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Maxime Merli, Tristan Roger

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Maxime MERLI, Tristan ROGER*

1. Introduction

The herding behavior is defined in a broad way as an investor's imitation of the actions of others. Devenow and Welch (1996) emphasize three reasons for herding.[1] The first reason is payoff externalities (the outcome of an action is increasing in the number of agents undertaking it). For instance, investors tend to trade at the same time to benefit from a deeper liquidity (see Admati and Pfleiderer, 1988; Dow, 2004). The second reason is reputational concerns and issues related to the princi-

* Maxime Merli is from the LaRGE Research Center, EM Strasbourg Business School, University of Strasbourg; Tristan Roger is from CNRS (Eurofidai) and University of Grenoble (CERAG) and is a Visiting Scholar at the Haas School of Business, University of California, Berkeley. The authors are grateful to the brokerage firm that provided the data for this study. The authors thank Raphaëlle Bellando, Patrice Fontaine, Sonia Jimenez-Garces, Achim Mattes, Franck Moraux (the editor), Terrance Odean, 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.

1. Herding can be rational or irrational. Irrational herding is extremely difficult to capture empirically because it is driven by fashion and fads. We therefore do not address this issue in the rest of the paper.

pal-agent theory (see Scharfstein and Stein, 1990; Rajan, 1994; Graham, 1999). When the performance of a manager is assessed relative to a benchmark (*i.e.*, by using the average performance of other managers, or the performance of a market/industry index), it is quite tempting for her to mimic the benchmark. By doing so, the manager sacrifices the potential to perform better than average but hedges herself against a poor relative performance. It is often said that the manager hides in the herd. Finally, the third explanation for rational herding is informational externalities. In Bikhchandani, Hirshleifer, and Welch (1992) and Welch (1992), investors acquire (noisy) information by observing the actions of the other agents. The externalities may be so strong that an investor can voluntary decide to ignore her own information. In the most extreme cases, individuals' actions do not carry information anymore because they result only from the imitation of others' actions. In that case, an informational cascade occurs.

Early studies such as Lakonishok, Shleifer, and Vishny (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, Shleifer, and Vishny (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, Shleifer, and Vishny 1992; Grinblatt, Titman, and Wermers, 1995; Wermers, 1999). Similar studies have been performed outside of the U.S., in particular in Germany (Oehler, 1998; Frey, Herbst, and Walter, 2007), the United Kingdom (Wylie, 2005), Portugal (Loboa and Serra, 2007) 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, Odean, and Zhu, 2009), Germany (Dorn, Huberman, and Sengmueller, 2008), Israel (Venezia, Nashikkar, and Shapira, 2011) and China (Feng and Seasholes, 2004). 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 it exhibits a strong persistence over time (Barber, Odean, and Zhu, 2009). This behavior is positively and significantly correlated with the volatility of the market returns (Venezia, Nashikkar, and Shapira, 2011). Addressing the drivers of these findings, Barber, Odean, and Zhu (2009) show that psychological biases contribute to the 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.

Despite its popularity, the LSV 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 investigated.

A key contribution of this paper is to provide a new measure of herding behavior at the individual level. Our measure (the Individual Herding Measure, denoted IHM hereafter) evaluates the individual herding for a given quarter as the weighted sum of the signed LSV measures of the stocks for which changes in holdings, for the quarter under consideration, occur. This measure allows for tracking dynamics of individual herding and therefore has the potential to highlight sources of individual heterogeneity. We conduct an empirical analysis of the herding behavior of individual investors using a unique database of the trading records of 87,373 investors for the 1999-2006 period. Our results demonstrate a high level of herding and a significant persistence of this behavior over time at the investor level. Our analysis of the individual heterogeneity of the herding behavior shows 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 improve their returns 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. In the first section, we describe the methodological framework and introduce our individual herding measure. In the second section, we present the data used in this article. The third section focuses on the herding behavior measured at the stock level. In the fourth section, we examine the level and the persistence of the herding behavior at the investor level and highlight the factors that impact this behavior. The last section concludes the paper.

2. The framework

We first define notations that are common to all measures. We denote by $n_{i,j,t}$, the number of shares (adjusted for splits and corporate actions) of stock j held by investor i at time t. The universe contains J stocks.

2.1. Measuring herding at the asset level: the LSV measure and extensions

In Lakonishok, Shleifer, and Vishny (1992), herding is defined as the tendency for traders to accumulate on the same side of the market for a given stock and during a given period. To measure this tendency, we observe the difference between the number of shares held at time t and at time $t-1$.[2] If the difference $n_{i,j,t} - n_{i,j,t-1}$ is positive (resp. negative), then it means that investor i increases (resp. decreases) her holdings of asset j during the period $[t-1; t]$. The investor is said to be on the buy side (*resp.* sell side). We denote by $b_{i,j,t}$ (resp. $s_{i,j,t}$) a binary variable that takes the value 1 if the investor i increases (resp. decreases) her holdings of stock j between $t-1$ and t and the value 0

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.

otherwise. 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

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

where $I_{j,t}$ is the number of active traders over the period $[t-1;t]$. Notice that the number of traders $I_{j,t}$ varies across stocks and over time. The purchase intensity (thus the LSV measure) is computed for a subgroup of investors only. Formally, the LSV measure of stock j at time t is written as

$$LSV_{j,t} = \left|p_{j,t} - p_t\right| - \underbrace{E\left[\left|p_{j,t} - p_t\right|\right]}_{AF_{j,t}}, \tag{2}$$

where $E[.]$ stands for the expectation, p_t is the purchase intensity across all stocks[3] and $AF_{j,t}$ is an adjustment factor given by

$$AF_{j,t} = \sum_{k=0}^{I_{j,t}} \binom{I_{j,t}}{k} (p_t)^k (1-p_t)^{I_{j,t}-k} \left|\frac{k}{I_{j,t}} - p_t\right|. \tag{4}$$

The quantity p_t is subtracted to account for systematic liquidity shocks, that is, when the aggregation of investors on a given side (buy or sell) is not the consequence of herding but rather the reaction to a common shock. The adjustment factor $AF_{j,t}$ makes the LSV measure unbiased in the case of no herding.

3. The purchase intensity across all stocks is computed as

$$p_t = \frac{\sum_{j=1}^{J} \sum_{i=1}^{I_{j,t}} b_{i,j,t}}{\sum_{j=1}^{J} I_{j,t}}. \tag{3}$$

As mentioned before, the LSV measure suffers from a few drawbacks and has therefore been exposed to a 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. We address this issue in the following subsection 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, she prevents herself from making an investment she would have made otherwise (or conversely, she undertakes an investment that she 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, Herbst, and Walter (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, Huberman, and Sengmueller (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, Herbst, and Walter (2007) propose using square values instead of absolute values in the expression of the LSV measure. Formally, their new measure is defined as

$$FHW_{j,t}^2 = \left(\left(p_{j,t} - p_t\right)^2 - E\left[\left(p_{j,t} - p_t\right)^2\right]\right) \frac{I_{j,t}}{I_{j,t} - 1}, \quad (5)$$

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

For a given time period $[t - 1; t]$ and a universe of J stocks, the average FHW measure is computed as

$$\overline{FHW_t} = \sqrt{\frac{1}{J} \sum_{j=1}^{J} FHW_{j,t}^2}. \quad (6)$$

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

However, Bellando (2010) shows that the measure is unbiased only in the particular setting considered by Frey, Herbst, and Walter (2007). As soon as the probability of no herding is not null or when some asymmetry is introduced, the measure is biased upward. It follows that it is virtually impossible to compute the true value of the herding intensity. Nonetheless, we know that this true value is bounded below by the LSV value and above by the FHW value.

2.2. Measuring herding at the investor level: the Investor Herding Measure

We introduce now the new measure called the Investor Herding Measure (IHM hereafter). IHM considers herding only for the stocks currently traded by the investor. To analyze the tendency of individual investors to herd, we first discriminate between buy herding ($p_{j,t} > p_t$) and sell herding ($p_{j,t} < p_t$). In the spirit of Grinblatt, Titman, and Wermers (1995) and Wermers (1999), we define the signed herding measure as[4]

$$SLSV_{j,t} = \begin{cases} LSV_{j,t} \,|\, p_{j,t} > p_t \\ -\, LSV_{j,t} \,|\, p_{j,t} < p_t \end{cases}$$

$$= p_{j,t} - p_t \begin{cases} -\, AF_{j,t} \,|\, p_{j,t} > p_t \\ +\, AF_{j,t} \,|\, p_{j,t} < p_t \end{cases}. \tag{7}$$

For a given transaction, there are six possible scenarios

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

The IHM is then defined as

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

where $\overline{P}_{j,t}$ is the average price of asset j over the period $[t-1; t]$. The value $\left(n_{i,j,t} - n_{i,j,t-1}\right) \overline{P}_{j,t}$ is the average value of the transaction made on stock j and the denominator in the formula is the total value of all transactions[5] made by investor i in the considered period. In this

4. As in Grinblatt, Titman, and Wermers (1995), we set the LSV measure equal to 0 if there are less than 10 investors trading the stock.

5. 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 use the average price to evaluate the value by which the investor increases or decreases her holdings.

way, we account only for the herding coefficient of the stocks that are traded during the considered period, and we weight them by the size (euros-volume) of the transactions. The IHM measure indicates that investor i is herding if it takes a positive value and that she is going against the herd if the value is negative.

To compare with, Grinblatt, Titman, and Wermers (1995) define the "Fund Herding Measure" as

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

where $\omega_{i,j,t}$ is the weight of asset j in the portfolio of the i^{-th} fund at time t. A potential issue associated with this measure is that an investor can be seen as herding on an asset she does not trade (a transaction in one asset – or a price variation – causes the weights of all the assets in the portfolio to change.).

3. Data and descriptive statistics

The primary data for our study consists of a eight-year panel (from 1999 to 2006) of all executed trades and daily portfolio holdings of French individuals at a major European brokerage house. We exclude investments in mutual funds, warrants and options from the database. The total number of stock transactions is slightly below 8 millions. The database contains information on the opening date of the accounts (if ever, closing date), the birth date, the gender and the state of residence of the investors. At the beginning of the sample period, 33,130 investors had open positions. The representative mean investor holds 4.8 stocks worth 19,113 euros and she executes 89 trades over the period. The median investor holds 2.92 stocks worth 5,163 euros and trades 32 times.

In addition to the individual investor database, for each stock in our sample, we obtain daily prices, returns, market capitalization and volumes from Bloomberg (1,180 stocks) and Eurofidai[6] (1,311 stocks).

6. European Financial Data Institute, www.eurofidai.org

Note that, due to missing data, we must ignore a little over one thousand securities that represent only 1.51% of the total number of transactions. Of the 2,491 stocks under consideration, 1,190 stocks are listed on the French market, 1,020 in the U.S., 62 in Great Britain, 35 in Canada, 34 in Netherlands, 31 in Germany, 15 in Italy and 104 somewhere else. As one may expect, the trading volume is not homogeneous across countries. The stocks listed on the French market represent more than 90% of the total volume of trading, while the stocks from U.S. account for less than 1%.

Figure 1 below shows the evolution, from January 1999 to December 2006, of the number of investors, the average number of stocks, and the average portfolio value (measured at the beginning of each quarter). 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 stocks held, at three points in time.

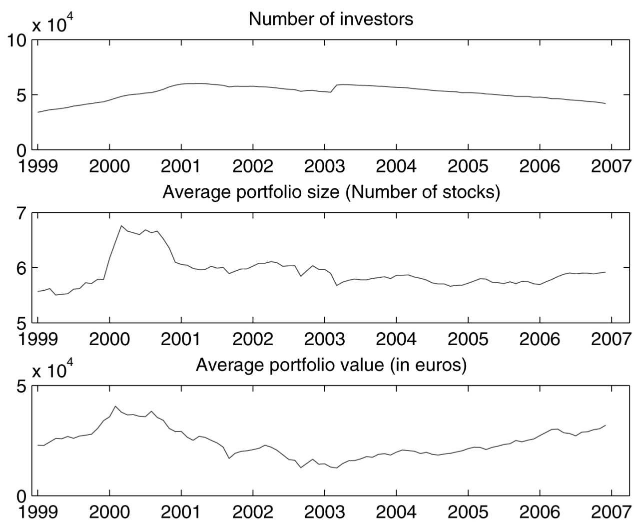

Figure 1. – Characteristic of the sample

This figure presents the number of investors, the investors' average number of stocks and their portfolio average value in euros for each quarter of the January 1999 to December 2006 period.

Table 1. – Descriptive statistics

		Portfolio Value (€)			
Portfolio Size	Nb. of Observations	Mean	25th percentile	Median	75th percentile
Panel A: Portfolios as of January 2000					
1	9,109	6,973	740	1,640	3,930
2	6,797	9,717	2,038	3,782	7,755
3	5,321	15,479	3,623	6,265	12,067
4	4,046	19,734	5,366	9,038	16,888
5	3,131	24,223	7,262	12,184	21,318
6-9	7,640	41,694	11,263	18,797	35,279
10+	7,593	105,255	27,578	48,552	91,609
All	43,637	34,039	3,179	9,317	26,336
Panel B: Portfolios as of January 2003					
1	11,421	2,154	218	502	1,329
2	7,925	3,738	700	1,417	3,115
3	6,087	6,377	1,330	2,532	5,304
4	4,793	7,585	2,040	3,750	7,561
5	3,692	10,275	3,002	5,254	10,061
6-9	9,256	16,380	4,969	8,714	16,297
10+	9,866	44,771	13,471	24,499	46,293
All	53,040	14,341	1,160	4,027	12,572
Panel C: Portfolios as of January 2006					
1	11,221	4,216	381	993	2,487
2	7,349	7,878	1,243	2,769	6,250
3	5,468	11,025	2,456	4,796	10,190
4	4,131	16,214	3,772	7,104	14,428
5	3,344	20,720	5,189	9,537	19,292
6-9	8,073	31,114	8,856	16,137	31,167
10+	8,065	83,783	23,769	44,358	87,414
All	47,651	25,784	1,923	6,831	21,720

The dataset consists of the transaction records of 87,373 investors at a major European broker for the period from January 1999 to December 2006. The 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 the portfolio (of investors). The four remaining columns indicate the mean, the 25th percentile, the median and the 75th percentile of the portfolio values in euros, conditional on the number of stocks held.

4. Herding behavior at the stock level

4.1. Herding and stock characteristics

Table 2 provides the average values, on the 1999-2006 period of the semiannually, quarterly and monthly LSV and FHW measures. The first line provides the average value across all stocks of the LSV and FHW measures. The following lines report averages on subsets based on the capitalization (Large, Medium, Small), on the volume of trading (High, Medium, Low) and on the industry classification (based on the Industry Classification Benchmark).

The average value across all stocks of the LSV measure computed on a monthly basis is equal to 0.1263. This means that, for a given stock and during a given month, approximately 13% more investors are "on the same side" than what would be predicted if decisions were randomly taken. Hence, French individual investors exhibit a high degree of herding. These results are consistent with typical findings for U.S. individual investors (Barber, Odean, and Zhu, 2009, find an average of monthly LSV measures on all stocks equal to 0.1279), but slightly higher than the value of 0.064 obtained by Dorn, Huberman, and Sengmueller (2008) for Germany. This result also supports previous findings that individual investors herd more than institutional investors. In the U.S., Lakonishok, Shleifer, and Vishny (1992) provide an average value of 0.02 for institutional investors and Wermers (1999) reports a value of 0.036. More recently, in Israel, Venezia, Nashikkar, and Shapira (2011) obtain an average herding measure of 0.058.

As in Dorn, Huberman, and Sengmueller (2008), our results highlight correlated trading across all horizons and all industries. Concerning the impact of the capitalization, our results, using the LSV measure, confirm the findings of Dorn, Huberman, and Sengmueller (2008) and contrast with those of Barber, Odean, and Zhu (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. However, this result is not robust when using the FHW measure. Indeed, with this last measure, we find that the herding behavior is more pronounced for smaller capitalizations.

Table 2. – The LSV and FHW measures

	Semiannually		Quarterly		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

The LSV measure for stock j in period t is computed to be $LSV_{jt} = |p_{jt} - p_t| - E[|p_{jt} - p_t|]$, 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 to be $FHW_{jt} = ((p_{jt} - p_t)^2 - E[(p_{jt} - p_t)^2])\dfrac{I_{jt}}{(I_{jt} - 1)}$ 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 fewer than 10 active traders in period t are excluded from the analysis for this period. The average semiannual, quarterly and monthly LSV and FHW measures are calculated for all stocks over the 1999-2006 period. The LSV and FHW measures are calculated for 3 levels of 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 the stocks that belong to the industry (using the Industry Classification Benchmark, ICB). The results are expressed in percentages.

Finally, the LSV measure takes a higher value for the stocks ranked in the “left high volume of trading” category. Although further investigations are needed, this result could be due to a concentration of purchases in attention-grabbing stocks (Barber and Odean, 2008; Barber, Odean, and Zhu, 2009) or to informational signals. Once again however, this result is not robust when using the FHW measure instead. 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 (Table 2), it is apparent that the values of FHW are sharply higher whatever the category under study. The monthly average value across all stocks of the FHW measure is equal to 21.70%. The herding behavior is estimated as being 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). We can conclude, for monthly observation intervals, that the true value of herding for the French individual investors in our sample is high and takes a value between 12.63% and 21.70%.

4.2. Persistence

In this section, we adopt another approach (following the methodology used by Barber, Odean, and Zhu, 2009) to test whether investors' trading decisions are correlated. We also analyze the persistence, at the stock 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, Odean, and Zhu (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 $\tau = 0,...,36$. Note that $\tau = 0$ corresponds to a test of the null hypothesis of no herding while $\tau > 0$ corresponds to a test of the persistence in herding. 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 3 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

Table 3. – Mean contemporaneous and time-series correlation of purchase intensities by individual investors

Horizon (τ)	Correlation of % buys in month t with % buys in months $t + \tau$		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***

The results are based on trades data from a large European brokerage house for the January 1999 to December 2006 period. 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 the purchase intensities at month t and month $t + \tau$ with $\tau = 1,...,36$. The third column gives the correlations between the purchase intensities by group 1 at time t with the purchase intensities 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 the standard deviation of the calculated correlations. The results are expressed in percentages.

Barber, Odean, and Zhu (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, Odean, and Zhu (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, Odean, and Zhu, 2009).

5. Herding behavior at the individual level

5.1. First results

We first provide a brief overview of the computed IHM values. Figure 2 gives the distribution of the IHM at three time points (first quarter of 2000, 2003 and 2006). Not 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. Medians are, respectively, 0.0954, 0.0887 and 0.0675.

5.2. Persistence

Using the same methodology as the one 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

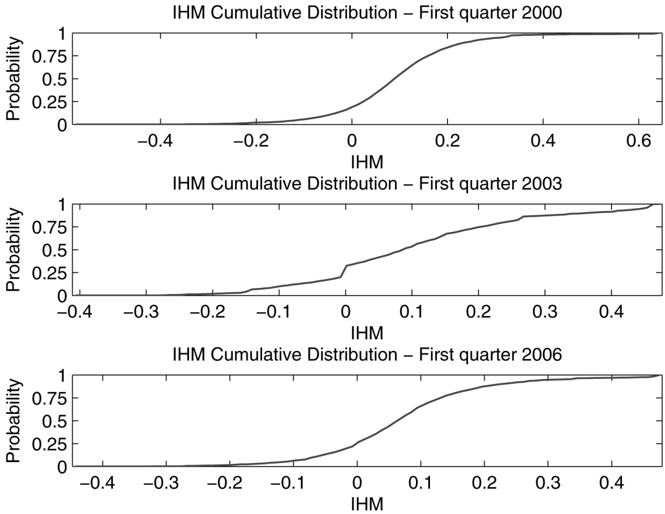

Figure 2. – The IHM cumulative distribution

This figure presents the cumulative distribution of the IHM at three points in time (First quarter of 2000, 2003 and 2006).

results in Table 4 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.

5.3. Herding and investor characteristics

We test here 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.

Table 4. – Mean contemporaneous and time-series correlation of individual investors' herding measure (IHM)

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***

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

The gender differences in investment behavior are well-documented. For instance, Barber and Odean (2001) investigate overconfidence by using a "left 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.

The second attribute we consider is the investor's sophistication. Our hypothesis is that 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.

We proxy sophistication using three different variables. The first proxy is the total number of transactions made by an investor over the sample period. The second proxy is a dummy variable that equals one if the investor is trading warrants in addition to common stocks (and zero otherwise).[7] The third proxy is the investor average portfolio value. It accounts for the wealth of the individuals. Of course, this variable captures the wealth of individuals only imperfectly, because it neglects assets such as real estate investments.

Table 5 reports the average IHM values for the different categories: a) men *versus* women, b) investors who trade warrants *versus* investors who do not, c) investors with less than 100 trades *versus* investors with more than 200 trades d) investors with an average portfolio value below 5,000€ *versus* an average portfolio value above 100,000€.

For each attribute and each quarter, we aim at testing, for each category, whether the average IHMs are equal. Under the null, there is no difference between the average IHMs (*i.e.*, males *vs* females). Because we do not know the theoretical distribution of the difference, we run Monte-Carlo simulations to estimate the $p-$values. 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

7. Trading warrants requires familiarity with option-like payoffs.

Table 5. – The Individual Herding Measure (IHM) and investors' attributes

		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	.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

This table reports the 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 sub-samples of investors. The reported p-values (computed with Monte-Carlo simulations) correspond to the test of no difference between the average IHM values of the two sub-samples of investors.

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

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 5. It appears that, on average, women herd more than men. The overall 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.

5.4. Relationship between past performance and herding

To go deeper in analysis, we investigate now whether and how investors' past performance can influence herding. To this end, 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 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 6 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[8] are less clear because only 20/28 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.[9] 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:

8. Mitton and Vokink (2007) show that individual investors have a heterogeneous preference for skewness. This heterogeneity helps explain why individual investors are underdiversified.

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

Table 6. – Correlation between investors's portfolio past returns and herding behavior

		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***

The quarterly returns are based on the 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.

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

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 include two lags for IHM; more lags would too dramatically reduce the size of our sample. Thus, we consider the observations that correspond only to investors trading three quarters consecutively.

The results are presented in Table 7 (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 matters as θ 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 100 trades while it is not significant for the investors associated with a high number of transactions. For the

Table 7. – Influence of past performance on herding behavior

Explanatory Variable	Model 1 Coefficients	Model 2 Coefficients	Model 3 Coefficients	Model 4 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

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 the IHM (quarters $t-1$ and $t-2$) 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 to 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 otherwise. 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 winsorized at the 1^{st} and 99^{th} percentiles. Coefficients are standardized.

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).

5.5. Payoff implications

A question that was not yet addressed in the literature is whether there exist some (positive) payoffs externalities for herding. 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 (see 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).

A preliminary analysis consists in computing the Spearman rank correlation between the IHM values and the investors' average return, standard deviation, skewness and kurtosis for each quarter. The results in Table 8 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. Her return is calculated as

Table 8. – Correlation between investors's portfolio contemporary returns and herding behavior

		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***

Quarterly returns are based on the 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.

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

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 $-0.05 \leqslant IHM \leqslant 0.05$) and investors engaging in a herding behavior ($IHM > 0.05$).[10] The anti-herder quarterly return R_t^{AH} is estimated to be

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

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

$$R_t^{IT} = \frac{1}{I_t^{IT}} \sum_{i=1}^{I_t} R_{i,t} 1_{\{-0.05 \leqslant IHM_i \leqslant 0.05\}}, \quad (14)$$

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

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

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

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

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 (1997) four-factor model. The intercept is obtained by estimating the following time-series regression

$$
\begin{aligned}
&R_{i,t} - R_{f,t} \\
&= \alpha + \beta \left(R_{m,t} - R_{f,t} \right) + \theta SMB_t + \lambda HML_t + \eta MOM_t + \varepsilon_{i,t},
\end{aligned} \tag{16}
$$

where $R_{f,t}$ is the EURIBOR 3-month rate, $R_{m,t}$ is the quarterly return on the French CAC All-Tradable index[11], SMB_t and HML_t are the two additional Fama and 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.[12]

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 9. 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 the Individual Herding Measure (IHM). It appears that the investors who trade against the crowd dramatically increase their performance by trading

11. This index (also called SBF250) is composed of the 250 largest capitalizations on the French market.

12. The index and the Carhart (1997) factors are provided by Eurofidai (www.eurofidai.org).

Table 9. – Panel regression of individual herding and performance

	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)	

Quarterly returns are based on the investors' daily portfolios from January 1999 to December 2006. Panel A corresponds to the average investor who is representative of the entire population. Panel B corresponds to the anti-herders ($IHM < -0.05$), Panel C to the independent traders ($-0.05 \leqslant IHM \leqslant 0.05$) and Panel D to the herders ($IHM > 0.05$). The own-benchmark abnormal return is the result of the difference between the realized return and the return of the beginning-of-quarter portfolio. The market-adjusted return corresponds to the investor's realized return minus the return of the market (SBF 250) for the same period. The p-values are computed using the t-statistics based on the 32 observations of the time-series. The Carhart four-factor model is a regression of the individual investor excess return (using the 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). The quarterly returns are winsorized 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.

contrary to the rest of the population.[13] 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 remainder 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, it does not need to be linear. The component of the chi-square CS_{ij} for decile i and category j is calculated as

13. This result is an indirect proof of the validity of our measure. Indeed, as documented by Barber and Odean (2000), most of the individual investors decrease their performance by trading. The fact that the investors with a negative IHM value increase their performance by trading shows that our measure is successful in determining investors who trades against the crowd.

$$CS_{ij} = \frac{\left(\alpha_{ij} - \alpha^*_{ij}\right)^2}{\alpha^*_{ij}}, \tag{17}$$

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

$$GCS = \sum_{i=1}^{10} \sum_{j=1}^{3} CS_{ij} \rightsquigarrow \chi^2\left((10-1)(3-1)\right). \tag{18}$$

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 do not have any information concerning its type. 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.[14] 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 esti-

14. 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.

mate it. The process that is used is similar to the one used for Table 5. Each decile (category) contains $d_i, i = 1,...,10$ ($c_j, j = 1,...,3$) investors. For a given quarter, we randomly separate the investors in the sample into ten categories (corresponding to the deciles) of size $d_i, i = 1,...,10$ and in three categories of size $c_j, j = 1,...,3$. 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

$$\xi_{ij} = \frac{1}{10000} \sum_{k=1}^{10000} \mathbf{1}_{\left\{\left|I_{ij} - I_{ij}^*\right| < \left|\overline{I_{ijk}} - I_{ij}^*\right|\right\}}, \tag{19}$$

where $\mathbf{1}$ is an indicator function, 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 and $\overline{I_{ijk}}$ corresponds to the number of investors observed at draw k (where the sample is randomly divided).

Table 10 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 between parentheses indicate the number of quarters for which the observed number of investors is significantly different than the theoretical number at the 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 completely 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.

Table 10. – The influence of herding behavior on investors' portfolio performance

	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)

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. The values in brackets correspond 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). Quarterly returns are winsorized at the 1^{st} and 99^{th} percentiles.

The results for Panel B (using Sharpe ratios instead of returns) are even more striking. For the anti-herders, the proportion 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 show that these investors concentrate 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).

6. 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 over time, we are able to investigate 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 the 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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