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The Relationship between Herding and Skill – A Study of the Swedish Mutual Fund Industry

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Abstract

The aim of the present thesis is to examine the presence of herding behavior among Swedish fund managers. It is further investigated whether herding is a sign of sophistication, or strictly a behavioral phenomenon. Strong evidence of small levels of fund herding on the Swedish mutual fund market is found. Managers who engage in moderate herding behavior can generate abnormal gross returns in the short run but fail to cover for fees and expenses. In contrast, we find weak evidence of antiherding funds being able to consistently generate net abnormal returns in the long run. Furthermore, fund managers who exhibit moderate antiherding behavior seem to possess superior stock picking ability. Finally, stocks bought by herds are shown to underperform stocks sold by herds in the short run. In conclusion, herding on the Swedish mutual fund market cannot be attributed to sophistication since herding funds do not generate significant abnormal net returns, regardless of the time perspective. This infers, in turn, that herding is a strictly behavioral phenomenon caused by reputational concerns or behavioral biases. Our results further indicate that sophistication may reside with moderately contrarian managers.

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Introduction

Investment decisions are classically considered to be rational and built upon solid information available to the investor. However, Keynes (1936), argued that investors make investment decisions driven by a desire to follow the actions of other actors, largely disregarding their own personal beliefs.

For a long time, financial markets have been described as driven by "animal spirits", where investors herd like animals (Avery & Zemsky, 1998; Devenov & Welch, 1996). Herding behavior constitutes the act of mimicking the actions of a group, either on sophisticated grounds or as a behavioral phenomenon. In contrast, antiherding or contrarian behavior involves those investors that deviate from the actions of the herd to a large extent. This type of behavior is believed to be employed by individuals who possess private information different from that of the crowd, and who choose to act on it (Wei, Wermers, & Yao, 2015). Although the notion of rationality within finance has reduced the amount of research conducted regarding herding behavior, many papers support its importance (Avery & Zemsky, 1998). The research on herding behavior in financial markets is particularly relevant as it can shed further light on the development of price destabilization, bubbles and excess volatility (Avery & Zemsky, 1998; Scharfstein & Stein, 1990; Sias, 2004; Singh, 2012). In addition, the study of herding behavior is relevant since it causes significant informational inefficiencies in the financial markets, with an estimated effect that accounts for approximately 4 percent of the expected price of the asset (Cipriani & Guarino, 2014).

There is vast empirical work detailing herding and the reasons behind it. On the one hand, there are reputational models that explain herd behavior as a consequence of managers who do not want to lose their reputation or fail alone so they choose to follow the crowd (Scharfstein & Stein, 1990; Zwiebel, 1995). On the other hand, models of informational cascades explain herd behavior as a consequence of investors copying the actions of others and ignoring their own private information (Banerjee, 1992; Bikhchandani, Hirshleifer, & Welch 1992; Welch, 1992). Other studies, moreover, explain herding as a consequence of investors getting correlated signals that 'arrive' in different time periods, so their correlated actions are not due to mimicking each other but using the same type of private information (Froot, Scharfstein, & Stein, 1992; Hirshleifer, Subrahmanyam, & Titman, 1994; Lakonishok, Schleifer, & Vishny, 1992). Another body of research explains herding as a behavioral phenomenon caused by fads, biases, noise or disposition effects (Shefrin & Statman, 1984; Strong & Xu, 2003; Schiller, Fischer, & Freidman, 1984).

The role of herding conducted by institutions has a considerably larger impact on the financial markets as compared to the herd behavior pursued by individual investors. The major reason is that trades conducted by institutions are much larger in size as compared to those conducted by individuals, especially when their trades are correlated (Grinblatt, Titman, & Wermers, 1995; Lakonishok et al., 1992; Sias, 2004). For decades, it has been discussed whether superior ability or skill exists among institutional investors. Many studies have found that fund managers fail to outperform the market and that active funds underperform their passive counterparts on average (Berk & Van Binsbergen, 2015; Wermers, 2000). However, more recent research has proven the existence of managerial skill (Kaperczyk, Sialm, & Zheng, 2009; Kosowski, Timmermann, Wermers, & White, 2006; Wermers, 2000). Several studies have examined, moreover, the connection between herding behavior and sophistication. Some argue that there is a connection (Jiang & Verardo, 2018; Lin, Tsai, & Lung, 2011), while others find that herding is behavioral to a large extent (Schiller, Fischer, & Freidman, 1984).

In the present paper, we first replicate the methodology used by Jiang and Verardo (2018) with the aim of investigating whether similar herding tendencies can be found in the Swedish open-end fund market. This methodology has the advantage of capturing mimicking behavior while controlling and filtering for common investment strategies. Second, we implement both short and long-term tests of fund performance to discern whether herding funds possess superior ability compared to antiherding funds in terms of average abnormal returns. Following this, the results are supported by our own novel approach to measuring sophistication among herds. Lastly, the stock level herding measure of Jiang and Verardo (2018) is constructed to conclude whether herding funds possess superior stock picking ability. The results are supported by various robustness checks. If either herding or antiherding is a sign of sophistications, the funds exhibiting these behaviors can be expected to generate significant abnormal returns. However, if it is strictly behavioral, we expect to find little to no abnormal returns amongst these funds. We find strong evidence of herding behavior in Sweden, with a large level of heterogeneity. It is concluded that neither extreme herding funds nor extreme antiherding funds significantly outperform the other, which indicates that neither behavior is a sign of sophistication, nor are they able to generate significant abnormal net returns in the short run. The long-term analysis finds weak evidence of moderate antiherding funds being able to generate abnormal net returns.

Furthermore, superior stock picking ability is found amongst funds exhibiting neutral to moderate levels of antiherding behavior. The performance analysis concerning the returns of portfolios sorted based on stocks sold in herds versus stocks bought in herds further indicates that herding is strictly behavioral or reputational. To date, very little research on institutional herding behavior has been conducted in Sweden and to our knowledge, these novel measures of fund herding and skill have yet to be tested on the Swedish market. Furthermore, we implement a new method to measure sophistication amongst herders which, to our knowledge, has not been previously performed in this context.

After this introductory section, the thesis is structured as follows. The second section discusses previous studies about herding behavior in general, the reasons behind it and the relationship between herding and skill. Then, the third section presents the data and methodology used in this thesis. The fourth section contains the estimated results obtained from the analysis. To conclude, the last section discusses the implications as well the limitations of these results.

Research Questions

The aim of this thesis is to examine the relationship between herding behavior and fund manager sophistication. More specifically, the thesis examines whether herding behavior is present in the context of the Swedish mutual fund industry from 2010 to 2019. Second, it is examined whether herding is pursued by sophisticated fund managers or if it is merely a behavioral phenomenon.

Literature Review

The following theoretical framework discusses the main concepts that have been suggested to explain the patterns of herding behavior.

Herding

The presence of herding behavior has been studied for several decades and the findings have been contradictory. In their seminal study of herding behavior, Lakonishok, Schleifer and Vishny (1992) found little evidence of dramatic herding behavior among institutions. As the authors reason, the variety of investment styles pursued by fund managers may offset each other's actions. In line with this, Grinblatt, Titman, and Wermers (1995) found that the majority of mutual funds invest on momentum, greatly outperforming other funds in doing so. They argued that this finding alone was indicative of herding behavior. However, the overall herding tendencies found were small. When controlling for momentum, the herding tendencies disappeared, suggesting that the herding observed may have been solely due to momentum strategies. In a later study, Wermers (1999) also provided evidence of low levels of herding activity for the average stock.

In contrast to these findings, several studies documented stronger evidence of herding among institutional investors. For instance, Frey, Herbst, and Walter (2014) developed a new measure that provided higher absolute levels of herding as compared to those obtained with the traditional LVS-measure as well as smaller differences between the different classes of stocks. Similarly, Sias (2004) argued for strong evidence of institutional herding. However, a small fraction of herding is accounted for by momentum trading.

Since these studies appear to come to different conclusions regarding the presence of herding behavior, the present study aims at examining whether herding behavior is present in the context of fund managers in Sweden.

Reasons behind herding

There is vast empirical work that examines herding and the underlying motivations. The body of literature can be divided into informational models, reputational models, models of correlated signals and behavioral explanations.

According to various informational models, individuals tend to herd instead of acting on their own information. Based on this, the actions of others are informative but if every individual follows the actions of others, it reduces the aggregated amount of information in the market (Banerjee, 1992; Welch, 1992). In the short run, speculators may show herding behavior as way to learn information that other speculators possess. Bikhchandani, Hirshleifer, and Welch (1992) found that higher-precision individuals acted earlier and that these actions could facilitate other individuals to follow their actions, neglecting their own private information. Yet, Avery and Zemsky (1998) argued that when there is uncertainty about the true value of an asset, informational cascades do not occur since new information can enter the market at any time. However, when there are doubts about whether the true value of an asset has changed, informational cascades do occur.

Another aspect that has been suggested to explain herding behavior is reputational concerns. Scharfstein and Stein (1990) proposed the widely known model of reputation-based herding, which conceptualizes herding behavior as a consequence of managers who do not want to fail alone, as compared to their peers, and who therefore choose to follow and 'copy' other's actions, even when they possess valuable private information. Tout court, Scharfstein and Stein posit that herding behavior is most prevalent in markets where relative ability is not appropriately compensated. This idea may be corroborated by Zwiebel's (1995) study, which found that since managers are evaluated based on relative performance against their peers, they fail to take innovative actions, given that they are judged according to their portfolio choices and its performance (Chevalier & Ellison, 1999). Trueman (1994) found that analysts also exhibit herding tendencies, releasing forecasts very similar to those of other analysts. In addition, this herding behavior is more prevalent if the analysts' initial reputation is high and serves as a way of protecting their status. According to Avery and Chevalier (1999), fund managers are more prone to herd early in their careers when it is more likely that they do not possess private information of their own ability and less so as confidence in their own ability increases. Furthermore, herding behavior may be pursued by investors with low ability when there is public evidence that contradicts their private information (Graham, 1999; Zwiebel, 1995). Yet, investors who have already acquired information of their own low ability will also choose to antiherd as a way of demonstrating that they too possess private information. Similarly, it was documented that 'contrarian' managers are usually those with the highest and lowest levels of ability (Zwiebel, 1995). Lakonishok and colleagues (1992) discussed that contrarian strategies can lead to poor short-term performance and bad reputation even though antiherding strategies can be beneficial in the long run. Thus, investors choose to herd in order to protect their reputation.

In contrast to the above insights, Hirschleifer, Subrahmanyam, and Titman (1994) developed a model of correlated signals, where investors do not receive information simultaneously. Due to higher ability or as a matter of luck, investors who are earlier informed can get advantages from this information. Those who trade later, seem to herd because their transactions show a positive correlation with earlier trades. However, this is not due to imitation, but due to the signal being observed in different time periods.

Another body of literature proposes that herding is a consequence of behavioral biases and that less sophisticated individual investors are more prone to herd (Calvet, Campbell, & Sodini, 2009; Korniotis, Kumar, & Page, 2017). Barber, Odean, and Zhu (2009) documented herding behavior amongst individual investors and found that when following the herd, they pushed and paid prices above the stock's fundamental value. Many assume these behavioral biases to be strongly connected to individual investors, and less so to institutional investors (Menkhoff & Schmeling, 2010; Schiller, 1984). This assumption is opposed by Friedman (1984) who argues that institutional investors may be even more susceptible to social trends since the community of institutional investors are exposed to the same correlated signals and news, attend the same gatherings and are better informed about each other's trades than individual investors (Lakonishok et al., 1992; Schiller, Fischer, & Friedman ,1984). In line with this, Dennis and Strickland (2002) found that institutional investors engage in herding behavior to a larger extent than individual investors. There are many behavioral factors that may drive herding behavior such as heuristics[1], home bias[2], the disposition effect[3] and style investing.[4]

[1] Heuristic techniques are often used to simplify the assessment of values and probabilities, saving time and effort in the process. They can also lead to large systematic errors (Tversky & Kahneman, 1974).

[2] It has been shown that investors in the same geographical area tend to herd more compared to investors separated by large geographical distances (Choi, 2016). Further, Strong and Xu (2003) found that fund managers from all over the world tend to prefer stocks from their home market.

[3] It is the action characterized by keeping losers and selling winners due to lose aversion.

[4] The process of choosing among styles rather than individual securities is called style investing (Barberis & Schleifer, 2003).

Performance

This section outlines the ongoing discussion of whether superior ability in the form of stock picking expertise and "market timing" can be found in managers of actively managed funds.

On the one hand, a body of research suggests that actively managed funds consistently underperform the market and it is thus concluded that managers of these funds lack skill (Berk & Van Binsbergen, 2015). However, more recent studies have documented the existence of skill among fund managers[5] (Berk & Van Binsbergen, 2015; Kosowski et al., 2006).

However, in one of the most influential publications on the relationship between performance and skill, Carhart (1997) suggests that manager skill cannot be determined by the performance persistence of funds. He found that fund managers who achieve high returns by following the momentum strategy have their gains completely cancelled out by equally high transaction costs. Fama and French (2010) claim that when measuring gross returns, skilled managers could be detected from their high abnormal returns, and on the other end, less skilled managers seemed to reduce overall expected returns. However, when adding back management fees and other costs, very few funds had sufficient expected returns to cover for these. In conclusion, while there seemed to be diversity in skill across fund managers, it remained unclear as to whether there are managers skilled enough to cover costs and thus justify investment in actively managed funds. This uncertainty has led to the use of gross abnormal returns in place of net, which has been argued to be the true measure of managerial skill (Berk & Van Binsbergen, 2015). In contrast to the results obtained by Fama and French (2010), Kosowski and colleagues (2006) tested the relationship between abnormal alphas and whether they are produced as a consequence of luck. They found that there was a minority of fund managers able to pick stocks that could cover their cost and that they persist over time controlling for sample variability (luck), which indicates that superior skill can be identified by abnormal returns. However, there is no consensus on whether risk-adjusted alphas are the true measure of fund persistence and many argue that it is a return measure rather than a value one (Berk & Van Binsbergen, 2015).

[5] For instance, Kacperczyk, Sialm, and Zheng (2008) developed the "performance gap" measure and found that fund managers do create value on average that is sufficient to cover transaction costs and other types of costs. Wermers (2000) found that stock picking talent does exist and that the stocks that fund managers hold in their portfolios outperform the market if trading costs are not taken into account.

Performance and herding

This section further adds to the previous discussion by detailing the connection between herding, performance and skill.

Regarding the relationship between herding and asset prices, Dasgupta, Prat, and Verardo (2011) found that in the short run, buy herds are followed by positive price changes as long as several managers are willing to buy the asset due to their positive market beliefs. These market beliefs, in turn, prevent managers from selling off the asset even if their private information indicates the opposite. However, in the long run, buy herds are followed by negative returns since the price paid at the time period *t* is higher than the liquidation price. The opposite effects are expected when the shares are sold in herds. Nofsinger and Sias (1999) also found that stocks that experienced the greatest change in institutional ownership outperformed those with the smallest change. Yet, in contrast, there was no sign of return reversals when analyzing a time period of two years after the transactions took place, which suggests that the transactions were not a consequence of irrational behavior.

The previous literature is similarly divided when it comes to the relationship between herding and performance. Bhattacharya and Sonaer (2018) showed that in the months following the herding act, funds benefited from this behavior through higher abnormal returns. However, when looking farther ahead, there was no significant difference in returns between antiherding funds and herding funds. Furthermore, the abnormal returns were not sustained in the long run, which indicates the absence of superior skill in the long run.

In contrast, Wei, Wermers and Yao (2015) conclude that contrarian funds significantly outperform herding funds during the four subsequent quarters, which cannot be merely a result of excessive risk-taking or overconfidence, but possession of superior information. In addition, there was no correlation between the trades of the contrarian funds, suggesting that they do not simply go against the actions of the herd. In support of these results, Jiang and Verardo (2018) found evidence of the presence of herding behavior on the American mutual fund market. It is further concluded that antiherding funds consistently outperform herding funds according to their average and abnormal monthly returns, both in the short- and long-run. Additionally, superior stock picking ability was found amongst antiherding fund managers.

Data and Methodology

Data

The structure of the main data is a panel data set covering the examination period starting in March 2010 until December 2018, containing data on 116 distinct funds and 773 stocks, which results in 806,744 distinct observations. The shareholdings composition data of the funds are presented in quarterly form since data are not available in higher frequency form for the major part of the Swedish open-end funds. The lack of data on institutional ownership prior to March 2010 prevented the examination period from starting any earlier.

The funds included in the present study are all Swedish actively managed open-end funds that were active at any point during the examination period starting in January 2010 to December 2018 and for which the data was available in Morningstar Direct.[6] Since the present paper concerns actively managed funds, index funds were excluded. Furthermore, in accordance with Kacperczyk, Sialm and Zheng (2008), to make the data more complete and dependable, only funds that invest primarily in domestic equity were included. Accordingly, balanced, bond, money market, sector and international funds were excluded. A minimum of 80% of the total assets and a maximum of 105% invested in equity is required. In addition, the funds included invest a minimum of 75% of their assets in Swedish equity. According to Elton, Gruber and Blake (2001), the most prominent databases for fund data, Morningstar and CRSP, are prone to include biases such as incubation bias. Incubation is a strategy used by fund families and consists, in short, of opening several funds with small amounts of capital and observing how they perform during a certain period of time. When this period ends, well performing funds are opened to the public while others are shut down or put on observation for yet another trial period (Evans, 2010). In order to exclude this bias, only the oldest funds that were a part of fund families were included in order to prevent the occurrence of incubation bias. Additionally, the observations obtained before the inception date of the fund were also eliminated. Lastly, all funds were required to hold at least ten different share types under each period. After sorting the data according to the aforementioned criteria, a total of 116 funds remained for analysis.

Information regarding fund characteristics such as fund age, fund size, turnover ratio, expense ratio, quarterly fund returns as well as fund holdings in the form of number of shares held by

[6] For descriptive statistics, see Appendix A.1

each institution in each quarter was obtained from Morningstar Direct and completed with information collected from Bloomberg.

In certain funds, data regarding share holdings were not available for all time periods the present study covers, so the share values shown in the last period for which data is available before the gap was carried forward until data became available again. This procedure was used to alter a total of 101 time periods scattered across 36 funds. These procedures were deemed reasonable for the benefit of the present paper since the number of shareholdings or the value of a company cannot be expected to differ significantly from one quarter to the next. In total, the funds invested in 773 different share types. Data regarding market capitalization, quarterly returns, institutional ownership as well as market to book ratio were obtained from Bloomberg. Additionally, shares related to share rights and share emission were excluded from the study.

For the fund performance analysis, monthly net- and gross fund returns were downloaded using Morningstar Direct. Since the data on net returns was more complete than that of gross returns, missing values of gross return were filled using net return in place of carrying values forward when possible. In cases where missing values occurred in both gross- and net returns, values were carried forward to fill in the gaps. Monthly stock returns for use in the stock performance analysis were downloaded from Bloomberg. The monthly factors needed for the calculation of the risk-adjusted returns using the Fama-French three-factor model and the Carhart four-factor model were downloaded from The Swedish House of Finance. The market return was proxied by the SIX RX Index that tracks the development of the Swedish market taking into account dividends (Six Group, 2019) and the risk-free rate was proxied by the 1-month Swedish Treasury-bill rate (Swedish House of Finance, 2019).

Methodology

The fund herding measure used in the present study was developed by Jiang and Verardo (2018) and measures herding as the correlation between trades through different time periods. This measure has the advantage of enabling the estimation of a herding measure at a fund level and takes into account the relationship between a fund’s trade activity and the actions taken by the crowd. Further, this measure controls for common preferences, signals as well as common investments styles.

The percentage change of share trades is regressed on the independent variables, with the main independent variable being the past periods' percentage change in institutional ownership. In the model, the share trades represent the actions taken by each fund and the institutional ownership represents the actions taken by fund managers as a crowd. Importantly, initiations and deletions of stocks are not accounted for in this measure of trade. The change in share trades represents the change in specific stock holdings for each fund and quarter according to the formula:

$$Trade_{i,j,t} = \frac{N_{i,j,t} - N_{i,j,t-1}}{N_{i,j,t-1}} \tag{1}$$

The variable labeled *institutional ownership* is the percentage change in institutional ownership for each stock over each quarter. For each fund *j* and for each time period *t*, the following cross-sectional regression model is conducted, where *i* represents the individual stock:

$$Trade_{i,j,t} = \alpha_{j,t} + \beta_{j,t}\Delta IO_{i,t-1} + \gamma_{1,j,t}Mom_{j,t-1} + \gamma_{2,j,t}MC_{i,t-1} + \gamma_{3,j,t}BM_{i,t-1} + \varepsilon_{i,j,t} \tag{2}$$

Other variables included in the model are aimed to control for different investments styles in the form of different share characteristics. The variables included are the natural logarithm of the market capitalization during time period *t-1* (Market Capitalization), the natural logarithm of the book to market ratio in time period *t-1* (Book to Market) as well as the arithmetic share return in time period *t-1* (Momentum).

Since the share returns seem to not be normally distributed, the variable is winsorized at a one percent level in order to alter the values of extreme observations at both ends of the tails where the correct values cannot be found. Some of the values of the quarterly percentage change in institutional ownership are extremely high. According to Bloomberg (2019), this is due to shortcomings regarding the logic of the calculation of the field which can result in largely inflated values for certain companies. Based on this fact, the variable is winsorized. However, since the values of the top percentiles are heavily inflated while the bottom percentiles show no reason for concern, this variable is winsorized to a higher degree (2 percent) on the right tail of the distribution. According to Bloomberg (2019), a maximum change of 1000% is considered as the limit of being reliable. The logarithms of market capitalization as well as book to market appear to be normally distributed with little skewness and are not altered to any extent. After taking the logarithms and adjusting for skewness through winsorization, the dependent and independent variables are standardized over the same date and fund, with a mean of 0 and a standard deviation that equals 1, following the methodology used by Sias (2004). This procedure is done to make the coefficients more comparable across funds and time.

Table 1
Descriptive Statistics - Regression Variables

This table contains descriptive statistics for the variables included in the Fund Herding regression. The sample includes 773 distinct stocks. The variable Trade is the dependent variable and equal to the percentage change in shareholdings for a certain share *i* in a specific fund *j* each quarter *t*. Log Mc is the natural logarithm of the market capitalization of each share *i* in quarter *t*. Log Bm is the quarterly natural logarithm of the market-to-book ratio for each share *i*. Institutional Ownership is the main independent variable and it is equal to the quarterly percentage change in institutional ownership for each share. Mom is the previous quarterly share return.

	Mean	Std. Dev	Min	25^{th} *Pctl*	Median	75^{th} *Pctl*	Max	Number obs.	Missing
Trade	0.140	0.696	-7.871	-0.127	0.011	0.176	4.568	74279	-
Log MC	16.492	1.987	-0.223	4.809	16.637	17.826	22.727	71122	3034
Log BM	-0.898	0.824	5.800	-1.353	-0.901	-0.359	5.801	69465	4691
IO	63.865	134.0	-42.65	4.97	19.785	57.540	754.5	69416	4740
Mom	0.026	0.155	-0.392	-0.067	0.024	0.115	0.503	73065	1091

After controlling for investment styles, the computed beta coefficients do not capture co-movements caused by common investments but rather mimicking behavior among fund managers. Following the method devised by Jiang and Verardo (2018), the beta coefficients, obtained for the main independent variable for each fund *j* and time period *t*, are used in the computation of the fund herding measure. Since information becomes less predictive of future behavior as time passes, this measure is computed by assigning higher weights to more recent trades compared to older ones, in order to capture the average herding tendency of each fund for each time period. The following formula is used to compute the fund herding measure:

$$FH_{j,t} = \frac{\sum_{h=1}^{t} \frac{1}{h}\beta_{j,t-h+1}}{\sum_{h=1}^{t} \frac{1}{h}} \quad (3)$$

Fund Performance

In order to analyze the relationship between herding behavior and skill, an examination of fund performance is conducted. If herding behavior is carried out by managers with superior ability, we expect their portfolios to outperform the antiherding ones.

At each quarter *t*, the funds are divided into 10 different portfolios based on the calculated fund herding measure. Portfolio 1 contains the lowest values, thus considered an antiherding portfolio and portfolio 10 represents the portfolio with the highest herding measures, meaning it contains the funds most prone to herding behavior. The equally weighted average gross and net returns of each portfolio are computed for the subsequent time period $t+1$. In order to make certain any abnormal returns are not due to risk, the risk-adjusted returns using the Market model, CAPM-model, Fama-French three-factor model as well as the Carhart four-factor model are computed. The resulting time series span from June 2010 to December 2018. Autocorrelated and heteroskedastic standard errors are controlled for using Newey-West standard errors[7] in the estimation of the risk-adjusted returns. Following Greene (2003), the optimal number of lags is calculated using the following formula:

$$lag = T^{1/4} \tag{4}$$

Where T is the number of observations.

Table 2
Descriptive Statistics - Fund Returns

This table contains descriptive statistics for fund and stock returns. Net fund return is the quarterly fund return after taking into account fund fees and fund expenses. Net Fund Return (CF) is the net fund return after carrying forward values when they were missing, which resulted in an alteration of 101 time periods scattered across 36 funds. Gross Fund Return is the quarterly fund return before fees and expenses and Gross Fund Return (CF) is the gross fund returns including values that were carried forward when the values were missing. Stock returns is the quarterly share return.

	Mean	Std. Dev	Min	25^{th} *Pctl*	Median	75^{th} *Pctl*	Max	Number obs.	Missing
Net Fund Return	0.796	4.212	-15.023	-1.171	1.055	3.324	16.249	8391	144
Gross Fund Return	0.904	4.212	-14.895	-1.594	1.154	3.425	16.342	8391	144
Net Fund Return (CF)	0.803	4.219	-15.023	-12.972	1.088	3.339	16.244	8390	0
Gross Fund Return (CF)	-0.911	4.225	-14.895	-1.601	1.199	3.443	16.342	8391	0
Stock Return	0.011	0.082	-0.738	-0.703	0.006	0.053	1.545	192853	1863

Performance persistence

After examining fund performance in relation to herding and antiherding behavior, it is investigated whether the performance differentials are a consequence of luck or mere coincidence. Thus, following the performance persistence analysis conducted by Carhart

[7] In the estimation, it is allowed for a maximum of three lag periods.

(1997), 10 portfolios are formed every 9 or 18 months (depending on the holding period) according to the lagged average fund herding. Then, fund performance is analyzed by computing the average monthly returns as well as the risk-adjusted returns.[8] If herding behavior is pursued by more sophisticated managers, the performance of their funds is expected to be superior compared to the antiherding funds in the long run. On the contrary, if superior performance is achieved by luck, then it is expected to reverse in the long run, since positive price changes are driven by managers overpaying for the assets they acquired (Dasgupta et al., 2011).

Skill

If herding is a behavior adopted by skilled fund managers, these fund managers should consistently pick better stocks than their peers. In order to investigate this matter, a stock level herding measure is constructed. Firstly, all stocks are sorted into terciles in each time period *t* according to the absolute lagged change in institutional ownership and only the lowest tercile is kept for analysis, since these stocks cannot be considered the drivers of the fund herding measure previously calculated. The skill measure is then constructed by scaling the weight of stock *i* in fund *j* in quarter *t*. First, all stocks were ranked by sorting them into deciles each quarter according to their respective fund's herding measure. Following this, the mean of the quarterly ranks (ranging from 1-10) is calculated for each individual fund and subtracted from the quarterly ranks, thus demeaning the decile ranks. Lastly, the sign of this value is changed, divided by 10 and multiplied by the corresponding weight. Each measure of *Stock Fund Herding (SFH)* is constructed by stock and quarter. The weights represent the weight of the stock in each quarter in the fund that owns it. The following formula was used to compute the stock herding measure:

$$S_{i,t}^{FH} = \sum_{j=1}^{J} w_{i,t}^{j} \left(-\frac{rank(FH_t^j) - \overline{rank(FH_t)}}{10}\right) \qquad (5)$$

This formula results in stocks belonging to herding portfolios gaining a negative weight while stocks belonging to funds prone to antiherding get a positive weight. In order to test whether the stock herding measure predicts higher return, the remaining stocks are sorted into quintiles by the calculated value of stock herding of the previous time period. The comparison includes

[8] The risk-adjusted returns were obtained using the Market model, CAPM, Fama and French three-factor model as well as the Carhart four-factor model.

equally weighted average monthly portfolio returns as well as several risk-adjusted measures. [9]

Portfolios sorted based on lagged percentage change of institutional ownership

We next develop a test on whether herding behavior is driven by superior ability by analyzing the price development of the stocks bought and sold by herds. If herding is a sign of sophistication, we expect stocks bought in herds to outperform those sold by herds, since these managers are supposed to possess valuable information and should not keep underperforming stocks. If, however, the herd is irrational, stocks sold by herds are expected to outperform stocks bought by herds. As mentioned in the theory section, irrational retail investors are prone to the disposition effect and often sell winners and buy losers. This test will discern if institutional investors are also affected by this bias. All stocks included in the study are sorted into 10 different portfolios based on their past change in institutional ownership. The change in institutional ownership is a common measure of institutional demand since a high absolute value, either positive or negative, indicates that a specific stock has been heavily bought or sold (Sias, 2004). The lowest portfolios will contain stocks with large negative values, representing stocks sold in herds, while the high portfolios will contain stocks bought in herds. Then, the average monthly returns as well as the risk-adjusted returns are computed.[10]

Robustness tests

a. Controlling for own past transactions

The existence of persistency in fund flows (Chevalier & Ellison, 1997; Sirri & Tufano, 1998) could alter the estimations of the fund herding measure (Jiang & Verardo, 2018). The "smart money effect" discussed by Lou (2012) implies that funds that receive capital inflows will expand their current share holdings. Sias (2004) also provided evidence that fund managers follow their own past transactions, trying to minimize transaction costs by selling off their assets gradually instead of a direct execution of huge amounts of shares.

[9] The risk-adjusted alphas were obtained using the Market model, CAPM, Fama-French three-factor model and Carhart four-factor model. In order to control for possible autocorrelated standard errors and heteroscedastic ones, Newey-West standard errors were computed using the same formula as previously, with an allowed maximum of lag time periods equal to 3 months.

[10] The risk-adjusted alphas were obtained using the Market model, CAPM, Fama-French three-factor model and Carhart four-factor model. In order to control for possible autocorrelated standard errors and heteroscedastic ones, Newey-West standard errors were computed using the same formula as previously, with an allowed maximum of lag time periods equal to 3 months.

Thus, following the methodology implemented by Jiang and Verardo (2018), the fund herding measure previously presented is modified by controlling for the funds own past transactions.

$$Trade_{i,j,t} = \alpha_{j,t} + \beta_{j,t}\Delta IO_{i,t-1} + \gamma_{1,j,t}Mom_{j,t-1} + \gamma_{2,j,t}MC_{i,t-1} + \gamma_{3,j,t}BM_{i,t-1} + Trade_{i,j,t-1} + \varepsilon_{i,j,t} \quad (6)$$

This modification enables the analysis of solely mimicking behavior without including the effect of the imitation of their own past actions. The new betas from the regression are used in the calculation of the fund herding measure. In order to analyze whether the new herding measure is related to higher returns, the funds are sorted in each quarter *t* into decile portfolios. The average net and gross monthly returns are calculated in the following quarter *t+1* as well as the risk-adjusted returns. [11]

b. Trades with initiations and deletions

As stated in the description of our baseline model of fund herding, the trade variable does not account for initiations or deletions of stocks. In this robustness check, we modify our trade variable to take on a value of 1 (100%) for initiations and -1 (-100%) for deletions. Given this modification, trade now captures all trades performed by the funds. The fund performance analysis is then replicated using the new fund herding measure. The results are presented in table 10.

c. Revealing skill through investments 3 portfolios

In order to verify the results obtained with the baseline skill measure, the stocks are sorted into tercile portfolios instead of quintile portfolios. This modification allows for a clearer differentiation between the portfolios.

[11] The models used are the Market Model, CAPM, Fama-French three-factor model and Carhart four-factor model. In order to control for possible autocorrelated standard errors and heteroscedastic ones, Newey-West standard errors were computed using the same formula as previously, with an allowed maximum of lag time periods equal to 3 months.

Results and Analysis

In this section, the main results of the fund herding measure estimations are first presented and then followed by the results from the fund performance tests conducted in the short and long run. Then, the regression results related to unobservable skill are discussed. The results of performance of stocks bought by herds versus stocks sold by herds conclude the section.

1. Fund Herding

The estimated average herding level is equal to 1.89 percent over the period 2010-2016, which indicates that on average, Swedish funds tend to herd but to a small extent. The estimated standard deviation is equal to 12.21 percent, which is very large and indicates that there is a large heterogeneity regarding the level of fund herding differences between the funds and across all time periods. These differences can be driven by funds that show extreme herding or antiherding tendencies, since the left tail of the distribution is heavier than the right. Note that the estimated values are quite similar when further observations from 2017 and 2018 are included. The only difference is that the minimum and the maximum values become more extreme when adding more observations. These results are in line with Jiang and Verardo (2018), who found slightly higher levels of herding behavior with an average of 2.42 percent, which is very similar to the values estimated for the Swedish funds. In addition, the estimated standard deviation almost doubles the values obtained for the American funds and the grade of heterogeneity is much larger in the distribution. This can be due to the fact that the sample included in the present study includes a smaller amount of funds as well as fewer time periods compared to the ones used in that study. Further, the maximum fund herding measure estimated equals to 33.27 percent, which is very extreme and large compared to the values obtained by Jiang and Verardo (2018). As Schiller (1984) noted, investment attitudes and biases can differ significantly between countries due to social settings which might, in part explain these differences.

Table 3

Cross-Sectional Descriptive Statistics, *FH*

The following table details descriptive statistics obtained for our fund herding measure (FH). These statistics are computed across each quarter *t* and for each fund *j*, and then averaged over time.

	Mean	*Std. Dev.*	*Min*	25^{th} *Pctl*	*Median*	75^{th} *Pctl*	*Max*	*Obs.*	*Missing Obs.*
FH	1.89	12.21	-32.23	-4.58	1.53	9.18	33.27	107	0
FH (2019)	1.77	12.72	-34.85	-5.71	1.61	9.94	40.09	117	0

Nevertheless, the results are not consistent with those obtained by Lakonishok and colleagues (1992), who found herding levels that were very small on average. Grinblatt and colleagues (1995) came to similar conclusions, where the herding levels almost disappeared when controlling for momentum strategies.

2. Fund Performance

Since the presence of herding behavior is proven to exist in Sweden, we further test whether this herding behavior is related to superior performance in the form of abnormal returns, thus indicating the presence of skill. As reported in table 4 below, the value of the average fund herding measure of the antiherding portfolio (portfolio 1) is very large and equal to negative 42.1 percent and the average herding shown by the herding fund (portfolio 10) equals 50.6 percent. In addition, the Swedish antiherding funds go against the crowd to a much larger extent compared to their American counterparts. Additionally, the Swedish herding funds herd to a much larger extent. Thus, the behavior of fund managers appears to be “more dispersed” due to more extreme cases of herding as well as contrarian behavior.

Moreover, the antiherding portfolio underperforms the herding portfolio on average both when using monthly net and gross returns into the calculation, respectively. On average, the performance differentials are approximately 1 percent per month. The estimated alphas for the period until 2016 show that portfolio 10 outperform portfolio 1 in all estimations except for the estimated alpha obtained with the Carhart method in the net return panel. The return differentials are small regardless of the estimation method used, with the highest performance differential estimated to be 2 percent. It can be noted that the alpha differentials slightly increase when the time series length is increased by including observations obtained in 2017-2018. However, these return differentials are not significant which indicates that neither portfolio is able to consistently generate superior returns compared to the other.

As displayed in table 4, portfolio 5 and 8 show partially and strongly significant gross abnormal returns, respectively, which implies that it can be considered more optimal to herd in ‘a moderate manner’ compared to going against the crowd. This mimicking behavior should be evaluated and only conducted when considered advantageous. These findings are in line with the study conducted by Bhattacharya and Sonaer (2018), since moderate herding funds appear to be the only funds to consistently generate abnormal returns. This supports the intuition that moderate herding behavior is carried out by managers with superior ability since abnormal gross returns can be considered a sign of ability (Berk & Van Binsbergen, 2015). However, the abnormal significant returns are obtained without taking transaction costs and fees into account. According to Fama and French (2010), skilled managers can be identified by their higher net performance but in this case, the abnormal returns disappear when including net returns. Consequently, these abnormal returns obtained for the herding portfolios cannot be attributed to higher ability or skill. Thus, it can be deduced that herding is a behavioral phenomenon that is not associated with superior ability as informational models propose, since there is no information contained in the cascade. These results are not in line with those obtained by Jiang and Verardo (2018), or by Wei and colleagues (2015), as they found that contrarian funds outperform herding in the short run while this study does not. It appears as if information is not contained in the actions of those that go against the crowd either.

One possible explanation to why managers do herd is because of reputational concerns. Fund managers' performance is often evaluated in comparison to the market and what other managers do (Scharfstein & Stein, 1990). The 'termination' possibility is also reduced when managers hold similar portfolios compared to their peers and when they do not fail alone by taking independent actions as discussed by Chevalier and Ellison (1999). Furthermore, herding behavior can be a result of low ability managers that do not want to be evidenced as one or show that they do not possess the superior information that other managers appear to have. In addition, home bias, the disposition effect and heuristic techniques may further explain these irrational behaviors. Observe, however, that as Lakonishok and colleagues (1992) discussed, antiherding behavior can lead to poor performances in the short run.

Table 4

Fund Herding and Fund Performance

This table shows the performance of 10 portfolios formed at the end of each quarter *t* based on the lagged estimated herding measure and they are held for one quarter. It results in time series starting in June 2010 to December 2018. Portfolio 1 represents the antiherding portfolio since it contains the funds with the lowest fund herding levels. On the contrary, portfolio 10 represents the herding portfolio containing the highest values of fund herding. The average herding measure estimated for each portfolio is presented below as well as the monthly average net and gross portfolio returns and differentials between the herding and antiherding portfolios. In addition, risk-adjusted alphas obtained using the Market Model, CAPM, Fama and French three-factor model and Carhart four-factor model are presented. For the time period until December 2018, only risk-adjusted alphas obtained with the Market model and CAPM are included. The corresponding Newey-West t-statistics are shown in parentheses and ***, ** and * denote significance at the 1%, 5% and 10% level, respectively.

FH rank	1	2	3	4	5	6	7	8	9	10	D10-D1
FH	-0.421	-0.205	-0.119	-0.057	-0.013	0.024	0.072	0.139	0.253	0.506	0.927
						Net Returns					
Average	1.041	1.141	1.047	1.104	1.102	1.085	1.118	1.231	1.073	1.023	-0.018
MM	-0.142	-0.039	-0.107	-0.064	-0.050	-0.070	-0.051	0.070	-0.069	-0.141	0.010
	(-1.15)	(-0.39)	(-1.37)	(-0.65)	(-0.55)	(-0.81)	(-0.39)	(0.57)	(-0.57)	(-1.55)	(0.01)
CAPM	-0.071	0.032	-0.039	0.006	0.019	0.001	0.019	0.139	-0.001	-0.071	0.010
	(-0.62)	(0.35)	(-0.55)	(0.07)	(0.22)	(-0.01)	(0.15)	(1.20)	(-0.01)	(-0.81)	(0.00)
FF	-0.053	0.048	0.017	0.038	0.037	0.021	0.050	0.157	0.026	-0.043	0.010
	(-0.48)	(0.52)	(-0.23)	(0.40)	(0.41)	(0.25)	(0.39)	(1.36)	(0.23)	(-0.46)	(0.07)
Carhart	-0.061	0.023	-0.019	0.029	0.006	0.010	0.050	0.112	0.034	-0.063	-0.002
	(-0.59)	(0.25)	(-0.26)	(0.31)	(0.07)	(0.11)	(0.39)	(0.94)	(0.31)	(-0.64)	(-0.01)
2019											
MM	-0.057	0.086	0.000	-0.042	0.021	0.000	0.065	0.129	-0.005	-0.047	0.010
	(-0.33)	(0.54)	(0.00)	(0.27)	(0.14)	(0.00)	(0.39)	(0.75)	(-0.03)	(-0.32)	(0.04)
CAPM	-0.011	0.132	0.044	0.087	0.066	0.044	0.110	0.173	0.039	-0.002	0.009
	(-0.07)	(0.85)	(0.31)	(0.57)	(0.45)	(0.31)	(0.69)	(1.05)	(0.24)	(-0.02)	(0.04)
						Gross Returns					
Average	1.153	1.245	1.154	1.213	1.212	1.197	1.229	1.348	1.184	1.138	-0.015
MM	-0.032	0.063	-0.000	0.043	0.058	0.039	0.058	0.185	0.040	-0.027	0.005
	(-0.26)	(0.62)	(-0.00)	(0.44)	(0.63)	(0.45)	(1.49)	(1.49)	(0.33)	(-0.29)	(0.04)
CAPM	0.039	0.133	0.069	0.113	0.127	0109	0.128	0.254**	0.108	0.043	0.004
	(0.34)	(1.45)	(1.01)	(1.24)	(1.50)	(1.31)	(1.04)	(2.18)	(0.97)	(0.49)	(0.03)
FF	0.058	0.149	0.091	0.145	0.145*	0.129	0.159	0.272**	0.136	0.072	0.015
	(0.53)	(1.60)	(1.24)	(1.51)	(1.62)	(1.53)	(1.25)	(2.34)	(1.20)	(0.76)	(0.01)
Carhart	0.049	0.124	0.087	0.136	0.114	0.117	0.136	0.227*	0.145	0.051	0.002
	(0.48)	(1.36)	(1.18)	(1.43)	(1.27)	(1.34)	(1.08)	(1.91)	(1.33)	(0.51)	(0.02)
2019											
MM	0.053	0.190	0.105	0.150	0.126	0.105	0.172	0.243	0.103	0.064	0.011
	(0.30)	(1.17)	(0.70)	(0.95)	(0.83)	(0.71)	(1.04)	(1.42)	(0.61)	(0.44)	(0.05)
CAPM	0.099	0.235	0.149	0.194	0.171	0.150	0.217	0.288*	0.147	0.109	0.020
	(0.59)	(1.52)	(1.04)	(1.27)	(1.17)	(1.03)	(1.36)	(1.73)	(0.89)	(0.77)	(0.05)

3. Performance Persistence

The previous section found that it may be more optimal to herd in a moderate manner, although no funds are able to generate significant abnormal net returns. This test investigates whether these results are persistent or simply a matter of chance. If herding is a sign of sophistication, herding funds should outperform their counterparts in the long run. The persistence analysis is performed using 9- and 18-month intervals respectively. The results from the portfolios formed every 18 months are presented below, while the results from the portfolios formed every 9 months can be found in the Appendix.

In line to the findings presented in the previous section, portfolio 10 slightly outperforms portfolio number 1 when looking at average net and gross returns. These return differentials are larger than before at 16 and 12 basis points respectively, which suggests that herding funds, on average, outperform antiherding funds in the long run. The pattern is less conclusive when looking at the risk-adjusted alphas, since the performance differentials obtained are not consistent. When adding additional control variables (see FF and Carhart), antiherding funds outperform herding funds. This is also the case when looking at the time period running through 2018, where antiherding funds consistently outperform herding funds. As was the case previously, however, these differentials lack significance and neither portfolio is able to generate significant abnormal returns over the other.

The short-term results indicated that a moderate herding behavior is the most beneficial strategy, but the case is somewhat different using these 18-month holding periods. The majority of portfolios are able to generate partially to strongly significant abnormal gross returns, with portfolios 3 and 4 being especially significant. This would instead indicate that moderate antiherding is the more skilled approach. These portfolios are even able to generate (partially) significant abnormal net returns, which no portfolios in the other tests have been able to do. There is an ongoing discussion of whether gross or net returns are the true measures of managerial skill, but the most influential papers still argue that net returns are the appropriate measure since managers have to be able to cover their costs (Carhart, 1997; Fama & French, 2010).

Table 5

Performance Persistence – 18 months

This table shows the performance persistence analysis of 10 portfolios when the portfolios are held for 18 months. The portfolios are formed every 18 months, at the end of the month, based on the lagged average herding measure. It results in time series starting in June 2010 to December 2018. Portfolio 1 represents the antiherding portfolio since it contains the funds with the lowest fund herding levels. On the contrary, portfolio 10 represents the herding portfolio containing the highest values of fund herding. The average herding measure estimated for each portfolio is presented below as well as the monthly average net and gross portfolio returns and differentials between the herding and antiherding portfolios. In addition, risk-adjusted alphas obtained using the Market Model, CAPM, Fama and French three-factor model and Carhart four-factor model are presented. For the time period until December 2018, only risk-adjusted alphas obtained with the Market model and CAPM are included. The corresponding Newey-West t-statistics are shown in parentheses and ***, ** and * denote significance at the 1%, 5% and 10% level, respectively.

FH rank	1	2	3	4	5	6	7	8	9	10	D10-D1
					Net Returns						
Average	1.256	1.285	1.417	1.428	1.367	1.420	1.364	1.412	1.331	1.272	0.016
MM	-0.069	-0.074	0.062	0.116	0.034	0.120	0.026	0.100	0.018	-0.046	0.023
	(-0.84)	(-0.92)	(0.66)	(1.04)	(0.31)	(0.83)	(0.24)	(0.74)	(0.14)	(-0.38)	(0.16)
CAPM	-0.022	-0.025	0.110	0.163	0.081	0.167	0.074	0.148	0.065	0.001	0.022
	(-0.28)	(-0.32)	(1.26)	(1.54)	(0.80)	(1.18)	(0.68)	(1.12)	(0.49)	(0.01)	(0.16)
FF	0.028	0.022	0.164*	0.189*	0.113	0.163	0.076	0.159	0.127	-0.004	0.032
	(0.74)	(0.27)	(1.73)	(1.75)	(1.07)	(1.12)	(0.65)	(1.16)	(0.92)	(-0.03)	(0.21)
Carhart	-0.016	0.009	0.145	0.170	0.065	0.121	0.018	0.091	0.088	-0.024	-0.008
	(-0.19)	(0.11)	(1.46)	(1.52)	(0.62)	(0.83)	(0.16)	(0.67)	(0.62)	(-0.19)	(-0.05)
2019											
MM	0.121	0.117	0.126	0.228	0.187	0.194	0.213	0.204	0.186	0.022	-0.099
	(0.70)	(0.62)	(0.71)	(1.30)	(0.96)	(1.13)	(1.06)	(1.13)	(1.03)	(0.13)	(-0.40)
CAPM	0.148	0.145	0.154	0.255	0.214	0.221	0.239	0.231	0.212	0.049	-0.098
	(0.87)	(0.78)	(0.86)	(1.47)	(1.11)	(1.30)	(1.20)	(1.29)	(1.19)	(0.28)	(-0.41)
					Gross Returns						
Average	1.380	1.389	1.519	1.535	1.472	1.529	1.480	1.516	1.448	1.392	0.012
MM	0.053	0.027	0.162*	0.221*	0.135	0.227	0.139	0.203	0.133	0.072	0.019
	(0.62)	(0.34)	(1.74)	(1.98)	(1.28)	(1.55)	(1.29)	(1.51)	(0.97)	(0.60)	(0.13)
CAPM	0.100	0.076	0.210**	0.268**	0.183*	0.274*	0.188*	0.249*	0.180	0.119	0.019
	(1.24)	(0.98)	(2.42)	(2.51)	(1.84)	(1.93)	(1.72)	(1.91)	(1.35)	(1.02)	(0.13)
FF	0.151*	0.123	0.264***	0.293***	0.215**	0.269*	0.190	0.261*	0.242*	0.114	-0.037
	(1.76)	(1.49)	(2.79)	(2.67)	(2.05)	(1.83)	(1.61)	(1.93)	(1.75)	(0.88)	(-0.24)
Carhart	0.106	0.111	0.245**	0.273**	0.167	0.226	0.131	0.193	0.204	0.094	-0.012
	(1.20)	(1.28)	(2.46)	(2.42)	(1.58)	(1.54)	(1.14)	(1.44)	(1.43)	(0.75)	(-0.08)
2019											
MM	0.241	0.221	0.228	0.328*	0.287	0.302*	0.323	0.310*	0.303	0.132	-0.109
	(1.40)	(1.17)	(1.25)	(1.87)	(1.47)	(1.75)	(1.60)	(1.71)	(1.67)	(0.75)	(-0.45)
CAPM	0.268	0.249	0.256	0.355**	0.313	0.328*	0.350*	0.337*	0.329*	0.159	-0.108
	(1.58)	(1.33)	(1.42)	(2.05)	(1.63)	(1.92)	(1.74)	(1.87)	(1.84)	(0.91)	(-0.43)

These results do strengthen the conclusion that herding is behavioral and furthermore, it shows that moderate antiherding may be the most optimal recourse in the long run. Importantly, and in line with Carhart (1997), these significant abnormal returns disappear when controlling for momentum, which indicates that the abnormal returns may be due to momentum strategies.

Nevertheless, the findings are supported by Lakonishok and colleagues (1992) who stipulate that contrarian strategies require longer time periods before they start paying off and as a consequence, this strategy is highly risky and may be less appealing to fund managers since poor managerial performance may have consequences in the short-run as reputational models propose (Chevalier & Ellison, 1999; Shaferstein & Stein, 1990; Zwiebel, 1995). It is also more in line with the findings of Jiang and Verardo (2018), since they find that antiherding funds consistently outperform herding funds in the long run.

4. Unobservable Skill

In the previous sections, it was found that moderate herding leads to abnormal average gross returns in the short-run, while moderate antiherding is superior in the long run. In this section, the stocks that drive the herding measure are excluded in order to test whether herding behavior can be indicative of superior stock picking ability. Specifically, if herding or antiherding is related to unobservable skill, then the corresponding portfolios should hold stocks that outperform the other stocks.

As stated in the model description, stocks included in the funds most prone to herd received a negative weight and are thus sorted into portfolio ‘low’, while stocks belonging to antiherding funds can be found in the higher numbered portfolios. As illustrated in the table below, portfolio ‘low’ has a higher average return than portfolio ‘high’ in the period spanning from 2010 to 2017. A similar pattern can be seen when extending the examination period which would indicate that stocks belonging to herding funds greatly outperform, on average, stocks belonging to antiherding funds. The same trend can be seen when looking at the risk-adjusted differentials. However, since the differentials are not significant, neither the ‘high’ nor the ‘low’ portfolio can be concluded to have higher skill compared to the other strategy. Portfolio number 4, which can be viewed as the portfolio of stocks belonging to funds with a less extreme antiherding behavior, generates significant abnormal returns. Additionally, in the period extending to 2019, portfolio 3 also achieves significant abnormal returns. This further indicates that skill may not be linked to either extreme end of herding/antiherding behavior, but to those funds with more moderate behaviors. It further demonstrates that not only are their strategies more advantageous, in the form of abnormal returns in the long run, but they are also more adept at picking well performing stocks.

Table 6
Revealing Skill through Investment Choices

The following table shows the average stock level herding estimated for 5 portfolios formed at the end of each quarter *t*, based on their lagged stock level measure. Stocks included in funds that are more prone to herd are found in portfolio 'low' while stocks included in antiherding funds are found in portfolio 'high'. Average monthly returns and risk-adjusted alphas obtained using the Market Model, CAPM, Fama and French three-factor model as well as Carhart four-factor model are presented below. The corresponding Newey-West t-statistics are presented in parentheses. ***, **, and * denote significance at the 1%, 5% and 10% level, respectively. In addition, average return and alpha differentials are presented under "High-Low".

S^{FH}	Low	2	3	4	High	High-Low
Average	1.199	0.890	1.127	1.301	0.805	-0.394
MM	0.178	-0.073	0.284	0.495*	-0.368	-0.546
	(0.47)	-(0.23)	(0.81)	(1.83)	(-1.45)	(-1.43)
CAPM	0.239	-0.019	0.332	0.541**	-0.298	-0.537
	(0.64)	(-0.05)	(0.95)	(2.03)	(-1.16)	(-1.42)
FF	0.328	-0.030	0.360	0.557**	-0.215	-0.543
	(0.91)	(-0.09)	(0.98)	(2.08)	(-0.77)	(-1.47)
Carhart	0.238	-0.003	0.470	0.492*	-0.130	-0.368
	(0.96)	(-0.01)	(1.28)	(1.72)	(-0.45)	(-1.35)
2019						
Average	1.014	0.717	1.359	1.205	0.817	-0.197
MM	0.155	-0.139	0.691*	0.439*	-0.105	-0.260
	(0.52)	(-0.42)	(1.92)	(1.75)	(-0.45)	(-1.29)
CAPM	0.197	-0.095	0.720**	0.474*	-0.060	-0.257
	(0.67)	(-0.30)	(2.02)	(1.92)	(-0.26)	(-1.23)

Our results are partially consistent with Jiang and Verardo (2018), since, on the one hand, the estimations show that abnormal significant results are obtained for portfolios formed by stocks held by funds exhibiting a moderate antiherding behavior. On the other hand, our estimations do not show a consistent outperformance of the stocks picked by antiherding funds over stocks held by herding funds. However, observe that this methodology does not take into account possible transactions costs related to the formation of the portfolios.

5. Do herding managers buy outperforming stocks and sell underperforming stocks?

In this section, we present the results obtained measuring the sophistication of herding behavior by sorting stocks into portfolios based on their past change in institutional ownership. If herding behavior is related to skill, then it is expected that those stocks sold by herds underperform the stocks that the managers choose to keep in their portfolios.

The results reported in table 7 show that, on average, the portfolio containing stocks sold in herds (portfolio 1) has the highest average return and greatly outperforms the portfolio of stocks bought in herds (portfolio 10) in the subsequent three months. Observe that all the return differentials obtained with risk-adjusted alphas are negative and only partially significant for the Fama-French and Carhart models. Nevertheless, note that the risk-adjusted alphas of portfolio 1 are significant in all estimations, which implies that the stocks with the greatest negative institutional ownership show abnormal returns persistently. If herding was a rational behavior where skilled investors lead the herd or show herding behavior, one would expect that the herds buy well performing stocks and sell underperforming stocks. However, this does not seem to be the case. These results are not in line with those presented by Dasgupta and colleagues (2011) and Nofsinger and Sias (1999), since the stocks that are sold by herds outperform those bought by herds in the short run, instead of the opposite. According to theory, this reversal should occur in the long run.

Since our results are significant regardless of the estimation method used, they constitute a strong indication that herding is in fact not a sign of sophistication, but rather a behavioral or reputational phenomenon containing no information, as our previous results have also indicated. It further shows that institutional investors may not be immune to the disposition effect.

Table 7

Performance of stocks bought and sold by herds

The following table shows average monthly returns and alphas obtained from our portfolio regressions as well the corresponding Newey-West t-statistics. ***, **, and * denote significance at the 1%, 5% and 10% level, respectively. The portfolios are sorted into deciles based on the stock level value of past institutional trades. Portfolio 1 contains stocks sold by herds while portfolio 10 contains stocks bought by herds.

Rank	1	2	3	4	5	6	7	8	9	10	10-1
Average	1.427	1.316	1.143	0.922	1.061	1.004	1.097	0.761	0.834	1.003	-0.424
MM	0.611**	0.440*	0.299	-0.017	0.097	-0.011	0.187	-0.221	-0.126	0.151	-0.460
	(2.21)	(1.89)	(1.11)	(-0.07)	(0.31)	(-0.03)	(0.67)	(-0.53)	(-0.34)	(0.47)	(-1.07)
CAPM	0.555**	0.379*	0.242	-0.082	0.030	-0.079	0.125	-0.287	-0.192	0.093	-0.462
	(1.97)	(1.63)	(0.89)	(-0.33)	(0.10)	(-0.21)	(0.44)	(-0.67)	(-0.51)	(0.29)	(-1.17)
FF	0.586**	0.439*	0.259	-0.034	0.017	-0.043	0.208	-0.279	-0.220	0.045	-0.541*
	(2.19)	(1.88)	(0.93)	(-0.14)	(0.06)	(-0.12)	(0.75)	(-0.67)	(-0.63)	(0.16)	(-1.88)
Carhart	0.564**	0.488**	0.247	0.039	0.037	-0.010	0.044	-0.222	-0.288	0.052	-0.512*
	(2.56)	(1.97)	(0.88)	(0.15)	(0.11)	(-0.03)	(0.16)	(-0.55)	(-0.78)	(0.17)	(-1.71)
2019											
Average	1.082	1.098	0.891	0.741	0.882	0.865	0.868	0.692	0.585	0.919	-0.163
MM	0.355	0.345*	0.167	-0.057	0.055	-0.018	0.057	-0.157	-0.252	0.159	-0.196
	(1.24)	(1.74)	(0.66)	(-0.24)	(0.19)	(-0.06)	(0.21)	(-0.40)	(-0.76)	(0.54)	(-0.54)
CAPM	0.392	0.385*	0.205	-0.016	0.098	0.026	0.099	-0.115	-0.208	0.198	-0.194
	(1.38)	(1.94)	(0.82)	(-0.07)	(0.33)	(0.08)	(0.37)	(-0.30)	(-0.64)	(0.67)	(-0.68)

6. Robustness tests

Fund Performance with own past trades

This section presents the fund performance results obtained when adding the past trades of the fund into the fund herding equation. As illustrated in table 8 below, the modification of the equation induces changes in the estimated results. First, the estimated fund herding measure is larger when the past trades are added into the calculation. The modified fund herding measure obtained triples the values previously estimated. Moreover, the standard deviation increases by 3.4 and 4.97 percent respectively, which indicates that the heterogeneity across groups has been augmented, a fact that can also be observed since the maximum and minimum herding values have also increased, which denotes more extreme herding and antiherding behavior.

Table 8

Cross-Sectional Descriptive Statistics, *FH and FH Robust*

The follow table details descriptive statistics obtained for our fund herding measure (FH). FH is the fund herding measure used in all the previous tests. FH Robust are the values of FH obtained when controlling for the fund´s own past trades in the main fund herding regression. A comparison of the values obtained when using a dataset that spans from 2010 to 2016 to a dataset with additional observations until 2019 are also presented. These statistics are computed across each quarter and for each fund, and then averaged over time.

	Mean	Std. Dev.	Min	25^{th} Pctl	Median	75^{th} Pctl	Max	Obs.	Missing Obs.
FH	1.89	12.21	-32.23	-4.58	1.53	9.18	33.27	107	0
FH Robust	6.00	17.18	-45.85	-3.24	2.12	13.70	62.19	107	0
2019									
FH	1.77	12.72	-34.85	-5.71	1.61	9.94	40.09	117	0
FH Robust	4.38	16.22	-40.88	-4.81	0.56	10.94	62.19	117	0

When controlling for past transactions, the average and risk-adjusted performance differentials are reversed and enlarged. However, the risk-adjusted differentials are still insignificant. Moreover, the alphas that belong to portfolio 8 and 9 are significant when estimated with the CAPM model, Fama and French as well as with the Carhart four-factor model, which implies that moderate levels of herding lead to abnormal returns. Although, all abnormal returns disappear when accounting for fees and expenses. In summary, these results remain unchanged from the previous version, which implies that the short-run fund performance analysis conducted is robust to the inclusion of past trades.

Table 9
Fund Performance Controlling for own Past Trades

This table shows the fund performance analysis conducted after controlling for the fund's own past trades in the fund herding regression. Ten portfolios were formed at the end of each quarter *t* based on the lagged estimated herding measure and they are held for one quarter, it results in time series starting in September 2010 to December 2018. Portfolio 1 represents the antiherding portfolio since it contains the funds with the lowest fund herding values. On the contrary, portfolio 10 represents the herding portfolio containing the highest values of fund herding. The average herding measure estimated for each portfolio is presented below as well as the monthly average net and gross portfolio returns as well as the differentials between the herding and antiherding portfolios. In addition, risk-adjusted alphas obtained using the Market Model, CAPM, Fama and French three-factor model and Carhart four-factor model are presented. For the time period until December 2018, only risk-adjusted alphas obtained with the Market model and CAPM are included. The corresponding Newey-West t-statistics are shown in parentheses and ***, ** and * denote significance at the 1%, 5% and 10% level, respectively.

FH rank	1	2	3	4	5	6	7	8	9	10	D10-D1
FH	-0.545	-0.215	-0.102	-0.033	0.011	0.048	0.107	0.192	0.346	0.755	0.810
Net Returns											
Avg	1.023	1.007	0.947	0.920	1.041	1.028	0.995	1.023	1.006	0.893	-0.130
MM	-0.072	-0.061	0.109	-0.127	-0.028	-0.048	-0.070	-0.015	-0.065	-0.138	-0.065
	(-0.63)	(-0.47)	(-1.06)	(-1.45)	(-0.24)	(-0.45)	(-0.53)	(-0.15)	(-0.79)	(-1.50)	(-0.72)
CAPM	0.001	0.010	-0.039	-0.058	0.042	0.023	0.00	0.054	0.006	-0.069	-0.070
	(0.01)	(0.08)	(-0.41)	(-0.74)	(0.39)	(0.23)	(0.00)	(0.59)	(0.08)	(-0.80)	(-0.78)
FF	0.014	0.045	-0.009	-0.033	0.074	0.062	0.019	0.081	0.021	-0.048	-0.062
	(0.13)	(0.38)	(-0.10)	(-0.39)	(0.70)	(0.60)	(0.15)	(0.86)	(0.28)	(-0.52)	(-0.54)
Carhart	-0.006	0.059	-0.006	-0.055	0.067	0.023	0.002	0.039	0.011	-0.041	-0.047
	(-0.05)	(0.50)	(-0.06)	(-0.62)	(0.70)	(0.22)	(0.01)	(0.44)	(0.14)	(-0.42)	(-0.42)
2019											
MM	0.000	0.056	-0.020	-0.025	0.027	0.044	0.055	0.030	0.008	-0.035	-0.039
	(0.00)	(0.33)	(-0.12)	(-0.16)	(0.17)	(0.26)	(0.31)	(0.17)	(0.06)	(-0.22)	(-0.19)
CAPM	0.046	0.101	0.024	0.019	0.072	0.089	0.100	0.073	0.054	0.008	-0.039
	(0.27)	(0.62)	(0.14)	(0.13)	(0.46)	(0.54)	(0.58)	(0.43)	(0.38)	(0.05)	(-0.14)
Gross Returns											
Avg	1.135	1.111	1.055	1.031	1.156	1.136	1.105	1.136	1.114	1.003	-0.132
MM	0.039	0.042	-0.001	-0.017	0.086	0.059	0.039	0.097	0.042	-0.029	-0.069
	(0.34)	(0.32)	(-0.20)	(-0.20)	(0.73)	(0.55)	(0.29)	(0.98)	(0.52)	(-0.31)	(-0.72)
CAPM	0.112	0.113	0.069	0.052	0.157	0.130	0.109	0.166*	0.113	0.039	-0.073
	(1.05)	(0.92)	(0.73)	(0.65)	(1.44)	(1.31)	(0.88)	(1.81)	(1.54)	(0.45)	(-0.82)
FF	0.125	0.148	0.098	0.076	0.189*	0.169	0.128	0.193**	0.128*	0.060	-0.065
	(1.17)	(1.23)	(1.02)	(0.88)	(1.77)	(1.62)	(1.02)	(2.04)	(1.70)	(0.65)	(-0.46)
Carhart	0.105	0.162	0.102	0.054	0.182*	0.130	0.110	0.151*	0.118	0.066	-0.039
	(1.01)	(1.37)	(1.11)	(0.61)	(1.89)	(1.25)	(0.92)	(1.68)	(1.54)	(0.67)	(-0.44)
2019											
MM	0.110	0.159	0.088	0.082	0.137	0.149	0.162	0.142	0.114	0.072	-0.038
	(0.62)	(0.94)	(0.51)	(0.53)	(0.85)	(0.87)	(0.91)	(0.83)	(0.77)	(0.46)	(-0.19)
CAPM	0.156	0.203	0.132	0.126	0.182	0.193	0.207	0.185	0.160	0.115	-0.042
	(0.91)	(1.25)	(0.80)	(0.85)	(1.16)	(1.17)	(1.20)	(1.10)	(1.12)	(0.75)	(-0.16)

Revealing skill through investments 3 portfolios.

The test performed in section 4 is replicated with stocks sorted according to their lagged stock herding value into 3 portfolios instead of 5. With this modification, it is easy to distinguish between stocks belonging to antiherding, neutral or herding funds. Looking at the period spanning from 2010 to 2019, portfolio 2 generates significant abnormal returns, which is consistent with the previous analysis (see table 6). This further supports our assumption that skill resides with those who invest according to a more diversified strategy. However, it is worth noting that the antiherding portfolio does not obtain abnormal returns. Additionally, no portfolio is able to generate abnormal returns in the period running through 2016. The fact that portfolio 1 does not earn a significant abnormal return is further indicative of herding being a strictly behavioral phenomena rather than a sign of sophistication.

Table 10

Revealing Skill through Investment Choices (three portfolios)

The following table shows average monthly returns and risk-adjusted alphas obtained from our portfolio regressions using the Market model, CAPM, Fama and French three-factor model and Carhart four-factor model. At the end of each quarter *t*, the stocks are sorted according to their SFH value and three portfolios are formed. In the column '3-1' portfolio differentials are presented. The portfolios are held for one quarter. Stocks included in the funds most prone to herd are found in portfolio 3 while stocks included in the herding funds are found in portfolio 1. Portfolio 2 is considered a "neutral" portfolio. The estimated Newey-West t-statistics are shown in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% level, respectively.

S^{FH}	1	2	3	3-1
Average	0.991	1.187	1.023	0.032
MM	-0.029	0.338	0.001	-0.028
	(-0.09)	(1.08)	(0.01)	(-0.08)
CAPM	0.030	0.386	0.062	0.032
	(0.10)	(1.26)	(0.28)	(0.08)
FF	0.081	0.385	0.135	0.054
	(0.26)	(1.25)	(0.55)	(0.14)
Carhart	0.093	0.436	0.172	0.079
	(0.30)	(1.34)	(0.65)	(0.20)
2019				
Average	0.907	1.163	0.992	0.085
MM	0.087	0.509*	0.192	0.105
	(0.34)	(1.93)	(0.85)	(0.42)
CAPM	0.134	0.545**	0.238	0.104
	(0.54)	(2.11)	(1.07)	(0.45)

Including initiations and deletions of trade

Including initiations and deletions of stocks into our model does alter the value of FH, although not as much as when accounting for past trades. The main results do not differ significantly from the baseline model. There are still no signs of sophistication in antiherding or herding behavior since none of them enjoy significant abnormal returns. Thus, the results obtained previously are robust to the inclusion of initiations and deletions.

Table 11

Fund Performance, including initiations and deletions

This table shows the performance of 10 portfolios formed at the end of each quarter *t* based on the lagged estimated herding measure and they are held for one quarter. It results in time series starting in June 2010 to December 2018. Observe that the herding measure used in this analysis includes initiations and deletions since it includes the change in holdings when a fund buys a certain share for the first time as well when the funds sell off the entire position in that stock. Portfolio 1 represents the antiherding portfolio since it contains the funds with the lowest fund herding levels. On the contrary, portfolio 10 represents the herding portfolio containing the highest values of fund herding. The average herding measure estimated for each portfolio is presented below as well as the monthly average net and gross portfolio returns and differentials between the herding and antiherding portfolios. In addition, risk-adjusted alphas obtained using the Market Model, CAPM, Fama and French three-factor model and Carhart four-factor model are presented. For the time period until December 2018, only risk-adjusted alphas obtained with the Market model and CAPM are included. The corresponding Newey-West t-statistics are shown in parentheses and ***, ** and * denote significance at the 1%, 5% and 10% level, respectively.

FH rank	1	2	3	4	5	6	7	8	9	10	10-1
FH	-0.476	-0.201	-0.120	-0.068	-0.028	0.004	0.041	0.095	0.186	0.410	0.886
						Net Returns					
Average	1.129	1.150	1.218	1.208	1.178	1.261	1.329	1.201	1.213	1.162	0.033
MM	-0.015	-0.117	-0.040	-0.042	-0.123	-0.026	0.056	-0.088	-0.045	-0.088	-0.072
	(-1.64)	(-1.49)	(-0.47)	(-0.37)	(-1.60)	(-0.27)	(0.47)	(-0.71)	(-0.43)	(-0.77)	(-0.76)
CAPM	-0.087	-0.048	0.028	0.026	-0.060	0.045	0.124	-0.017	0.023	-0.020	0.067
	(-0.98)	(-0.67)	(0.37)	(0.25)	(-0.79)	(0.51)	(1.14)	(-0.15)	(0.24)	(-0.19)	(0.70)
FF	-0.074	-0.034	0.069	0.037	-0.034	0.065	0.159	0.018	0.034	0.006	0.080
	(-0.87)	(-0.44)	(0.87)	(0.35)	(-0.40)	(0.75)	(1.45)	(0.15)	(0.33)	(0.06)	(0.98)
Carhart	-0.105	-0.046	0.075	0.014	-0.069	0.027	0.155	0.014	0.011	0.007	0.112
	(-1.23)	(-0.58)	(0.97)	(0.14)	(-0.77)	(0.29)	(1.46)	(0.12)	(0.11)	(0.06)	(1,38)
2019											
MM	-0.044	-0.036	0.006	0.051	0.011	0.065	0.125	0.025	-0.015	0.018	0.062
	(-0.28)	(-0.24)	(0.04)	(0.31)	(0.08)	(0.06)	(0.78)	(0.15)	(-0.09)	(0.11)	(0.41)
CAPM	0.001	0.009	0.051	0.095	0.057	0.111	0.170	0.070	0.031	0.062	0.061
	(0.00)	(0.06)	(0.34)	(0.60)	(0.40)	(0.76)	(1.10)	(0.44)	(0.19)	(0.38)	(0.42)
						Gross Returns					
Average	0.945	0.946	0.986	1.018	1.016	1.052	1.117	1.022	0.962	0.989	0.044
MM	-0.047	-0.016	0.074	0.064	-0.026	0.078	0.171	0.023	0.065	0.024	0.071
	(-0.49)	(-0.20)	(0.84)	(0.56)	(-0.32)	(0.81)	(1.45)	(0.18)	(0.61)	(0.21)	(0.74)
CAPM	0.024	0.054	0.142*	0.132	0.046	0.149*	0.239**	0.094	0.133	0.092	0.068
	(0.27)	(0.74)	(1.79)	(1.26)	(0.59)	(0.01)	(2.21)	(0.79)	(1.34)	(0.85)	(0.76)
FF	0.037	0.067	0.184**	0.144	0.072	0.168*	0.274**	0.129	0.144	0.119	0.082
	(0.43)	(0.85)	(2.21)	(1.36)	(0.85)	(1.97)	(2.50)	(1.10)	(1.41)	(1.04)	(1.02)
Carhart	0.005	0.056	0.188**	0.119	0.037	0.130	0.269	0.126	0.120	0.120	0.115
	(0.06)	(0.70)	(2.38)	(1.21)	(0.42)	(1.41)	(2.53)	(1.11)	(1.24)	(1.13)	(0.95)
2019											
MM	0.069	0.067	0.118	0.156	0.114	0.168	0.237	0.134	0.092	0.129	0.060
	(0.42)	(0.44)	(0.76)	(0.95)	(0.75)	(1.11)	(1.48)	(0.81)	(0.58)	(0.77)	(0.38)
CAPM	0.112	0.112	0.162	0.199	0.160	0.213	0.282*	0.179	0.137	0.173	0.061
	(0.73)	(0.76)	(1.08)	(1.26)	(1.10)	(1.46)	(1.82)	(1.12)	(0.88)	(1.06)	(0.41)

Conclusion

The present paper examined the presence of herding behavior on the Swedish open-end fund market following the methodology developed by Jiang and Verardo (2018). We find evidence of herding behavior amongst Swedish open-end funds, albeit to a small extent. The herding behavior conducted by Swedish funds show higher levels of heterogeneity compared to their American counterparts, likely due to a greater presence of extreme antiherding and herding behavior. The analysis of fund performance in the short-run finds no evidence of either extreme portfolio being able to consistently generate abnormal returns in the short run. Instead, we find a moderate approach to herding being the most beneficial, generating significant gross abnormal returns. However, when accounting for fees and expenses, no funds are able to generate significant returns, which indicates a lack of managerial skill. However, when looking at long-term performance, moderate antiherding portfolios show some indication of being able to generate significant abnormal net returns while herding is still deemed behavioral or reputational. This is in line with previous literature since contrarian strategies can perform badly in the short run but, given time, they can generate positive returns. The examination of stock picking ability finds no evidence of superior ability amongst either of the extreme portfolios. In line with the previous results, significant abnormal returns are achieved by funds exhibiting more moderate antiherding behavior. However, it is worth noting that this test does not account for fees and expenses, which may cancel out any abnormal net returns. Further testing whether stock bought in herds outperform those sold by them reveals that this is not the case, since the stocks sold in herds are the only ones to generate significant abnormal returns in the short run.

In conclusion, our results indicate that herds contain no information since they cannot generate significant abnormal net returns, nor do they possess superior stock picking ability. This implies that herding behavior is not conducted by sophisticated fund managers. Rather, herding seems to be driven by reputational concerns or behavioral biases. Moreover, this paper finds weak evidence of antiherding fund managers being able to generate significant net returns in the long run, which can be considered a sign of superior skill. While these results find support in previous literature, we also find opposing views. Most notably, our results are not completely in line with Jiang and Verardo (2018), the paper upon which the present thesis is built upon.

Fund managers may herd as a consequence of behavioral biases or reputational concerns. This may, in turn, push stock prices from their fundamental values, leading to the creation of bubbles. Since there is no information contained in the herd, these reputational concerns may be solved by altering incentive schemes to account for long-term strategies rather than focusing on short-term returns. Regarding the behavioral biases, further research is needed in order to identify which of the biases are the drivers of this behavior amongst fund managers.

The limitations of this thesis are mainly due to data constraints. The present study was restricted to a time period spanning from 2010 through 2017 or 2019 depending on the test and may greatly benefit from extending this period. The time frequency of data may also affect the results, since monthly data is more accurate than quarterly data and may reveal transactions that cannot be observed with quarterly frequencies. The Swedish market is relatively small, which inevitably leads to small sample sizes, and less precision. Most studies on herding behavior are performed on US markets and enjoy much larger sample sizes.

This thesis has contributed to the ongoing body of literature regarding herding behavior in connection to performance and skill in the context of Swedish open-end fund market by using up to date methods and novel approaches. As mentioned before, further studies should be performed on a larger sample examining longer time periods. This would allow for the inclusion and analysis of the effect of the financial crisis on herding behavior, as herding might be more prevalent in times of market uncertainty. An interesting continuation of this research would be to analyze the relationship between herding, skill and management fees, since more recent research has shown that managers are appropriately rewarded in the form of fees and that aggregate fees can predict long-term performance. The current paper has not, nor did we intend it to, been able to discern the specific behavioral biases exhibited by fund managers. Future research may focus more on identifying the drivers of this seemingly irrational behavior.

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Appendix

In this appendix, we include further descriptive statistics and additional tests, as referred to in the text.

A1. Fund Characteristics

Table 12 reports the descriptive statistics of the characteristics of the funds included in the present study.

Table 12
Fund Characteristics

In this table, descriptive statistics of fund characteristics are presented. The sample consists of 116 mutual funds over the period 2010-2019. Age is time in years from the funds' inception date up until 2019. Fund size is the net fund size in millions of SEK. Expense ratio is denoted "expense". Turnover ratio is denoted "Turnover".

	Mean	Std. Dev	Min	25th *Pctl*	Median	75th *Pctl*	Max	Number obs.	Missing
Age	17	10	1	10	18	23	45	116	-
Turnover	64.12	65.81	-100	20.50	46	79	331	104	12
Expense	1.28	0.45	0.00	0.30	1.41	1.58	2.19	102	14
Fund Size	3 750	6 810	1.96	254	970	3 670	3 7300	112	4

A2. Performance Persistence (9-month holding period)

A performance persistence analysis was also performed using a 9-month holding period in order to examine whether the holding period impacted on the tests. The table below reports the results obtained for the estimation, and as illustrated, no major changes can be perceived.

Table 13
Performance Persistence – 9 months

This table shows the performance persistence analysis of 10 portfolios when the portfolios are held for 9 months. The portfolios are formed every 9 months, at the end of the month, based on the lagged average herding measure. It results in time series starting in June 2010 to December 2018. Portfolio 1 represents the antiherding portfolio since it contains the funds with the lowest fund herding levels. On the contrary, portfolio 10 represents the herding portfolio containing the highest values of fund herding. The average herding measure estimated for each portfolio is presented below as well as the monthly average net and gross portfolio returns and differentials between the herding and antiherding portfolios. In addition, risk-adjusted alphas obtained using the Market Model, CAPM, Fama and French three-factor model and Carhart four-factor model are presented. For the time period until December 2018, only risk-adjusted alphas obtained with the Market model and CAPM are included. The corresponding Newey-West t-statistics are shown in parentheses and ***, ** and * denote significance at the 1%, 5% and 10% level, respectively.

FH Rank	1	2	3	4	5	6	7	8	9	10	D10-D1
						Net Returns					
Average	0.987	0.947	0.893	1.069	0.972	1.061	1.119	0.966	0.866	1.067	0.080
MM	-0.160*	-0.091	-0.136	-0.110	-0.160*	0.055	0.091	-0.058	-0.213*	-0.060	0.100
	(-1.66)	(-0.74)	(-1.60)	(-1.36)	(-1.65)	(0.49)	(0.63)	(-0.53)	(-1.89)	(-0.54)	(1.09)
CAPM	-0.090	-0.021	-0.066	-0.040	-0.090	0.120	0.160	0.009	-0.143	0.010	0.112
	(-1.02)	(-0.18)	(-0.89)	(-0.53)	(-1.02)	(1.14)	(1.16)	(0.09)	(-1.37)	(0.10)	(1.11)
FF	-0.060	0.009	-0.039	-0.014	-0.062	0.149	0.170	0.019	-0.125	0.031	0.090
	(-0.70)	(0.08)	(-0.52)	(-0.18)	(-0.66)	(1.34)	(1.23)	(0.19)	(-1.15)	(0.31)	(1.00)
Carhart	-0.081	0.006	-0.033	0.013	-0.091	0.122	0.117	0.008	-0.139	0.010	0.091
	(-0.96)	(0.05)	(-0.42)	(0.16)	(-0.94)	(1.14)	(0.83)	(0.08)	(-1.22)	(0.10)	(1.13)
2019											
MM	-0.045	-0.056	0.049	-0069	-0.033	0.119	0.089	0.032	-0.044	0.063	0.108
	(-0.27)	(-0.32)	(0.28)	(-0.47)	(-0.19)	(0.72)	(0.52)	(0.17)	(-0.24)	(-0.37)	(0.63)
CAPM	-0.001	-0.012	0.092	-0.025	0.010	0.159	0.133	0.074	-0.001	-0.019	-0.018
	(-0.01)	(-0.07)	(0.54)	(-0.18)	(0.06)	(0.99)	(0.80)	(0.40)	(-0.01)	(-0.12)	(-0.11)
						Gross Returns					
Average	1.104	1.055	0.993	1.167	1.072	1.175	1.241	1.079	0.978	1.182	0.078
MM	-0.045	0.017	-0.041	-0.015	-0.056	0.165	0.211	0.056	-0.103	0.054	0.099
	(-0.46)	(0.14)	(-0.49)	(-0.20)	(-0.58)	(1.49)	(1.46)	(0.52)	(-0.91)	(0.48)	(0.64)
CAPM	0.025	0.088	0.028	0.054	0.014	0.230**	0.281**	0.122	-0.033	0.124	0.099
	(0.28)	(0.75)	(0.39)	(0.73)	(0.16)	(2.18)	(2.03)	(1.24)	(-0.32)	(1.21)	(1.10)
FF	0.055	0.118	0.055	0.079	0.041	0.259**	0.289**	0.133	-0.016	0.146	0.091
	(0.64)	(1.00)	(0.73)	(1.01)	(0.44)	(2.33)	(2.09)	(1.31)	(-0.14)	(1.42)	(1.00)
Carhart	0.033	0.115	0.062	0.106	0.011	0.232**	0.237*	0.121	-0.029	0.125	0.092
	(0.39)	(1.02)	(0.81)	(1.34)	(0.11)	(2.16)	(1.68)	(1.27)	(-0.26)	(1.21)	(0.84)
2019											
MM	0.067	0.053	0.146	0.031	0.069	0.229	0.207	0.142	0.061	0.051	-0.016
	(0.40)	(0.30)	(0.83)	(0.21)	(0.39)	(1.38)	(1.21)	(0.75)	(0.33)	(0.30)	(-0.09)
CAPM	0.111	0.096	0.189	0.075	0.110	0.269*	0.251	0.183	0.104	0.095	-0.016
	(0.68)	(0.57)	(1.11)	(0.53)	(0.67)	(1.67)	(1.50)	(1.00)	(0.58)	(0.57)	(-0.08)

In contrast to the findings presented in the 18-month analysis, portfolio 10 outperforms portfolio number 1 when looking at average net and gross returns. The return differentials are larger than before at roughly 80 basis points, which suggests that herding funds perform well above antiherding funds in the long run. The same pattern can be inferred from the risk-adjusted alphas, although the antiherding funds seem to perform better than the herding funds in the period running through 2018. As was the case previously, however, these results are insignificant and neither portfolio is able to generate significant abnormal returns.

In line with the short-term results, a moderate herding behavior appears to be the more optimal approach since portfolio 6 and 7 are both able to generate significant gross abnormal returns. However, as stipulated by Fama and French (2010), in order to identify skilled managers, transaction costs and fees have to be taken into account. The significant abnormal returns mostly disappear when accounting for net returns, although there is some partial significance in the market model. These returns can be identified in portfolio 1, 5 and 9, which is rather confounding since they represent both extreme ends of the herding spectrum as well as a neutral portfolio. However, when accounting for addition risk factors, the significance disappears. Thus, it can be concluded that the results of the persistence analysis support our finding that herding is a behavioral phenomenon.