to a p-value of 0.01, ** to a p-value of 0.05 and * to a p-value of 0.1.

		Spearman correlation with IHM			
		Average Return	Standard Deviation	Skewness	Kurtosis
1999	Q1	0.0426***	−0.0228***	−0.0041	−0.0136*
	Q2	0.0338***	0.0574***	0.0043	−0.0040
	Q3	−0.0026	0.0555***	0.0330***	−0.1112***
	Q4	0.0399***	0.0211***	0.0045	−0.0262***
2000	Q1	−0.0910***	−0.0628***	0.0388***	0.0324***
	Q2	0.1421***	−0.1835***	−0.0574***	−0.1102***
	Q3	−0.0298***	−0.0979***	0.0441***	0.0691***
	Q4	0.1007***	−0.1111***	−0.0289***	0.0089
2001	Q1	0.0411***	−0.1038***	−0.0028	−0.0677***
	Q2	−0.0444***	−0.1142***	−0.0722***	−0.0827***
	Q3	0.0105*	−0.0595***	−0.0322***	0.0270***
	Q4	−0.0961***	−0.1089***	−0.0212***	−0.0153**
2002	Q1	0.0322***	−0.0831***	−0.0648***	−0.1073***
	Q2	−0.0164***	−0.0160**	−0.0189***	−0.0020
	Q3	0.0647***	−0.1072***	0.0216***	−0.0435***
	Q4	−0.0468***	−0.0680***	−0.0112*	−0.0196***
2003	Q1	−0.0481***	−0.1023***	−0.0419***	−0.0521***
	Q2	−0.1517***	−0.2037***	−0.0892***	−0.0190***
	Q3	−0.0069	−0.1688***	0.0237***	−0.0365***
	Q4	0.0219***	−0.0811***	−0.0014	0.0088
2004	Q1	0.0139**	−0.0907***	−0.0649***	0.0387***
	Q2	0.0669***	−0.0654***	−0.0110	0.0121*
	Q3	0.1045***	−0.1522***	0.0001	−0.0386***
	Q4	−0.0333***	−0.1009***	−0.0192***	−0.0796***
2005	Q1	0.0063	−0.0537***	−0.0113	0.0168**
	Q2	−0.0496***	−0.1310***	0.0074	−0.0441***
	Q3	−0.1339***	−0.1474***	0.0051	0.0365***
	Q4	0.0395***	−0.1161***	0.0223***	−0.0337***
2006	Q1	−0.0231***	−0.0921***	0.0067	−0.0129*
	Q2	0.0605***	−0.1272***	−0.0279***	−0.0334***
	Q3	0.0814***	−0.1153***	−0.0180**	−0.0656***
	Q4	0.0016	−0.0840***	0.0088	−0.0422***

Table 10: Quarterly returns are based on investors daily portfolios from January 1999 to December 2006. Panel A corresponds to the average investor representative of the whole population. Panel B corresponds to anti-herders ($IHM < -0.05$), Panel C to independent traders ($-0.05 \leq IHM \leq 0.05$) and Panel D to herders ($IHM > 0.05$). Own-benchmark abnormal return is the result of the difference between the realized return and the one of the beginning-of-quarter portfolio. Market-adjusted return corresponds to the investor's realized return minus the return of the market (SBF 250) on the same period. P-values are computed using the t-statistics based on the 32 observations of the time-series. Carhart four-factor is regression of the individual investor excess return (using EURIBOR 3-month rate) on the market excess return $R_{mt} - R_{ft}$, a zero-investment size portfolio (SMB_t), a zero-investment book-to-market portfolio (HMB_t) and a zero-investment momentum portfolio (MOM_t). Quaterly returns are windsorised at the 1^{st} and 99^{th} percentiles. *** corresponds to a p-value of 0.01, ** to a p-value of 0.05 and * to a p-value of 0.1.

	Excess Return	$R_{mt} - R_{ft}$	HML_t	SMB_t	MOM_t	Adjusted R^2
			Panel A: Average investor			
Own-benchmark abnormal return	-0.0023***					
	(-2.7867)					
Market-adjusted return	0.0054					
	(0.4592)					
Carhart four-factor	0.0004	1.3274***	-0.0678	0.4287*	-0.1780	0.9144
	(0.0400)	(10.6648)	(-0.3915)	(1.9444)	(-1.4301)	
			Panel B: Average anti-herder ($IHM < -0.05$)			
Own-benchmark abnormal return	0.0069***					
	(5.8519)					
Market-adjusted return	0.0034					
	(0.2641)					
Carhart four-factor	-0.0026	1.3734***	-0.0383	0.4099	-0.1670	0.9030
	(-0.2217)	(10.0789)	(-0.2020)	(1.6982)	(-1.2251)	
			Panel C: Average independent trader ($-0.05 \leq IHM \leq 0.05$)			
Own-benchmark abnormal return	0.0008					
	(1.4912)					
Market-adjusted return	0.0069					
	(0.5293)					
Carhart four-factor	-0.0008	1.3859***	-0.0912	0.5016*	-0.1423	0.8907
	(-0.0657)	(9.6000)	(-0.4545)	(1.9616)	(-0.9858)	
			Panel D: Average herder ($IHM > 0.05$)			
Own-benchmark abnormal return	-0.0051***					
	(-4.1973)					
Market-adjusted return	0.0049					
	(0.4431)					
Carhart four-factor	0.0008	1.2976***	-0.0574	0.3927*	-0.1831	0.9239
	(0.0859)	(11.2751)	(-0.3584)	(1.9264)	(-1.5910)	

Table 11: Quarterly returns are based on investors daily portfolios from January 1999 to December 2006. Investors are sorted into deciles on quarterly return (Panel A) and Sharpe ratio (Panel B). Decile 1 corresponds to the lowest returns (respectively Sharpe ratios) while Decile 10 contains investors with the highest ones. Investors are separated into three categories: Anti-herders ($IHM < -0.05$), Independent traders ($-0.05 \leq IHM \leq 0.05$) and Herders ($IHM > 0.05$). We compute, for each intersection of a performance decile and a herding category the ratio of the number of investors on the theoretical number under independence between herding and performance. *** corresponds to a p-value of 0.01, ** to a p-value of 0.05 and * to a p-value of 0.1. P-values are computed using the t-statistics based on the 32 observations of the time-series. *** corresponds to a p-value of 0.01, ** to a p-value. The values in brackets correpond to the number of quarters for which the difference between the realized number of investors and the theoretical one is significant (with a significance level of 5 % and using Monte-Carlo simulations to assess the significance). Quaterly returns are windsorised at the 1^{st} and 99^{th} percentiles.

	Panel A: Investors sorted on return									
	Lowest Returns	2	3	4	5	6	7	8	9	Highest Returns
Anti-herder	1.2709***	1.0729***	1.0064	0.9255***	0.9066***	0.8878***	0.8866***	0.9153***	0.9848	1.1476***
($IHM < -0.05$)	(28)	(14)	(2)	(10)	(15)	(18)	(18)	(15)	(8)	(21)
Independent trader	1.0457	1.0315*	0.9914	0.9720**	0.9683***	0.9660***	0.9641***	0.9825	1.0286	1.0503*
($-0.05 \leq IHM \leq 0.05$)	(21)	(16)	(11)	(10)	(8)	(7)	(12)	(8)	(16)	(23)
Herder	0.9330***	0.9768***	1.0057	1.0278***	1.0331***	1.0362***	1.0385***	1.0200***	0.9850	0.9445***
($IHM > 0.05$)	(24)	(17)	(10)	(15)	(19)	(22)	(20)	(16)	(14)	(22)

	Panel B: Investors sorted on Sharpe ratio									
	Lowest Sharpe Ratio	2	3	4	5	6	7	8	9	Highest Sharpe ratio
Anti-herders	1.1772***	1.0691***	1.0401**	0.9946	0.9678**	0.9585***	0.9499***	0.9473***	0.9341***	0.9657
($IHM < -0.05$)	(20)	(11)	(8)	(6)	(5)	(4)	(9)	(7)	(15)	(17)
Independent traders	1.0284	1.0213	0.9986	0.9820**	0.9911	0.9873	0.9850	0.9758*	1.0125	1.0184
($-0.05 \leq IHM \leq 0.05$)	(18)	(12)	(9)	(6)	(4)	(4)	(8)	(10)	(14)	(19)
Herders	0.9623***	0.9796**	0.9929	1.0091*	1.0127***	1.0138***	1.0165***	1.0164***	1.0046	0.9925
($IHM > 0.05$)	(23)	(18)	(12)	(7)	(11)	(5)	(9)	(14)	(14)	(18)

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