Herding in French stock markets: Empirical evidence from equity mutual funds

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Abstract

Using the traditional herding measure of Lakonishok, Shleifer and Vishny (1992) (LSV) and the more recent measure of Frey, Herbst and Walter (2007) (FHW), we assess herding by French equity mutual funds between 1999 and 2005. We show that LSV herding amounts to 6.5%, while FHW herding is approximately 2.5 times stronger. We find that herding is stronger in small-capitalisation firms than in medium- and large-capitalisation firms. Herding is also more severe among foreign stocks than among EU-15 or French stocks. Moreover, French mutual funds are shown to partially use positive feedback strategies. Finally, we establish that sell-herding has a destabilising impact on stock prices and that this impact is larger for foreign stocks.

1. Introduction

Herding is a behaviour that involves imitating other agents' actions. Although it is referenced in many fields of economics, herding is particularly often invoked to explain financial market anomalies, such as the excessive volatility of asset prices or the emergence of financial bubbles. Herding may be practiced by analysts when they issue recommendations or firm earnings forecasts but also by investors when they make transactions in financial markets. Among the latter, institutional investors, such as funds, banks or insurance companies, now carry a very important weight in financial markets. They are also considered particularly prone to herding. First, they are better informed than individuals about other market participants' transactions. Second, they may be particularly sensitive to reputation effects (Scharfstein & Stein, 1990) and based payment schemes (Maug & Naik (1996)).[1] There now exists abundant empirical literature on institutional herding (Vaubourg (2010)). In this study, we follow a large stream of literature, in line with Lakonishok, Shleifer & Vishny (1992), which proposes a measure of herding based on portfolio data. It assesses herding as an excessive concentration of transactions on the same side of the market for particular stocks. This literature focuses primarily on American, German and British mutual and pension funds (Lakonishok & al. (1992), Grinblatt, Titman & Wermers (1995), Oehler (1998), Wermers (1999), Oehler & Chao (2000), Wylie (2005), Haigh, Boyd & Buyuksahin (2006), Walter & Weber (2006) and Puckett & Yan (2007)). Due to its ease of implementation, the indicator proposed by Lakonishok et al. (1992), below denoted as 'LSV indicator', allows for interesting refinement in the analysis of institutional herding. First, it allows herding among sub-categories of stocks or funds to be studied. Second, it can be used to examine feedback trading strategies and the impact of institutional herding on stock returns. However, various arguments have been put forward against this indicator. Among them, the criticism made by Frey, Herbst & Walter (2007) appears particularly interesting. Resorting to simulations, the authors argue that the LSV indicator undervalues herding. Thus, they propose an alternative indicator, below denoted by as 'FHW indicator', based on the spread between the empirical variance of the proportion of buying transactions

[1] For thorough reviews of the theoretical literature on these issues, see Bikhchandani & Sharma (2001) and Hirshleifer & Teoh (2003).

and its expected value under the no-herding assumption. Computing their indicator on a biannual dataset of German mutual funds, they show that herding turns out to be higher than when measured with the LSV indicator. However, Bellando (2010) establishes that the FHW indicator is biased and overestimates herding. Hence, the LSV and FHW indicators provide lower and upper bounds for the true value of herding intensity, respectively.

Although a large empirical body of literature has been developed on institutional herding, studies of herding in French mutual funds are still lacking; this deficiency can be viewed as a paradox, as the French investment funds industry is the largest in Europe. In terms of asset under management, it represents more than 20% of the European market. It also exhibits a particularly high concentration. The lack of studies on the French market is mainly because portfolio data on French mutual funds had, until now, been unavailable. The goal of this paper is to fill this gap. We make use of a new dataset provided by the Banque de France, containing 1 891 French equity OPCVM (Organismes de Placement Collectif en Valeurs Mobilières) between March 1999 and June 2005. OPCVM are collective management entities that encompass SICAV (Société d'Investissement à CApital Variable) and FCP (Fonds Communs de Placement). Controlled primarily by banks and insurance companies, OPCVM show notable success, particularly with households, and are now among the most significant investors in financial markets. At the end of 2010, their assets under management amounted to approximately 1 340 billion euros for OPCVM in its entirety and 280 billion for equity OPCVM.[2]

In contrast to most literature on institutional herding, we use both the traditional indicator of Lakonishok et al. (1992) and the recent indicator of Frey et al. (2007) to measure the intensity of herding by French OPCVM. This process allows us to bind the level of herding and show that the French mutual funds market has a herding intensity of between 6% and 20%. Using the standard LSV measure, we establish that herding by French mutual funds is higher than that reported in other empirical studies on the US and UK stock markets. However, it is quite similar to the herding level obtained for the German case. We provide no robust evidence that herding monotonically rises with the number of investors trading on a given stock during a particular quarter. However, when restricting the analysis to large transactions from the fund point of view, the estimated level of herding turns out to be systematically higher than when one considers all transactions. This finding is in line with Wermers (1995), Ohler (1998) and Bikhchandani & Sharma (2000), who note one drawback to the LSV indicator. Because it only considers the number of buyers and sellers in the market regardless of the volume of assets bought and sold, it does not take trading intensity into account. Our results confirm that trading intensity affects herding and likely increases its level.

In line with results reported by the majority of previous works on developed stock markets, we also show that although some herding is observed for large capitalisation stocks, herding is particularly strong in small-capitalisation firms. Moreover, our findings reveal that French equity mutual funds only partially practice momentum strategies: they buy past winners but do not significantly sell past losers. Finally, our paper provides two original conclusions for literature on institutional herding. An important innovation of our paper is examining whether stocks' geographical origin affects herding intensity. Herding is less severe among French or EU-15 (the 15 countries of European Union) stocks than among foreign stocks (from countries other than EU-15). However, in contrast to most previous papers on developed stock markets, the price dynamics of herded stocks suggest that French equity mutual fund sell-herding has significant destabilising effects on stock prices and that these destabilising effects are more pronounced for foreign stocks.

[2] Source: Association Française de Gestion Financière (AFG). For more details about the French mutual funds industry, see the AFG Website: www.afg.asso.fr/.

The article is organised as follows. Section 2 reviews the theoretical underpinnings of herding and the empirical literature based on LSV and FHW indicators. In Section 3, we introduce our data and methodology. The results are discussed in Section 4, and our conclusions are presented in Section 5.

2. Institutional and fund herding in the literature

2.1 Theoretical literature

There now exists a large theoretical body of literature on herding. Particular attention has been devoted to rational herding, where herders act rationally against their private information by following the crowd.[3] In the rational view, optimal decision making can be distorted by information imperfections or incentive issues. Studies on informational herding consider a profit maximising investor who revises his decisions after observing others' actions. Because other investors may know something that he does not know about stock returns, observing their actions allows him to infer information and leads to so-called informational cascades (Welch (1992), Bikhchandani, Hirshleifer & Welch (1992)). However, Avery & Zemsky (1998) show that if asset prices are endogenous, prices should aggregate all information contained in past trades. Hence, they should converge to the fundamental value such that traders have no incentive to herd. Herding, however, can arise if there is uncertainty regarding not only asset fundamental value but other characteristics as well, such as the proportion of informed traders in the market. Other theoretical contributions have been developed in line with Avery & Zemsky (1998). For example, Park & Sabourian (2011) show that herding can be observed when information is sufficiently dispersed in the market because investors assign a higher probability to extreme outcomes than to moderate ones. In Cipriani & Guarino (2008), informational cascades also occur in financial markets when participants trade for non-informational (liquidity or hedging) motives. It is worth noting that the literature on informational cascades relates to herding for any type of investor. Another strand of literature concentrates on herding by fund managers, for whom there exist two particular incentive schemes: reputation and compensation concerns. Contrary to previous works, this literature mainly considers partial equilibrium models with exogenous prices. Maug & Naik (1996) establish that the compensation scheme may provide managers certain incentives to herd. Notably, if their compensation is linked to a benchmark performance, managers will reproduce the benchmark.[4] Scharfstein & Stein (1990) focus on reputation concerns. A manager may disregard his own information because he prefers making an unwise decision with others. Whereas informative signals received by good fund managers are correlated, uninformative (noisy) signals received by bad managers are not. Consequently, when a manager makes a bad allocation decision, his poor decision making is revealed only if other managers did not make the same decision. Consequently, even well-informed managers are enticed to follow the crowd. Finally, the contribution of Dasgupta & Prat (2008) is particularly interesting because the authors introduce career and reputation effects in a general equilibrium model with endogenous prices. They show that if traders are (even slightly) concerned about their reputation, then the informational role of prices, as highlighted by Avery & Zemsky (1998), declines. Hence, stronger career concerns lead to more conformity among traders.

[3] The non-rational view of herding focuses on investor psychology and argues that agents' behaviour is based on irrational rather than rational motivations. From an empirical point of view, such behaviours are normally associated with momentum strategies, where an investor buys high past-return stocks and sells low past-return ones.

[4] Whether such compensation schemes allow for reducing moral hazard and adverse selection has been discussed by Admati & Pfleiderer (1997). They show that benchmark-based compensation is inefficient in the case of multiple risky assets models.

2.2 Empirical literature

2.2.1 The LSV indicator

The most widely used measure of institutional herding is the index proposed by Lakonishok et al. (1992). It is defined as follows:

— — , where is the number of institutional buyers of stock *i* at *t*, the total number of institutional sellers and buyers of stock *i* at *t*, the probability for a mutual fund to be a buyer at *t* and *E* the expectation; follows a binomial distribution, with probability and number of drawings . — measures the average propensity to buy stock *i* at *t*. Hence, the first term of assesses the propensity of stock *i* to be more intensively bought or sold by mutual funds than all stocks as a whole at *t*. It is corrected by the second term, as even with no herding, the first term of is positive due to the absolute value and to the natural dispersion of stock transactions by mutual funds. This second term is simply the expectation of the first term when herding is null. Thus, measures the excess of selling or buying transactions' similarity. = 0 denotes that there is no herding among mutual funds, while > 0 indicates herding behaviour; the higher the , the stronger the herding. For instance, if the proportion of institutional buyers in the entire market is 50%, = 10% could indicate that at *t*, the proportion of institutional buyers (resp. sellers) of stock *i* is 40%, while the proportion of institutional sellers (resp. buyers) is 60%. An average indicator H_{LSV} can also be implemented to measure institutional herding in the entire market and over the entire dataset period.

The implementation of requires portfolio data, indicating the mutual fund by which each stock of the dataset is bought or sold. It has mainly been used in the case of stock transactions by American pension and mutual funds. As shown in Table 1 of the Appendix, the resort to H_{LSV} has been extended in terms of geographical area and in terms of stock and mutual fund categories. The first finding of this empirical literature is that institutional herding is very weak in American and Western European markets. It is higher in emerging markets as well as in Finnish, Portuguese and Polish markets due to information opaqueness (Loboa & Serra (2006)), high ownership concentration (Do, Tan & Westerholm (2008)) or stock regulation and mutual fund concentration (Borensztein & Gelos (2001)). Lakonishok et al. (1992), Wermers (1999), Voronkova & Bohl (2005) and Do et al. (2006) also establish that small-capitalisation stocks are particularly prone to herding behaviour. For example, Lakonishok et al. (1992) find that H_{LSV} equals 6.1% for the lowest market-capitalisation quantile firms, while it is only 1.6% for the highest market-capitalisation quantile firms. Information asymmetries may also entail stronger herding on stocks issued by Internet firms. This finding is confirmed by Sharma, Easterwood & Kumar (2005), who show that H_{LSV} is 6.58% for Internet businesses between 1998 and 2001, as opposed to 3.86% on the entire American equity market.

Grinblatt et al. (1995) also claim that herding by income funds (0.88%) is weaker than herding by growth funds (1.55%) because imitation is particularly attractive for funds whose allocation style is based on firms' fundamental value assessment. Kim & Wei (2001) and Borensztein & Gelos (2001) also show that herding is stronger among on-shore funds than off-shore funds, the latter being less transparent and more difficult to imitate.

Finally, the LSV indicator has been used to investigate feedback trading strategies, which consist of buying high past-return stocks and selling low past-return stocks. Grinblatt et al. (1995), Wermers (1999) and Sharma et al. (2005) confirm the existence of feedback trading by American funds. Walter & Weber (2006) obtain the same results for German funds. The “buy herding measure” (the value of

H_{LSV} conditioned on —) is higher for stocks with high performance during the previous quarter, while the "sell-herding measure" (the value of H_{LSV} conditioned on —) is higher for those who exhibited poor performance. Obtaining opposite results for mutual funds in the UK, Wylie (2005) concludes that they adopt contrarian strategies.

A first argument put forward against the LSV indicator is that it may be biased downward.[5] The undervaluation of herding behaviour may arise from an insufficient number of transactions. If there exists a positive relationship between market activity and herding, calculating H_{LSV} with small values of may bias the indicator downward. Indeed, reputation effects are more likely to take place when there are more than 2 or 3 transactions in the market. Hence, the stronger the market activity, the stronger the incentive to herd. Lakonishok et al. (1992), Grinblatt et al. (1995), Wermers (1999), Loboa & Serra (2006) and Wylie (2005) provide the values taken by H_{LSV} while progressively reducing the number of transactions below which stocks are excluded from the calculation. Only Grinblatt et al. (1995) and Wylie (2005) report a monotonic (and positive) relationship between the indicator and the level of parameter . For instance, in Wylie (2005), H_{LSV} = 2.5% for ≥ 5, while *HLSV* = 9% for ≥ 25. Wermers (1995), Ohler (1998) and Bikhchandani and Sharma (2000) note another drawback. The LSV measure only considers the number of buyers and sellers in the market regardless of the volume of assets bought and sold. If funds are more homogeneous for large transactions than for small transactions, then giving the same weight to all transactions causes the level of herding to be undervalued. However, Frey et al. (2007) put forth a major argument against the LSV measure in a paper where they also propose an alternative indicator of herding. Their findings are examined in detail in the following subsection.

2.2.2 The FHW indicator

In a recent paper, Frey et al. (2007) examine the relevance of the LSV herding measure. Using Monte Carlo simulations, they show that this measure is well suited for testing whether herding exists or not. However, the authors establish that in the presence of herding, the LSV measure systematically undervalues herding. Bellando (2012) examines this bias and shows that the second term in the LSV formula (i.e., the adjustment term) is biased upward in the case of herding.[6] This finding is confirmed by FHW simulations.[7] Furthermore, the bias decreases with the number of transactions in a stock quarter but remains positive, which can explain the increasing relationship between herding and the number of transactions mentioned above. Thus, comparisons of herding measures based on the LSV indicator across stocks, periods or subsamples potentially result in distorted results. Based on a simple trading model, Frey et al. (2007) introduce a new measure of herding. Using the same set of

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[5] Wylie (2005) suggests that the LSV indicator could also be biased upward because the impossibility of short-selling (a practice that consists of selling a stock without owning it first) implies a left-truncation of the distribution. Calculating H_{LSV} on the subset of stocks initially owned in funds' portfolios, Wylie (2005) obtains a value of 1.2%, which is much lower than that obtained for the entire sample.

[6] The aim of the H_{LSV} adjustment factor is to correct for the effect of the first term's absolute value (always positive). Bellando (2012) shows that this adjustment factor depends on herding level and must decrease when herding is increasing. However, as the adjustment factor remains constant regardless of herding intensity, the LSV indicator undervalues herding.

[7] They report 10 000 simulations for varying values of $n_{i,t}$ and diverse values of true herding h_t, but they always set stock probabilities to be bought (or sold) as 1/2.

simulations as above, they show that when herding exists, their indicator has better properties in terms of bias and convergence than does the LSV indicator.[8]

Their indicator goes from the basic idea of the LSV indicator and assesses the excess dispersion of trades on the buy- or sell-side in the case of herding. To do so, they use the second moment rather than the first absolute moment. For stock *i* at *t*, they compute:

The first term of is the empirical variance of the proportion of buying transactions for stock *i* at *t*, and the second term is its theoretical variance under the assumption of no-herding (H0), where follows a binomial distribution, with parameters and . The stronger the herding activity, the higher the difference between the empirical and theoretical variances. When herding intensity increases, the spread between and , as well as its squared value, tends to rise. As the expected variance under H0 is constant for given values of and , the gap between both terms increases in the same manner as the square of the herding intensity. Finally, can be computed as the average of for different samples of stocks and/or time periods. The estimated herding level is then obtained by taking the square root of this average.

However, Bellando (2010) finds that this indicator is biased upward when sell-herding and buy-herding intensity is asymmetric (i.e., when the weight of sell-herded stocks is different from the weight of those that are buy-herded). However, as suggested by Bellando (2010), the FHW indicator can be used as an estimated upward bound for herding intensity. Hence, although LSV and FHW indicators are shown to be biased, we use them to bind the true value of herding intensity.

3. Data description

Compared to other European and Anglo-Saxon markets, the French mutual fund industry is characterised by a high degree of concentration, as more than two thirds of French mutual fund assets are largely in the hands of institutional players, such as bank affiliates, large insurance companies, retirement institutions, associations and foundations. According to the AFG (Association Française de Gestion Financière (AFG)), asset management companies controlled by banking or insurance groups (some 200 companies among the 500 existing ones) represent 95% of the assets under management. One goal of this paper is to investigate whether this particularity of the French mutual fund industry leads to specific herding behaviours compared to other developed markets.

To study institutional herding by French mutual funds, we rely on a completely new dataset provided by the Banque de France. It contains quarterly portfolio data for approximately 1 891 French equity OPCVM between the first quarter of 1999 and the third quarter of 2005,[9] which represents a total of

[8] For instance, for 1 000 observations, 5 transactions and a 5% true herding level, the bias is equal to -4.6% for LSV and -1% for FHW. When the herding level rises to 15%, the LSV bias is -11.6%, whereas the FHW indicator becomes unbiased. With a higher number of transactions (20) and a 5% true herding, the LSV bias remains (-4.1%), while the FHW bias tends to 0.

[9] This data set is considered confidential by the Banque de France. This institution is currently reflecting on how to provide free access to this data set without disclosing the entire composition of funds. For this reason, it was impossible to update data to include the recent financial crisis. However, the French mutual fund industry is mature enough to warrant analysis and comparison to the Anglo-Saxon market, regardless of the recent financial crisis. Finally, it is interesting to note that our sample covers the 2000s Internet bubble period. To examine how institutional herding behaved during this period, we applied the LSV measure during three sub-periods: before, during and after the crash. The idea was to check whether herding on the buy-side was higher in times of bull markets and whether herding on the sell-side was stronger in times of bear markets. However, our findings

20 182 different shares and 192 804 stock-quarter observations. Some equities are quoted by funds only a few times, while others are quoted more than 5 000 times. The structure of the dataset is particularly well suited for the implementation of LSV and FHW indicators.

First, for each stock, the dataset indicates the stock weight in the OPCVM's portfolio, the growth rate of the stock price and the growth rate of the fund's net value. This information is important because it allows us to compute the so-called "Growth Rate of Stocks' Number" (below denoted as "GRSN"). To compute the GRSN, for every fund-stock-quarter observation, we calculate how much (in per cent) the number of stocks held by the fund has increased (or decreased) compared to the previous quarter. Considering the absolute value of the GRSN allows us to measure so-called fund trading intensity and assess whether a transaction on a given stock is *important* or not from a given fund point of view. We can then investigate whether herding intensity depends on fund trading intensity. To do so, we successively compute herding indicators on samples, excluding trades with low intensity from the fund point of view, i.e., for which > k, with k = 0%, 5% and 10%, respectively (a higher threshold k corresponding to stronger trading intensity).[10]

Stocks are made anonymous, but data also allow us to investigate whether herding depends on stock characteristics. The dataset is segregated into three groups according to the stocks' capitalisation (large, medium and small[11]) and geographical origin (French, EU-15 and foreign). Other characteristics, such as the β, quarter-on-quarter return and price-to-book-ratio of each stock, are also available.

Finally, we reprocess the initial dataset to exclude stock quarters for which information or data are missing. For example, GRSN can be calculated for only 155 492 of the observations. We also exclude stock quarters for which $n_{i;t} \geq 1$. At the end of this process, we obtain a dataset of 101 886 stock-quarter observations. The characteristics of the final sample are reported in Table 2 of the Appendix.

4. Results

We now turn to the results obtained when computing LSV and FHW indicators for our dataset. First, we discuss the overall levels of herding by French mutual funds, comparing our results with those obtained for other developed markets. Second, we investigate whether herding intensity changes with stock characteristics. Third, we address the impact of herding on stock prices.

4.1 Overall herding levels

Table 3 (Appendix) summarises the results we obtained by applying LSV and FHW indicators to our sample.[12] Following Wermers (1999), we consider that trading in the same direction by less than 5

reveal no significant differences. In other words, French institutional herding was not more pronounced during the Internet crash than during the calm period.

[10] Funds that introduce a new stock (GRSN = +) or liquidate their position (GRSN = -) are never excluded. The main drawback of GRSN is its sensitivity to initial holding levels. Unfortunately, we do not have further information about sold and bought stocks.

[11] We have no information about the thresholds used by the Banque de France to size-segregate the data set.

[12] Note that is different for each level of because is computed for the most intensively herded stocks.

investors does not qualify as herding. For both measures, we thus concentrate on stock-quarter observations for which there are at least 5 investors.[13]

Table 3 reveals some interesting facts. First, considering the LSV indicator, the overall level of herding for > 0 and $n_{i;t}$ > 5 is 6.5%. This result can be interpreted as meaning that if 100 French mutual funds trade a given stock in a given period, then approximately 6 more investors end up on the same side of the market than would be expected if all investors make their decisions randomly and independently. Turning to the FHW indicator, one observes that it is significantly larger than that obtained with the LSV indicator. Indeed, the overall herding level amounts to 16.5%. This finding is in line with Frey et al. (2007), who establish that the LSV measure undervalues the level of herding. As shown by Bellando (2010), FHW and LSV indicators provide lower and upper bounds, respectively, for the true level of herding. Thus, our results interestingly suggest that the true value of herding by French mutual funds lies between 6.5% and 16.5%,[14] which is significantly higher than the herding estimations obtained by previous empirical investigations implementing the LSV measure on American and British datasets (Lakonishok et al. (1992), Grinblatt et al. (1995), Wermers (1999), Wylie (2005) and Puckett & Yan (2007)). However, our results are quite similar to those obtained by Walter & Weber (2006) for German funds.

This finding can be partially explained by institutional differences between the French stock market and other developed stock markets. In particular, as explained in Section 3, the French mutual fund industry is highly concentrated, and most funds are owned by banks and insurance companies. This strong concentration could promote mimetic behaviours and thus lead to higher herding levels.

Second, Table 3 indicates that when measured by the LSV indicator, herding increases with .
For instance, for stocks traded by at least 10 investors, the LSV herding measure grows from 6.6% when > 0 to twice this value (13.2%) when > 10%. Table 3 shows that the positive link between herding levels and fund trading intensity as measured by also holds for the FHW herding measure. Taken together, these findings confirm that taking transaction volumes into account modifies the herding measure and increases its level.

Finally, LSV herding by French mutual funds is also slightly higher when the number of trading investors increases. Similar conclusions have been reported by several previous empirical investigations on institutional herding (Grinblatt et al. (1995) and Wylie (2005)). This finding suggests that the incentive to herd for reputation reasons may be comparatively higher when a large number of additional mutual funds are also strongly active in a stock quarter. Furthermore, French mutual funds may infer stronger informational signals and disregard their own private information when the number of traders and/or the fund trading activity increases. However, this finding does not appear very robust, as there is no positive link between the FHW measure herding level and the number of traders. As explained in subsection 2.2.2, this finding suggests that the slight positive link between the LSV indicator and the number of traders may be partly due to the bias inherent to the LSV indicator.

Finally, it is worth mentioning that the herding measures in Table 3 provide aggregate herding levels over all stock-quarter observations regardless of stock characteristics. Therefore, a more thorough analysis of different subsamples is necessary to better understand institutional herding in France.

4.2 Herding intensity and stock characteristics

4.2.1 Herding intensity and stock market capitalisation

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[13] Herding measures computed over all stocks traded during a quarter by at least 1 mutual fund are not reported here but are available from the authors upon request. They show very little difference with the results discussed here.

[14] In fact, the interval is slightly wider, as both values are estimations of the true bounds.

We now examine whether institutional herding in the French stock market varies with firm size.[15] Thus, based on firms' market capitalisation, we first segregate our stock-quarter observations into three groups: large, medium and small firms. We then compute the LSV and FHW indicators for each group. Finally, for each indicator, we resort to Student's t-tests to check whether herding for small firms is significantly different from herding for medium and large firms. Using the same approach, we investigate whether herding for medium firms is significantly different from herding for large firms. Our results are reported in Table 4 (Appendix).

In theory, we would expect higher levels of herding for small firms. According to Wermers (1999), informational cascades are more likely among small firms because mutual funds receive less information for these firms. The agency theory can also be used to justify a higher expected herding in small-capitalisation stocks. From this perspective, it is better to fail conventionally than to succeed unconventionally. Thus, mutual funds should be more sensitive to holding small, poor-performing stocks than large, poor-performing stocks, as the latter are held by many rival mutual funds.[16] Finally, the fact that the short-selling impossibility mainly affects small-capitalisation stocks may also explain more severe herding (on the buying side) on small-capitalisation stocks.

To begin, the values of the LSV and FHW indicators reported in Table 4 show that French institutional herding is larger for small-capitalisation stocks than for large- and medium-capitalisation stocks, as expected. The LSV indicator undervalues herding, as FHW herding levels are approximately 2.5 times stronger than those obtained when employing the traditional LSV measure. Table 4 also indicates that the stronger the fund trading intensity (assessed by), the larger the difference between LSV herding in small- and large-capitalisation stocks. The evidence is less clear according to the number of traders.

It is also interesting to note that LSV herding is higher for large stocks than for medium stocks. This result may partly arise from correlated signals. Sias (2004) establishes that correlation between signals is higher in large stocks with less noisy signals because mutual funds use the same indicators. Furthermore, mutual funds share similar preferences for liquidity and size, so high levels of herding can be observed in large-capitalisation stocks (Gompers & Metrick (2001) and Pinnuck (2004)). Taken together, our results support the idea that herding is consistent with the preference of mutual funds to hold large capitalisation stocks. Nevertheless, this finding lacks robustness, as it does not hold when using the FHW indicator.

4.2.2 Herding intensity and stocks' geographical origin

Next, we examine the hypothesis that institutional herding depends on stocks' geographical origin. This issue appears particularly innovative because to the best of our knowledge, it has yet to be examined in the literature on institutional herding. Information-based and cascade models suggest that herding is more likely to occur when public and private information is more difficult to obtain and use in portfolio management. As investors may know better domestic stocks and receive less information from foreign firms, they are more likely to disregard this information if the consensus opinion is different.

As we have observed, our dataset allows us to segregate our sample into three groups based on the geographical origin of the stock: foreign firms, French firms and EU-15 firms. As French mutual

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[15] Our tests, not reported here but available upon request, show that herding intensity does not depend on stock price-to-book ratio. We also measured herding based on stock betas (offensive versus defensive stocks). Our results reveal no evidence that herding on offensive stocks differs from herding on defensive stocks.

[16] This finding may explain why small firms are often sold by fund managers before performance disclosure (a practice called 'window dressing').

funds know EU-15 firms more than foreign firms but less than French firms, we should expect more pronounced herding in foreign and EU-15 stocks.

Calculating LSV and FHW indicators for each of the three groups of stocks, we adopt the same approach as in the previous section. For each indicator, we compute Student's t-tests to check whether herding in French stocks is significantly different from herding in foreign and EU-15 stocks. We also investigate whether herding in foreign stocks is different from herding in EU-15 stocks. Table 5 (Appendix) reports the institutional herding measures that we obtained. One of the most important original contributions of our paper is establishing that stocks' geographical origin significantly affects herding intensity. As expected, French funds herd much more in foreign and European stocks than in French stocks (when > 5%). The values reported in Table 5 for both indicators also reveal that herding is larger in foreign stocks than in Euro-15 stocks.[17] In line with information-based and cascade models, our estimates suggest that herding is more pronounced when public and private information is more difficult to obtain.[18]

4.2.3 Herding intensity and stock return

Several papers indicate that positive feedback trading strategies (momentum investment strategies) are commonly followed by mutual funds (Grinblatt et al. (1995) and Glaser & Weber (2010)).[19] Such behaviours are sometimes explained by behavioural finance bias, such as conservativeness or representativeness (Shleifer (2000)). Furthermore, this behaviour can be reinforced by window dressing practices, which consist of selling past losers and buying past winners. Thus, in this section, we investigate whether herding depends on past returns. In Tables 6 and 7 (Appendix), we partition stocks into three groups of similar size (each group contains 1/3 of the stock population) according to the previous quarter's returns: low past-performance, medium past-performance and high past-performance stocks. We distinguish between sell-side herding (H_{LSV} and H_{FHW} calculated on stocks for which —) and buy-side herding (indicators calculated on stocks for which —).[20] As in previous subsections, Student's t-tests are conducted to examine whether sell-herding is less intense for high past-performance than for low and medium past-performance stocks and whether sell-herding is less intense for low past-performance stocks than for medium past-performance stocks (Table 6). Similarly, we use Student's t-tests to check whether buy-herding is more intense for high past-performance stocks compared to low and medium past-performance stocks and whether buy-herding is more intense for low past-performance than for medium past-performance stocks.

Table 7 shows that buy-herding is more severe for high past-performance than for low past-performance and medium past-performance stocks. This result seems particularly robust, as it holds for both the LSV and FHW measures. However, the results reported in Table 6 are much less clear cut. Medium past-performance stocks are less sell-herded than low and high past-performance stocks, but no significant difference exists between low and high past-return stocks. Finally, Tables 6 and 7 suggest that French mutual funds buy-herd on high past-return stocks more strongly than they sell-

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[17] Again, computing sell- and buy-side herding, we found no significant differences.

[18] This result must be considered with caution because information about foreign stocks may be more strongly correlated than information about French stocks. Hence, our finding may simply reveal the existence of spurious herding.

[19] The momentum effect relates to inefficiency and market undervaluation, as positive return serial correlation during a period may react to the incorporation of news into stock prices.

[20] According to Tables 6 and 7, it is noteworthy that excluding trades for which $|GRSN| > 5\%$ leads to removing more observations on the sell-side than on the buy-side. The rationale for this phenomenon is not obvious. However, it suggests that French mutual funds have more intensively bought than sold during the data set period.

herd on low past-return stocks. This finding offers new evidence of a disposition effect for French fund managers. Because they dislike incurring losses much more than they enjoy making gains, investors hold past losers and are impatient to sell past winners (Shefrin & Statman (1985)).

4.3 The impact of herding on stock returns

In the previous section, we showed that herding by French funds is highly significant. Thus, one important question arises: does this herding have an impact on stock prices? To empirically assess the effects of French equity mutual funds' herding on stock prices, we use the approach initiated by Wermers (1999). Our results suggest that for some stocks, mutual funds tend to trade on the same side of the market. However, the effect of these transactions on prices depends on the quality of the information that triggered them. If transactions are motivated by "good" or fundamental information, they may improve market efficiency by allowing prices to incorporate information more rapidly. Such herding may have a long-term effect on prices.[21] Conversely, if herding transactions are not based on fundamental information, they are likely to have a destabilising impact on stock prices. In that case, one can expect that the effect of this "noisy" herding on stock prices will reverse: its impact should be temporary, and stock prices should finally return to their fundamental value.[22] Based on this approach, we try to assess whether herding by French mutual funds has a destabilising effect on prices. If so, we expect that the prices of highly buy-herded (resp. sell herded) stocks will increase (decrease) during the herding period and then decrease (increase) in subsequent periods.

To do so, we first split our dataset according to the sign of herding.[23] In the buy (sell) herding group, we rank stocks according to their herding intensity and segregate them into 5 groups, denoted by B1-B5 (S1-S5), thus creating ten quintile portfolios. B1 (S1) contains the most buy-herded (sell-herded) stocks, while B5 (S5) contains the least buy-herded (sell-herded) stocks. To simulate the return of the strategy that consists of herding on both (buy- and sell-) sides, we consider the portfolio B1-S1, which results in simultaneously buying the most buy-herded (B1) and selling the most sell-herded stocks (S1). Finally, quarterly equally weighted size-adjusted abnormal returns are computed for the ten portfolios during the herding quarter (denoted by Q_t) and the subsequent four quarters (Q_{t+1}, Q_{t+2}, Q_{t+3} and Q_{t+4}). We also include the two preceding quarters (Q_{t-2} and Q_{t-1}) to explore the effect of past returns on current herding levels. To measure abnormal returns, we classify herded stocks into three groups based on firm capitalisation. For a stock belonging to one of the three groups, the abnormal return is computed by subtracting the average equally weighted quarterly return of the group from the average quarterly return of the considered stock. Tables 8 and 9 (Appendix) report the average abnormal returns computed over our sample period for the ten portfolios. In Table 8, herding is measured with the LSV indicator, while in Table 9, it is measured with the FHW indicator.

4.3.1 *Overall analysis*

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[21] Regardless of whether this information is common or not, the effect on prices should be similar if funds share the same information and if funds systematically follow a better informed fund.

[22] However, also note that as we do not precisely know how long it takes for prices to return to the stock fundamental value, observing no reversal during the considered period should be interpreted as a sign, rather than proof, that herding is stabilising.

[23] Hereafter, we present results for stocks traded by at least five funds with an absolute value of > 5%. When using other thresholds, results are not qualitatively changed. To check for the robustness of our work, we also investigated the effects of herding on stock prices based on abnormal returns computed using the CAPM. More precisely, we first used the CAPM to estimate the expected equilibrium return on each stock; the abnormal return is then computed by subtracting this equilibrium return from the return of the considered stock. Our results, not reported here for reasons of space but available upon request, lead to very similar conclusions.

Before focusing on the effect of herding on abnormal stock returns, it is worth noting that Tables 8 and 9 provide further support of the existence of feedback trading by French equity funds. The results reported in Table 8 indicate that for higher values of buy-herding, stocks have higher past performance (7.19% during Q_{t-2} and 9.16% during Q_{t-1}), while for weaker values of buy-herding, they have lower past performance (4.31% during Q_{t-2} and 3.69% during Q_{t-1}). For higher levels of sell-herding, the findings are less clear-cut. Stocks have lower, although positive, past performance but only during Q_{t-2} (2.70%)), while stocks have higher past performance for weaker levels of sell-herding (4.86% during Q_{t-2} and 3.26% during Q_{t-1}). Thus, French mutual funds buy-herd on past winners. The results are less clear-cut for sell-herded stocks. These results partially confirm the findings obtained in subsection 4.2.3 and in the literature (Grinblatt et al. (1995) and Glaser & Weber (2010)).

Next, we turn to the potential effects of herding by French equity mutual funds on future returns. If investors herd with no fundamental justification, stock prices should be increased by buy-herding during the herding quarter Q_t and then decrease in subsequent periods. Symmetrically, stock prices should be decreased by sell-herding during the herding quarter and then increase in subsequent periods.

Regarding the most buy-herded stocks, one observes an increase in prices during the herding quarter (8.82%). This finding must be considered with some caution: as stock returns are computed on a quarterly basis, excess stock returns during the herding period Q_t may be partially due to intra-quarter feedback trading. For example, at the end of the herding quarter, French equity funds may heavily buy stocks that were past winners at the beginning of the herding quarter. This scenario may partially explain the particularly high level of excess stock returns in Q_t, thus overvaluing the effects of herding on stock prices. Moreover, this rise continues during the following quarters (2.66% during Q_{t+1}, 1.92% during Q_{t+2}, ...), indicating that there is no reversal effect.

Considering the most sell-herded stocks, one observes a decrease in prices (-2.10%). However, this decline is cancelled and more than compensated for during subsequent quarters (2.53% in Q_{t+1}, 2.95% in Q_{t+2}, 4% in Q_{t+3} and 3.87% in Q_{t+4}), testifying to a reversal effect. Finally, the last line of Table 8 suggests that buying the most buy-herded stocks and selling the most sell-herded stocks (B1-S1) during the herding quarter leads to a loss of approximately 5% during the four subsequent quarters. This loss results from the cumulated rise in prices of the sold stocks. Taken together, these findings reveal that sell-side herding by French equity funds may have destabilising effects.

The results reported in Table 9 show that our main findings hold when we use the FHW herding measure. In other words, herding by French mutual funds appears to be related to feedback trading strategies, and French institutional herding has significant destabilising effects on stock prices. Taken together, our findings are somewhat in contrast to those of previous works on developed stock markets, in which herding is shown to have permanent effects on stock prices on both buy- and sell-sides (Wermers (1999), Wylie (2005) and Walter & Weber (2006)).

4.3.2 *Herding effects and firm characteristics*

Finally, to check whether herding effects on stock returns change with firm characteristics, we repeat the portfolio analysis, separating the sample according to firm size and geographical origin. The results that only concern the effect of herding on subsequent returns are summarised in Tables 10 and 11 (Appendix).[24] To the extent that smaller capitalisations are less liquid and are subject to greater information and arbitrage constraints, we expect sell-herding to have a greater destabilising impact on smaller firms. Although the results in Table 10 are similar to those in Table 8 for B1 and S1, portfolio

[24] For reasons of space, we only report the results based on the LSV indicator. The results from the FHW indicator lead to similar conclusions and are available upon request.

B1-S1 exhibits slightly lower sell-side destabilising effects in Table 10 than in Table 8. However, when one considers only small firms (Table 10), the findings are less clear cut. Focusing on sell-herded stocks, results are never significant for S1 and S5, while they are always significant for S4. These findings may be explained by small sample statistical problems and by the distribution of small firms among portfolios.[25]

Next, we showed that because of information asymmetries and constraints, herding is more pronounced for foreign stocks. Thus, one might expect formation period returns and subsequent price reversals to be largest in foreign stocks. We examine here whether the impact of herding on stock returns changes with stocks' geographical origin. The results are reported in Table 11 (Appendix). When excluding foreign firms, one observes significant decreases in positive abnormal returns for sell-herd-side portfolios, suggesting higher destabilising effects for foreign firms. This finding is confirmed when we assess herding effects exclusively for foreign firms' stocks. For foreign firms, the sell-side corrections during the periods Q_{t+1}, Q_{t+2} Q_{t+3} and Q_{t+4} are considerably larger than those obtained for all non-foreign firms.

To summarise, our findings show that buy-side French equity fund herding has no destabilising impacts on stock returns. In contrast, sell-side French equity fund herding has significant reversal effects on stock prices. More interestingly, our findings suggest that the destabilising effects of French equity fund herding are stronger in foreign stocks, even if they remain statistically and economically significant for the other stocks.

5. Conclusion

This paper offers the first empirical investigation of herding by mutual funds in the French stock market. An interesting contribution made by this paper is the use of two different measures of herding to bind the level of herding. The widely used LSV indicator systematically undervalues herding. Moreover, the FHW herding levels are approximately 2.5 times stronger than those obtained with the LSV measure. Taken together, our results indicate that the French mutual funds market has a herding intensity of between 6% and 20%. More interestingly, we find that herding levels by French mutual funds are higher than those reported by previous empirical investigations for comparable financial locations. Our findings provide no robust support for the existence of a positive relationship between herding intensity and the number of trades, which may result from the bias of the LSV indicator, as is in line with the explanation given by the FHW indicator.

Herding levels also significantly increase with our measure of fund trading intensity. In line with most papers on institutional herding, herding is particularly strong for small-capitalisation firms. Moreover, French mutual funds buy past winners but do not significantly sell past losers. Finally, one of the paper's most original findings is that herding is more severe among foreign stocks than among EU-15 or French stocks. This result may be attributed to less available information and thus to mutual funds' inclination to herd. The second main finding of the paper is that in contrast to most previous findings on developed stock markets, sell-herding has a destabilising impact on stock prices. Moreover, we show that these sell-herd destabilising effects are more pronounced for foreign firms.

[25] For the entire data set, small firms are overrepresented in portfolio S5, thus strongly contributing to the reversal effect on the most herded stocks. In contrast, when the sample is reduced to small capitalisation, firms are more equally distributed among portfolios. This result means that in the subsample of small capitalisation stocks, the link between herding level and future adjusted returns is not clear.

There are several avenues for future research. First, further theoretical investigation should be carried out in line with Bellando (2010, 2012) to improve herding measures and reduce their bias. Second, as herding intensity and its impact on stock prices may vary across industries, a sector analysis of herding by French mutual funds would be informative. Finally, it would be interesting to refine our investigation by using high-frequency data.

Appendix

Table 1: H_{LSV} estimates in the empirical literature on institutional herding

References	Period	Stocks	Institutional investors	H_{LSV}
Lakonishok et al. (1992)	01/1985-12/1989[q]	Equities	769 American pension funds	2.7%
Grinblatt et al. (1995)	01/1974-12/1984[q]	Equities	274 American mutual funds	2.5%
Oehler (1998)	01/1988-06/1993[b]	Equities	28 German mutual funds	2.9%
Wermers (1999)	01/1975-12/1994[q]	Equities	All American mutual funds	3.4%
Oehler & Chao (2000)	01/1993-03/1995[b]	Bonds	57 German mutual funds	2.6%
Borensztein & Gelos (2001)	01/1996-12/1999[m]	Equities	467 emerging country mutual funds	7.2%
Loboa & Serra (2006)	01/1998-12/2000[q]	Equities	32 Portuguese mutual funds	11.4%
Wylie (2005)	01/1986-12/1993[b]	Equities	268 UK mutual funds	2.6%
Voronkova & Bohl (2005)	01/1999-09/2002[a]	Equities	17 Polish mutual funds	22.6%
Haigh et al. (2006)	01/2002-09/2006[q]	Equities	American hedge funds	9%
	01/2002-09/2006[q]	Equities	American brokers and traders	7%
Do et al. (2006)	03/1995-05/2004[q]	Equities	32 Finnish banks, mutual funds and brokers	9.9%
Walter & Weber (2006)	12/1997-12/2002[m]	Equities	50 German equity mutual funds	5.11%
Puckett & Yan (2007)	01/1999-12/2004[b]	Equities	776 American mutual and pension funds	3.78%
Frey et al. (2007)	01/1998-12/2004[w]	Equities	German mutual funds	4.43%

Mentions 'd', 'w', 'm', 'q', 'b' and 'a' in the second column indicate respectively daily, weekly, monthly, quarterly, biannual and annual data.

Table 2: Description of the data set

Number of stocks by quarters							
Quarter	*1999*	*2000*	*2001*	*2002*	*2003*	*2004*	*2005*
1		3 277	3 335	3 489	3 980	4 522	5 135
2	2 598	3 335	3 369	3 764	4 330	4 658	5 422
3	2 674	3 323	3 432	3 793	4 327	4 633	5 546
4	2 760	3 387	3 507	3 838	4 410	5 042	
On-stock average number of funds by quarter							
Quarter	*1999*	*2000*	*2001*	*2002*	*2003*	*2004*	*2005*
1		17.0	19.9	21.1	19.9	19.2	18.2
2	14.7	17.4	20.1	20.4	19.5	18.5	18.8
3	14.9	18.1	20.4	20.3	19.8	18.2	18.5
4	15.2	19.2	20.4	20.2	19.5	17.6	

Number of stock-quarter observations					
by capitalization-category			**by geographical origin-category**		
Large cap	*Medium cap*	*Small cap*	*French*	*EU-15*	*Foreign*
31 923	56 591	52 397	17 655	23 811	60 420

Table 3: Overall estimates of H_{LSV} and H_{FHW}

	$\|GRSN\| > k$					
	k=0		*k=5%*		*k=10%*	
	H_{LSV}	H_{FHW}	H_{LSV}	H_{FHW}	H_{LSV}	H_{FHW}
$n_{i,t}$>5	6.5%	16.5%	11%	21.5%	12.5%	22.7%
	(50 249)		(28 309)		(25 318)	
$n_{i,t}$>10	6.6%	15.1%	11.4%	20%	13.2%	21.1%
	(32 482)		(15 511)		(13 410)	
$n_{i,t}$>15	6.7%	14.6%	11.7%	19.1%	13.8%	20.6%
	(23 881)		(10 271)		(8 680	
$n_{i,t}$>20	6.9%	14.3%	12%	18.8%	14.3%	20.1%
	(18 557)		(7 547)		(6 115)	

Figures in brackets indicate the number of stock-quarter observations.

Table 4: Estimates of H_{LSV} and H_{FHW} according to firm market capitalization

	Large-capitalization firms					
	|GRSN| > k					
	k=0		*k=5%*		*k=10%*	
	H_{LSV}	H_{FHW}	H_{LSV}	H_{FHW}	H_{LSV}	H_{FHW}
$n_{i,t}$>5	6.7%†††	16.0%†††	11.1%†††	22.7%†††	12.6%†††	24.6%†††
	(17 380)		(11 973)		(11 020)	
$n_{i,t}$>10	6.9%††	15.1%†††	11.5%†††	21.7%†††	13.4%†††	23.9%†††
	(12 996)		(8 299)		(7 511)	
$n_{i,t}$>15	7.1%	14.7%†††	12.0%††	21.6%†††	14.0%†††	23.9%†††
	(10 706)		(6 389)		(5 598)	
$n_{i,t}$>20	7.3%	14.5%†††	12.4%	21.6%†††	14.7%†††	24.0%†††
	(9 271)		(5 087)		(4 326)	
	Medium-capitalization firms					
	|*GRSN*| > *k*					
	k=0		*k=5%*		*k=10%*	
	H_{LSV}	H_{FHW}	H_{LSV}	H_{FHW}	H_{LSV}	H_{FHW}
$n_{i,t}$>5	6.0%***†††	16.3%†††	10.5%***†††	23.7%***†††	11.9%***†††	25.6%***†††
	(25 464)		(13 583)		(12 012)	
$n_{i,t}$>10	6.2%***†††	15.1%†††	11.0%**†††	22.5%***†††	12.7%**†††	24.5%**†††
	(16 117)		(6 346)		(5 279)	
$n_{i,t}$>15	6.3%***†††	14.7%†††	10.9%***†††	21.4%†††	13.0%***†††	23.9%†††
	(11 185)		(3 526)		(2 845)	
$n_{i,t}$>20	6.4%***†††	14.3%†††	10.9%***†††	20.8%*†††	13.0%***†††	23.2%*†††
	(8 054)		(2 193)		(1 681)	
	Small-capitalization firms					
	|*GRSN*| > *k*					
	k=0		*k=5%*		*k=10%*	
	H_{LSV}	H_{FHW}	H_{LSV}	H_{FHW}	H_{LSV}	H_{FHW}
$n_{i,t}$>5	7.7%	20.0%	13.0%	28.0%	14.9%	30.4%
	(6 605)		(2 541)		(2 110)	
$n_{i,t}$>10	7.4%	17.6%	13.0%	25.7%	15.8%	28.9%
	(3 113)		(796)		(569)	
$n_{i,t}$>15	7.2%	16.3%	13.7%	25.8%	17.1%	29.6%
	(1 849)		(328)		(216)	
$n_{i,t}$>20	7.3%	15.8%	13.7%	25.5%	18.7%	30.7%
	(1 154)		(161)		(95)	

(i) Whatever the considered category, $p_{i,t}$ is calculated on the whole data set.
(ii) Figures in brackets indicate the number of stock-quarter observations.
(iii) †, †† and ††† denote significance difference of large and medium firms compared to the group of small firms, respectively at the 10%, 5% and 1% level.
(iv) *, ** and *** denote significance difference of medium firms compared to the group of large firms, respectively at the 10%, 5% and 1% level.

Table 5: Estimates of H_{LSV} and H_{FHW} according to firm geographical origin

	Foreign firms $\lvert GRSN \rvert > k$					
	k=0		*k=5%*		*k=10%*	
	H_{LSV}	H_{FHW}	H_{LSV}	H_{FHW}	H_{LSV}	H_{FHW}
$n_{i,t}$>5	6.6%	17.3%†††	11.6%†††	25.2%†††	13.1%†††	27.3%†††
	(27 379)		(13 800)		(11 885)	
$n_{i,t}$>10	6.7%	15.7%†††	12.1%†††	23.7%†††	13.9%†††	26.0%†††
	(16 023)		(5 814)		(4 645)	
$n_{i,t}$>15	6.9%	15.1%†††	12.4%†††	23.1%†††	14.8%†††	26.2%†††
	(10 631)		(2 999)		(2 158)	
$n_{i,t}$>20	7.2%†	14.9%†††	13.1%†††	23.4%†††	16.2%†††	27.1†††
	(7 571)		(1 616)		(1 001)	
	EU-15 firms $\lvert GRSN \rvert > k$					
	k=0		*k=5%*		*k=10%*	
	H_{LSV}	H_{FHW}	H_{LSV}	H_{FHW}	H_{LSV}	H_{FHW}
$n_{i,t}$>5	6.2%***†††	16.2%***	11.1%**†††	23.3%***†††	12.4%***†††	24.8%***†††
	(13 325)		(8 752)		(8 147)	
$n_{i,t}$>10	6.3%***††	15%***	11.7%†††	22.4%***†††	13.2%**††	24.2%***†††
	(9 404)		(5 683)		(5 166)	
$n_{i,t}$>15	6.4%***††	14.6%**	12.2%†††	22.3%**†††	13.8%***†††	24.1%***†††
	(7 440)		(4 114)		(3 670)	
$n_{i,t}$>20	6.6% ***	14.4%***	12.8%*†††	22.4%**†††	14.5%***†††	24.4%***†††
	(6 087)		(3 171)		(2 775)	
	French firms $\lvert GRSN \rvert > k$					
	k=0		*k=5%*		*k=10%*	
	H_{LSV}	H_{FHW}	H_{LSV}	H_{FHW}	H_{LSV}	H_{FHW}
$n_{i,t}$>5	6.6%	16.2%	9.5%	20.5%	11.5%	23.1%
	(9 545)		(5 757)		(5 286)	
$n_{i,t}$>10	6.7%	15.0%	10 .1%	19.8%	12.5%	22.5%
	(7 055)		(4 014)		(3 599)	
$n_{i,t}$>15	6.8%	14.5%	11.3%	19.3%	12.9%	22.2%
	(5 810)		(3 158)		(2 852)	
$n_{i,t}$>20	6.9%	14.1%	10.4%	18.9%	13.2%	22.0%
	(4 899)		(2 670)		(2 359)	

(i) Whatever the considered category, $p_{i,t}$ is calculated on the whole data set.
(ii) Figures in brackets indicate the number of stock-quarter observations.
(iii) †, †† and ††† denote significance difference of EU-15 and foreign firms compared to the group of French firms, respectively at the 10%, 5% and 1% level.
(iv) *, ** and *** denote significance difference of EU-15 firms compared to the group of foreign firms, respectively at the 10%, 5% and 1% level.

Table 6: Estimates of sell-herding (H_{LSV} and H_{FHW} calculated on stocks for which —) according to previous quarter stocks' return

	Low past-performance stocks $\lvert GRSN \rvert > k$					
	k=0		*k=5%*		*k=10%*	
	H_{LSV}	H_{FHW}	H_{LSV}	H_{FHW}	H_{LSV}	H_{FHW}
$n_{i,t}$>5	6.6%††	16.9%	8.3%	20.6%	9.2%†	22.0%
	(8 249)		(3 663)		(3 168)	
$n_{i,t}$>10	6.6%	15.0%	8.5%	19.2%	9.5%	20.6%††
	(5 262)		(1 967)		(1 649)	
$n_{i,t}$>15	6.7%	14.4%	8.5%	18.2†††%	9.8%	20.1%††
	(3 895)		(1 258)		(1 011)	
$n_{i,t}$>20	6.9%	14.2%	8 .7%	18.0††%	10.2%	20.0%††
	(3 051)		(913)		(669)	
	Medium past-performance stocks $\lvert GRSN \rvert > k$					
	k=0		*k=5%*		*k=10%*	
	H_{LSV}	H_{FHW}	H_{LSV}	H_{FHW}	H_{LSV}	H_{FHW}
$n_{i,t}$>5	6.1%***	15.9%***††	6.9%***††	19.1%***†††	7.3%***†††	19.8%***†††
	(8 609)		(3 120)		(2 636)	
$n_{i,t}$>10	6.2%**	14.6%**††	7.1%***†††	17.7%***†††	7.4%***†††	18.4%***†††
	(5 668)		(1 654)		(1 324)	
$n_{i,t}$>15	6.3%**	14.0%**†††	7.3%***†††	17.2%**†††	7.7%***†††	18.1%***†††
	(4 266)		(1 065)		(829)	
$n_{i,t}$>20	6.6%**	13.7%**†	7.2%***†††	16 .7%**†††	7.4%***†††	17.5%***†††
	(3 337)		(756)		(541)	
	High past-performance stocks $\lvert GRSN \rvert > k$					
	k=0		*k=5%*		*k=10%*	
	H_{LSV}	H_{FHW}	H_{LSV}	H_{FHW}	H_{LSV}	H_{FHW}
$n_{i,t}$>5	6.0%	16.2%	7.2%	20.1%	7.9%	21.4%
	(8 311)		(2 725)		(2 175)	
$n_{i,t}$>10	6.2%	14.9%	7.9%	19.4%	9.2%	21.3%
	(5 223)		(1 307)		(975)	
$n_{i,t}$>15	6.5%	14.6%	8.4%	19.5%	9.5%	21.1%
	(3 782)		(811)		(603)	
$n_{i,t}$>20	6.6%	14.1%	8.5%	19.2%	10.2%	21.6%
	(2 933)		(555)		(387)	

(i) Whatever the considered category, $p_{i,t}$ is calculated on the whole data set.
(ii) Figures in brackets indicate the number of stock-quarter observations.
(iii) †, †† and ††† denote significance difference of low and medium past-performance stocks compared to the group of high past-performance stocks, respectively at the 10%, 5% and 1% level.
(iv) *, ** and *** denote significance difference of medium past-performance stocks compared to the group of low past-performance stocks, respectively at the 10%, 5% and 1% level.

Table 7: Estimates of buy-herding (H_{LSV} and H_{FHW} calculated on stocks for which —) according to previous quarter stocks' return

	k=0		*k=5%*		*k=10%*	
	H_{LSV}	H_{FHW}	H_{LSV}	H_{FHW}	H_{LSV}	H_{FHW}
	Low past-performance stocks $\|GRSN\| > k$					
$n_{i,t}$ >5	5.7%†††	15.5%†††	10.8%†††	23%†††	12%†††	24.6%†††
	(7 276)		(5 074)		(4 676)	
$n_{i,t}$ >10	6%†††	14.3%†††	11.2%†††	21.5%†††	12.6%†††	23.2%†††
	(4 834)		(2 905)		(2 557)	
$n_{i,t}$ >15	6.2%†††	13.9%†††	11.4%†††	20.8%†††	13.1%†††	22.8%†††
	(3 512)		(1 940)		(1 687)	
$n_{i,t}$ >20	6.5%†††	13.8%†††	11.9%†††	20.7%†††	13.6%†††	22.7%†††
	(2 733)		(1 441)		(1 255)	
	Medium past-performance stocks $\|GRSN\| > k$					
	k=0		*k=5%*		*k=10%*	
	H_{LSV}	H_{FHW}	H_{LSV}	H_{FHW}	H_{LSV}	H_{FHW}
$n_{i,t}$>5	6.3%†††	16.4%***†††	12.1%†††	24.5%†††	13.7%**†††	26.5%†††
	(8 265)		(6 248)		(5 738)	
$n_{i,t}$ >10	6.4%†††	15%**†††	12.2%†††	22.6%†††	14.3%†††	24.9%†††
	(5 453)		(3 608)		(3 215)	
$n_{i,t}$ >15	6.6%*†††	14.5%***†††	12.7%†††	22.1%†††	14.8%†††	24.6%†††
	(4 050)		(2 462)		(2 140)	
$n_{i,t}$ >20	6.8%†††	14.3%***†††	13.1%†††	22%†††	15.5%†††	24.7%†††
	(3 128)		(1 814)		(1 566)	
	High past-performance stocks $\|GRSN\| > k$					
	k=0		*k=5%*		*k=10%*	
	H_{LSV}	H_{FHW}	H_{LSV}	H_{FHW}	H_{LSV}	H_{FHW}
$n_{i,t}$>5	7.1%	17.7%	14.1%	26.9%	16.3%	29.4%
	(8 779)		(6 901)		(6 374)	
$n_{i,t}$>10	7.2%	16.4%	14.5%	25.2%	17.0%	28.0%
	(5 615)		(3 777)		(3 414)	
$n_{i,t}$>15	7.2%	15.5%	14.4%	24.1%	17.3%	27.1%
	(4 083)		(2 537)		(2 224)	
$n_{i,t}$>20	7.3%	15.1%	14.7%	23.8%	17.6%	26.6%
	(3 163)		(1 831)		(1 559)	

(i) Whatever the considered category, $p_{i,t}$ is calculated on the whole data set.
(ii) Figures in brackets indicate the number of stock-quarter observations.
(iii) †, †† and ††† denote significance difference of low and medium past-performance stocks compared to the reference group of high past-performance stocks, respectively at the 10%, 5% and 1% level.
(iv) *, ** and *** denote significance difference of medium past-performance stocks compared to the reference group of low past-performance stocks, respectively at the 10%, 5% and 1% level.

Table 8: Average adjusted excess returns for LSV herding-sorted equal weighted portfolio (in %)

Portfolios	Q_{t-2}	Q_{t-1}	Q_t (herding quarter)	Q_{t+1}	Q_{t+2}	Q_{t+3}	Q_{t+4}
B1 (heavy buying)	7.19***	9.16***	8.82***	2.66***	1.92***	0.78*	2.24***
B2	6.70***	6.66***	6.87***	2.23***	1.12***	2.13***	2.11***
B3	5.71***	4.96***	4.80***	1.63***	1.15***	1.98***	2.30***
B4	4.58***	4.27***	3.40***	1.78***	1.87***	2.45***	1.82***
B5 (light buying)	4.31***	3.69***	2.74***	2.05***	2.66***	2.48***	3.05***
S5 (light selling)	4.86***	3.26***	1.93***	2.10***	2.97***	2.43***	3.31***
S4	3.60***	1.01*	-0.53	1.99***	3.04***	3.24***	3.11***
S3	3.32***	0.38	-0.98*	2.89***	2.38***	2.88***	2.51***
S2	2.33***	-0.96*	-2.45***	2.84***	2.52***	4.05***	3.87***
S1 (heavy selling)	2.70***	0.17	-2.10***	2.53***	2.95***	4.00***	3.87***
B1 - S1	4.49***	8.99***	10.92***	0.12	-1.03	-3.22***	-1.63**

*, ** and *** denote significance respectively at the 10%, 5% and 1% level.

Table 9: Average adjusted excess returns for FHW herding-sorted equal weighted portfolio (in %)

Portfolios	Q_{t-2}	Q_{t-1}	Q_t (herding quarter)	Q_{t+1}	Q_{t+2}	Q_{t+3}	Q_{t+4}
B1 (heavy buying)	7.29***	9.06***	9.08***	3.02***	2.06***	1.27*	2.43***
B2	6.83***	6.68***	6.64***	1.88***	1.33***	1.92***	2.09***
B3	5.49***	4.97***	4.88***	1.73***	0.83**	1.84***	2.12***
B4	4.23***	4.11***	2.94***	1.37***	1.89***	2.31***	1.81***
B5 (light buying)	4.71***	3.93***	3.14***	2.39***	2.61***	2.51***	3.11***
S5 (light selling)	5.00***	3.64***	1.93***	2.32***	2.55***	2.57***	3.21***
S4	3.39***	1.13**	0.02	2.02***	3.29***	3.18***	3.41***
S3	3.27***	-0.28	-1.58***	2.83***	2.69***	2.68***	2.20***
S2	2.53***	-0.82	-2.49***	3.07***	2.54***	3.95***	3.62***
S1 (heavy selling)	2.63***	0.22	-1.98***	2.04***	2.72***	4.26***	4.37***
B1-S1	4.66***	8.85***	11.06***	0.98	-0.65	-2.99***	-1.93**

*, ** and *** denote significance respectively at the 10%, 5% and 1% level.

Table 10: Average adjusted future excess returns for LSV herding-sorted equal weighted portfolio (in %) according to firm market capitalization

	all stocks except small cap				small cap			
Portfolios	Q_{t+1}	Q_{t+2}	Q_{t+3}	Q_{t+4}	Q_{t+1}	Q_{t+2}	Q_{t+3}	Q_{t+4}
B1 (heavy buying)	2,41***	1,68***	0,83**	2,39***	5,11**	2,98	0,17	-0,15
B2	1,96***	1,28***	2,26***	2,27***	4,78**	1,04	-0,07	1,02
B3	1,20***	1,09***	1,99***	2,22***	5,72***	1,49	2,92	2,90
B4	1,54***	2,06***	2,52***	1,75***	9,20***	0,43	3,65*	2,07
B5 (light buying)	1,82***	2,73***	2,28***	2,81***	2,28	1,20	2,72	6,63***
S5 (light selling)	2,63***	3,31***	2,56***	3,68***	-0,06	-1,62	1,97	2,11
S4	1,68***	2,74***	3,11***	2,57***	4,68**	7,66***	5,83**	4,80**
S3	2,50***	2,58***	2,26***	2,19***	6,17***	2,18	6,06***	7,50**
S2	2,71***	2,40***	4,10***	3,69***	2,86	4,91**	3,57	4,87*
S1 (heavy selling)	2,44***	2,27***	4,20***	3,87***	1,20	4,14	0,49	1,61
B1-S1	-0,03***	-0,60	-3,37***	-1,48	3,91	-1,17	-0,33	-1,76

*, ** and *** denote significance respectively at the 10%, 5% and 1% level.

Table 11: Average adjusted future excess returns for LSV herding-sorted equal weighted portfolio (in %) according to firm geographical origin Foreign firms

	all stocks except small cap				Foreign firms			
Portfolios	Q_{t+1}	Q_{t+2}	Q_{t+3}	Q_{t+4}	Q_{t+1}	Q_{t+2}	Q_{t+3}	Q_{t+4}
B1 (heavy buying)	2,02***	0,89	-0,17	1,51	3,18***	2,99***	2,17***	2,38***
B2	2,07***	0,21	0,77	1,59	2,04***	1,94***	3,13***	3,49***
B3	1,45***	0,43	0,65	1,48	2,14***	2,09***	3,02***	3,23***
B4	2,06***	1,59***	2,29***	1,54	1,87***	2,40***	3,05***	1,96***
B5 (light buying)	2,05***	1,98***	2,01***	2,91***	1,82***	3,28***	3,27***	3,31***
S5 (light selling)	0,36	1,82**	2,66***	3,46***	3,57***	3,35***	2,70***	3,22***
S4	1,00	3,66***	3,50***	2,87**	3,41***	3,04***	2,79***	2,45***
S3	2,90***	2,28***	2,64***	2,14	3,09***	2,82***	2,96***	3,16***
S2	2,41***	2,25***	3,37***	3,83***	2,98***	2,95***	4,93***	4,12***
S1 (heavy selling)	1,64**	1,34	3,38***	3,59***	3,74***	4,32***	4,16***	4,74***
B1-S1	0,38	-0,45	-3,56***	-2,08**	-0,55	-1,33	-1,99**	-2,37**

*, ** and *** denote significance respectively at the 10%, 5% and 1% level.

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