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# Does herding behavior reveal skill?
# An analysis of mutual fund performance

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# Does herding behavior reveal skill? An analysis of mutual fund performance*

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**Abstract**

This paper finds that fund herding, defined as the tendency of a mutual fund to follow past aggregate institutional trades, is an important predictor of mutual fund performance. Examining actively managed U.S. equity mutual funds over the period 1990-2009, we find that funds with a higher herding tendency achieve lower future returns. The performance gap between herding and antiherding funds is persistent over various horizons and is more pronounced in periods of greater investment opportunities in the active management industry. We show that fund herding is negatively correlated with recently developed measures of mutual fund skill and provides distinct information for the predictability of mutual fund performance. Overall, our results suggest that fund herding reveals information about the cross-sectional distribution of skill in the mutual fund industry.

**Keywords:** Mutual funds, performance, herding, imitation, alpha.

**J.E.L. codes:** G11, G20, G23.

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# 1 Introduction

A well-documented feature of the trading behavior of money managers is their tendency to trade in herds, following each other in their buying and selling decisions. Such correlated trading behavior can generate predictable patterns in stock returns.[1] Despite the extensive evidence on the stock-level association between institutional herding and returns, the link between the herding tendency of money managers and their performance remains largely unexplored. Yet the performance of money managers, and in particular of mutual funds, has received increasing attention in recent years. A growing literature shows that, although on average active mutual funds do not outperform passive benchmarks, at the tails of the cross-sectional distribution of mutual fund returns there are skilled and unskilled funds exhibiting extreme positive and extreme negative performance.[2]

Can investors identify skilled and unskilled funds by observing their tendency to herd? In this paper we ask whether herding behavior can predict the performance of mutual fund managers, thus revealing information about their ability. To answer this question we create a new fund-level measure of herding, which captures the tendency of a mutual fund manager to follow the collective trading decisions of other institutional investors. We then test whether differences in herding behavior across funds can systematically predict mutual fund performance.

Our measure of fund herding is based on the intertemporal correlation between the trades of a given fund and past aggregate institutional trades, to capture the idea of imitation in sequential decision making.[3] Specifically, each quarter we estimate the correlation between a given fund's trades and the collective trading decisions that other institutional investors have made in the past;

[1] For example, Lakonishok, Shleifer, and Vishny (1992), Grinblatt, Titman, and Wermers (1995), Nofsinger and Sias (1999), and Wermers (1999) find that the fraction of institutions buying or selling a given stock at the same time is positively associated with future short-term returns. Sias (2004) finds that the intertemporal correlation in institutional demand for a given stock is positively related to future short-term returns, whereas Dasgupta, Prat, and Verardo (2011a) estimate a negative association between persistent institutional trading and future long-term returns.

[2] Studies that document the poor track record of active mutual funds include Malkiel (1995), Gruber (1996), Carhart (1997), and Wermers (2000). Recently, Fama and French (2010) use simulations to provide evidence of inferior and superior performance in the extreme tails of the cross-section of mutual fund alphas; they estimate that about 16% of mutual funds have true alphas greater than 1.25% per year before expenses. Barras, Scaillet, and Wermers (2010) document a decrease in the fraction of skilled funds (funds with positive alphas) from 14.4% in early 1990 to 0.6% in late 2006, and an increase in the proportion of unskilled funds from 9.2% to 24.0%.

[3] Models of herd behavior are inherently dynamic and involve an agent making a decision after observing the actions of other agents (e.g., Scharfstein and Stein (1990), Bikhchandani, Hirshleifer, and Welch (1992)). In empirical studies, institutional herding is typically measured at the stock level, using either the propensity of institutional investors to buy or sell the same stock at the same time, or the intertemporal correlation of institutional trades in a given stock. In the former case, it is difficult to capture the dynamic nature of sequential decision making. Therefore, we construct a measure based on the intertemporal correlation in institutional trades.

we then average this estimate over previous periods in the lifetime of the fund, to obtain a measure of its average herding tendency. In estimating fund herding, we control for a stock's past returns to remove the component of the correlation between fund trades and past institutional trades that is attributable to mutual funds'momentum investment strategies. We also control for a stock's market capitalization and book-to-market ratio to account for potential correlated trading induced by common investing styles. We find a large degree of heterogeneity in herding behavior, with some funds exhibiting a prevalent following tendency and others exhibiting mainly contrarian trading patterns. We then investigate the predictive power of fund herding for the cross-section of mutual fund returns.

We find that fund herding negatively predicts mutual fund performance. The top decile portfolio of funds with the highest herding tendency underperforms the portfolio of antiherding funds by 2.28% on an annualized basis, both before and after expenses. We obtain similar results when we account for exposures to factors such as the market risk premium, size, value, momentum, and liquidity: the alphas from different multi-factor models vary between 1.68% and 2.52% on an annualized basis. Accounting for time-varying factor exposures still yields a predicted performance gap of 2.04% per year. These results hold for fund returns measured both before and after expenses and are robust to controlling for past performance, fund size, age, turnover, expense ratios, and net flows.

What can drive this strong negative association between fund herding and future performance? One intuitive explanation for our findings is that herding funds are less skilled than their antiherding peers. We conduct several tests to further investigate the link between fund herding, skill, and performance, and to rule out potential alternative explanations. Our results suggest that the herding behavior of mutual funds contains information about the cross-sectional distribution of skill in the mutual fund industry.

First, we find that funds that trade in herds are less skilled, according to recently developed measures of mutual fund ability: they have lower active share (Cremers and Petajisto (2009)), trade differently from managers with distinguished performance records (Cohen, Coval, and Pástor (2005)), and rely more heavily on public information (Kacperczyk and Seru (2007)). Even after including these alternative measures of skill in our performance regressions, fund herding retains its predictive power for mutual fund performance, suggesting that it captures a distinct dimension of mutual fund skill.[4]

Second, we find evidence of persistence in the performance gap between herding and antiherding funds, suggesting that the link between herding behavior and future performance is not due merely to chance. Our portfolio results show that the underperformance of herding funds is still large and significant over horizons of six, nine, or twelve months after the measurement of fund herding.

Third, we examine time-series variations in the performance gap between herding and antiherding funds. If herding behavior is related to skill, we should observe a widening of the performance gap between herding and antiherding funds during times of greater investment opportunities for mutual fund managers, as skilled funds should exploit their informational advantages better than unskilled funds. Using a measure of cross-sectional return dispersion for U.S. equities to capture time-series variations in investment opportunities, we find that the underperformance of herding funds is significantly larger during and after periods of high return dispersion, i.e., periods in which firm-specific information is more valuable. Therefore, a mutual fund investor could potentially benefit from a dynamic strategy that discriminates between herding and antiherding managers.

We then conduct a series of tests to assess the robustness of the predictive ability of fund herding. Our findings continue to hold when we use alternative measures of fund performance, whether based on portfolio holdings or on funds' trades. Furthermore, our results are not sensitive to the model that we use to estimate fund herding and continue to hold after controlling for stock characteristics such as liquidity, volatility, net issuance, industry membership, and revisions in analyst forecasts of earnings.

As a last set of robustness tests, we verify that the relation between fund herding and future mutual fund performance is not driven by two potential alternative channels leading to price pressure and subsequent reversals. First, we test the institutional trading channel. We show that, during our sample period, changes in institutional ownership do not predict stock returns at horizons of one to four quarters. We also show that our results continue to hold after controlling for persistent aggregate institutional trades. Therefore, we conclude that the link between herding and fund performance is not due to reversals following a destabilizing price pressure caused by aggregate institutional trading. Second, we test the capital flows channel. Recent studies show, both theoretically and empirically, that flows of capital experienced by mutual funds can cause

[4] This result shows that the underperformance of herding funds is not driven by "closet indexers", i.e., active mutual funds that track a benchmark index (as defined in Cremers and Petajisto (2009)).

price pressure and subsequent reversals in stock returns and fund performance.[5] To address this concern, we include a control for net flows in our predictive regressions of mutual fund performance. Moreover, we estimate fund herding after controlling for a fund's own past trades, to account for trade persistence induced by persistent capital flows (Chevalier and Ellison (1997), Sirri and Tufano (1998)). In both cases we confirm the robustness of the negative link between fund herding and future performance.

Our investigation brings together two bodies of empirical research that thus far have evolved separately. On the one hand, we contribute to the literature on mutual fund performance, which has focused on developing new measures of skill in an attempt to find reliable predictors of fund returns.[6] Recent studies emphasize the difficulty of identifying mutual fund managers with positive risk-adjusted performance and show that a large and increasing fraction of U.S. mutual funds exhibit negative skill, i.e., they have negative alphas.[7] Our analysis uncovers new evidence on the cross-sectional predictability of mutual fund performance, suggesting that herding behavior provides new information about the distribution of skill across mutual funds.

On the other hand, we contribute to the extensive empirical literature on institutional herding by linking herding behavior to mutual fund performance. Previous studies have measured institutional herding at the stock level and focused on assessing the impact of herding on asset prices. Our new measure of fund-level herding instead enables us to investigate the predictive power of herding behavior for mutual fund performance while controlling for fund characteristics as well as investing styles.[8] Our evidence of a strong negative association between fund herding and future fund performance suggests that the tendency to herd reveals information on managerial skill. Although theoretical models of herding behavior have not investigated the link between herding and ability explicitly, our findings are broadly consistent with some features of sequential decision

[5] For empirical evidence, see Coval and Stafford (2007) and Lou (2012); for a theoretical analysis, see Vayanos and Woolley (2011).

[6] Several papers study the predictability of mutual fund performance using information on portfolio holdings or trades; see Kacperczyk, Sialm, and Zheng (2005, 2008), Cohen, Coval, and Pastor (2005), Kacperczyk and Seru (2007), and Cremers and Petajisto (2009), among others.

[7] See, for example, Fama and French (2010), Barras, Scaillet, and Wermers (2010), and Cremers and Petajisto (2009).

[8] Grinblatt, Titman, and Wermers (1995) explore the link between mutual fund herding and performance. However, their analysis is based on the LSV stock-level measure of herding, i.e., the fraction of funds buying the same stock in the same quarter (Lakonishok, Shleifer, and Vishny (1992)), averaged across stocks for a given fund. Using data on 274 mutual funds during the period 1975 to 1985, they find that the association between this measure of herding and fund performance is subsumed by the tendency of mutual funds to buy past winners. In a similar spirit, Wei, Wermers, and Yao (2012) aggregate the LSV stock-level measure of herding across stocks traded by a given fund and show that funds with a lower herding measure (higher contrarian measure) outperform the rest of the funds.

making models developed within frameworks of reputational herding, informational cascades, or slow information diffusion. The results of our tests represent a first step towards understanding the link between herding behavior and managerial skill from both an empirical and a theoretical perspective.

The remainder of this paper is structured as follows. Section 2 describes the construction of our measure of fund-level herding and relates it to a wide variety of fund characteristics. Section 3 presents our main result on the ability of fund herding to predict mutual fund performance. Section 4 explores the link between fund herding, future performance, and mutual fund skill. Section 5 provides several robustness tests using alternative estimates of fund herding and performance. Section 6 concludes the paper.

# 2 Fund herding

This section describes the data for our sample and introduces our method to estimate the tendency of mutual funds to herd, i.e. to follow past institutional trades. We also investigate the characteristics of mutual funds in relation to their tendency to herd.

## 2.1 Data

Our sample consists of actively managed US equity funds from 1990 to 2009. Data on monthly fund returns and other fund characteristics come from the CRSP mutual fund database and data on fund stock holdings come from the CDA/Spectrum mutual fund holdings database. We merge these two databases using the mutual fund links (MFLINKS). As we wish to capture active mutual funds that invest primarily in US equities, we follow Kacperczyk, Sialm and Zheng (2008) and eliminate balanced, bond, money market, sector, and international funds, as well as funds that do not primarily invest in US common equity.[9] To address the incubation bias documented by Elton, Gruber, and Blake (2001) and Evans (2010), we exclude observations prior to the reported fund inception date, as well as funds whose net assets fall below $5 million. We then require funds to have at least 10 stock holdings to be eligible for consideration in our analysis. Finally, we exclude index funds from our sample. This process leaves us with 2,255 distinct mutual funds.

[9] We also exclude funds with any of the following investment objectives as provided by CDA/Spectrum: International, Municipal Bonds, Bond and Preferred, and Balanced. Furthermore, we use the portfolio composition data provided by CRSP to exclude funds that on average invest less than 80% or more than 105% in common equity.

To compute aggregate institutional trades, we use data from the CDA/Spectrum institutional holdings database that collects the 13F filings by institutional investors.[10] Finally, we use stock price and return data from the CRSP monthly stock files and accounting information from Compustat.

Panel A of Table 1 shows descriptive statistics for our pooled sample of 56,116 fund-quarters. The characteristics include fund size (total net assets under management in millions of dollars), fund age (in years), fund turnover, expense ratio, quarterly net flows (computed as the growth rate of assets under management after adjusting for the appreciation of the fund's assets), and quarterly net fund returns. An average fund in our sample manages 1.6 billion dollars of assets, is 17 years old, incurs an annual expense ratio of 1.27%, and has an annual turnover ratio of 85%. It achieves an average net return of 1.55% per quarter and attracts 1.32% net money flow. These numbers are in line with those reported in the mutual fund literature.

## 2.2 Estimating fund herding

Our fund-level measure of herding is defined as the tendency of a mutual fund to follow the collective trading decisions that other institutional investors have made in the past, so as to capture the idea of imitation in sequential decision making. We estimate the intertemporal correlation between the trades of a given fund in a given quarter and the aggregate institutional trades in the previous quarter. The regressions are specified as follows:

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

The variable $Trade_{i,j,t}$ is the percentage change in the holdings of stock $i$ in the portfolio of fund $j$ during quarter $t$; $\Delta IO_{i,t-1}$ is the change in the aggregate institutional ownership of stock $i$ that occurred during quarter $t-1$; $Mom_{i,t-1}$ is the return on stock $i$ measured during quarter $t-1$; $MC_{i,t-1}$ is the natural log of the market capitalization of stock $i$ at the end of quarter $t-1$; $BM_{i,t-1}$ is the stock's log book-to-market ratio at the end of the previous quarter. To make the magnitude of the slope coefficients comparable across funds and through time, we standardize both the dependent and independent variables to have a mean of zero and a standard deviation of one for each fund in each quarter.

[10] All institutions with more than $100 million under discretionary management are required to report to the SEC all equity positions greater than either 10,000 shares or $200,000 in market value.

The slope coefficient $\beta_{j,t}$ reflects the quarterly association between manager $j$'s trades and past institutional trades, and forms the building block for our measure of herding for fund $j$. Since the trading decisions of fund managers could be influenced by other stock characteristics, we include them in the regressions as controls. In particular, Grinblatt, Titman, and Wermers (1995) show that mutual funds tend to engage in positive feedback trading. We thus control for a stock's past returns to remove the component of the correlation between fund trades and past institutional trades that is attributable to mutual funds' momentum investment strategies. Furthermore, we control for the possibility that a common investing style may induce correlated trading by controlling for a stock's market capitalization and book-to-market ratio (Barberis and Shleifer (2003), Froot and Teo (2008)). In Section 5 we perform several robustness tests by estimating the coefficient $\beta_{j,t}$ using different regression specifications and by measuring past institutional trades over a longer horizon.

Panel B of Table 1 presents descriptive statistics for the quarterly coefficient $\beta_{j,t}$. We compute two sets of statistics to disentangle time-series and cross-sectional distributions. We first compute the cross-sectional mean, the standard deviation, and several quantiles of the distribution of $\beta_{j,t}$ in each quarter, and average these statistics over the 80 quarters in our sample. The mean of $\beta_{j,t}$ is 2.30%, while the standard deviation and the quantile statistics reveal a great degree of heterogeneity in herding across mutual funds. We also compute time-series summary statistics of $\beta_{j,t}$ for each fund, and then average them across all the funds in our sample. The mean of $\beta_{j,t}$ is 1.50%, while the time-series statistics show a wide variability in $\beta_{j,t}$ over the lifetime of the average fund, with a standard deviation of 17.43%.

Given the high variability of the quarterly coefficient $\beta_{j,t}$ over the lifetime of a fund, we construct a smoothed measure of fund-level herding, $FH_{j,t}$, to capture the *average* tendency of a given fund to follow past institutional trades. In particular, we adopt a rank inverse-weighting scheme which assigns higher weights to more recent observations. For each fund $j$ and quarter $t$, we compute the weighted average of $\beta_{j,t}$ during the fund's history up to quarter $t$, with weights that vary inversely with the distance of the coefficients from quarter $t$:

$$FH_{j,t} = \frac{\sum_{h=1}^{t} \frac{1}{h} \beta_{j,t-h+1}}{\sum_{h=1}^{t} \frac{1}{h}}. \tag{2}$$

By attributing higher weights to the more recent coefficients, this measure reflects more strongly the fund's most recent trading decisions. We require a fund to have a series of at least 12 estimated quarterly coefficients. As new information about the fund trades arrives over time, we update our fund herding measure $FH_{j,t}$.

We report summary statistics on the distribution of this new fund-level herding measure in Panel B of Table 1. The time-series statistics on the last row of the table show that, for the average mutual fund in our sample, the tendency to follow past institutional trades is 1.80%. The temporal averaging substantially reduces the time-series standard deviation to 5.72% (it was 17.43% for the quarterly coefficient $\beta_{j,t}$). However, the cross-sectional statistics (second row of the table) show that fund herding still exhibits substantial heterogeneity, varying from -8.81% (5th percentile) to 13.86% (95th percentile). It is precisely this cross-sectional heterogeneity in fund herding that we analyze for the predictability of mutual fund performance.

# 3 Fund herding and future performance

In this section we test whether fund herding has predictive power for the cross-section of mutual fund performance. We examine net fund returns as well as gross returns, which add back fees and expenses. Our analysis consists of both portfolio tests and predictive panel regressions.

## 3.1 Portfolio analysis

We first use portfolio-based analysis to examine the link between fund herding and future performance. At the end of each quarter, we sort mutual funds into ten portfolios based on our measure of fund herding $FH_{j,t}$. We then compute equally weighted returns for each decile portfolio over the following quarter, net of and before fees and expenses. We also estimate the risk-adjusted returns of these portfolios as intercepts from time-series regressions using the Capital Asset Pricing Model (CAPM), the three-factor model of Fama and French (1993), the four-factor model of Carhart (1997), and the five-factor model of Pástor and Stambaugh (2003). To allow for time variation in factor loadings, we follow Ferson and Schadt (1996) and assume a linear relation between factor loadings and five conditioning variables: a January dummy and four lagged macroeconomic variables, namely, the 1-month Treasury bill yield, the aggregate dividend yield, the term spread, and the default spread.

Table 2 presents the portfolio results. The panel for net returns shows that, in the quarter following portfolio formation, the funds with the highest herding tendency in Decile 10 underperform the funds with the highest antiherding tendency in Decile 1 by 19 basis points per month, a return differential of 2.28% per year. The inferior performance of herding funds in Decile 10 cannot be attributed to their lower propensity to take risk or to their different investment styles: the differences in alphas from the CAPM, Fama and French, Carhart, and Pástor and Stambaugh models are $-21$, $-17$, $-16$, and $-14$ basis points per month, all statistically significant. The Ferson and Schadt (1996) alpha shows that, after taking into account time-varying factor exposures, the relative underperformance of herding funds is $-17$ basis points per month. If we consider gross fund returns after adding back fees and expenses the results reveal essentially the same picture: herding funds in Decile 10 strongly underperform their antiherding peers in Decile 1. Overall, the performance differential between herding and antiherding funds ranges between 1.68% and 2.52% on an annualized basis.

These results suggest that mutual fund investors can significantly improve their returns by shifting their investments from herding funds to antiherding ones. The improvement in performance is economically meaningful, especially when considered in the light of the existing evidence on the cross-sectional dispersion of mutual fund performance.[11]

### 3.2 Predictive regressions

The portfolio results indicate that our measure of fund herding negatively predicts mutual fund performance, and that this negative association tends to be pervasive across funds with different characteristics. In this subsection we use multivariate regressions to examine the robustness of the predictive power of herding for mutual fund performance. Our measure of performance is the monthly four-factor alpha of Carhart (1997), estimated in the months of quarter $t+1$ as the difference between the realized fund return in excess of the risk-free rate and the expected excess fund return from a four-factor model which includes the market, size, value, and momentum factors. The factor loadings are estimated from rolling-window time-series regressions of fund returns in the

[11] Fama and French (2010), for example, argue that a normal distribution of true gross alpha with a mean of zero and standard deviation of 10 basis points per month captures the tails of the cross-section of alpha estimates for their entire sample of actively managed mutual funds. By ranking mutual funds on the basis of their propensity to follow the past trading decisions of institutional investors, we identify an important source of variation and predictability in mutual fund performance.

previous three years. Herding and fund characteristics are measured using information available at the end of quarter $t$. We control for fund size, age, portfolio turnover, expense ratio, net flows in quarter $t$, and past alpha measured over the previous three years.

Table 3 presents the results from the predictive panel regressions. The first two columns measure fund performance using net fund returns, while the last two columns use gross fund returns. To control for aggregate movements in fund returns over time we include fixed time effects in the regressions. Furthermore, since the residuals might correlate within funds, we cluster standard errors by fund.[12]

The results show that our measure of herding reliably predicts future fund performance. For example, the first column shows that a univariate regression of four-factor net alphas on past herding yields a slope coefficient of $-0.466$ with a $t$-statistic of $-5.16$. For some intuition on the economic magnitude of this coefficient, we can calculate that a fund with a herding tendency 1.65 standard deviations above average underperforms a fund with herding tendency 1.65 standard deviations below average by 11 basis points per month, or 1.32% per year.[13] Controlling for the influence of other fund characteristics only slightly reduces the slope coefficient to $-0.438$, with a t-statistic of $-4.83$. When we measure fund performance using 4-factor gross alphas, we obtain qualitatively and quantitatively similar results.

The fund characteristics included in the regression relate to future fund performance in a way that is consistent with previous findings. For example, consistent with Chen et al. (2004), fund size is negatively related to future performance. Fund turnover is negatively related to future performance (Carhart, 1997). Past flows have a positive relation with future performance, which is consistent with the smart-money effect documented by Gruber (1996) and Zheng (1999). A fund's past alpha is insignificantly related to future performance when we control for the stock price momentum effect (Carhart, 1997). Although a fund's expense ratio is unrelated to its future gross alpha, it negatively predicts future net alpha, which deducts fees and expenses from gross alpha.

In summary, the findings presented in this subsection show that a mutual fund's propensity to follow past institutional trades is a robust predictor of its future performance. The predictive

[12] Following Petersen (2009) and Thompson (2011), we also consider two-way clustering by both funds and time, obtaining similar results.

[13] In the pooled sample, the standard deviation of $FH_{j,t}$ is 0.0698.

power of fund herding is distinct from the effect of other fund characteristics.[14]

### 3.3 Fund characteristics

What are the characteristics of herding and antiherding funds? Panel A of Table 4 presents average characteristics of portfolios of mutual funds sorted each quarter into deciles based on fund herding, $FH_{j,t}$. We consider fund size, age, returns, net flows, turnover, and expense ratio (returns and flows are cross-sectionally demeaned). The table shows time-series means of these portfolio characteristics. The first row of Panel A reports the average value of fund herding for each decile portfolio: funds in the top decile exhibit a strong tendency to follow past institutional trades, with mean values reaching 15.3%, while funds in the bottom decile exhibit antiherding behavior, with large and negative values reaching −10.4%. The second row shows that both the herding funds in the top decile and the antiherding funds in the bottom decile tend to be smaller than other funds, with no significant difference in fund size between the two groups. Herding funds tend to be older than antiherding funds, and tend to have lower portfolio turnover and lower expense ratios, suggesting that these funds may be less active. Fund returns in the previous quarter, measured net of expenses, do not exhibit a strictly monotonic pattern across herding deciles, although herding funds have lower past returns that their antiherding peers, with a difference of −43 basis points per quarter. Finally, there is no significant difference in fund flows between herding and antiherding deciles.

We next relate fund herding to other fund characteristics by estimating cross-sectional regressions. Panel B of Table 4 reports time-series averages of coefficients from quarterly cross-sectional regressions, as in Fama and MacBeth (1973), where inference is based on standard errors adjusted for autocorrelation following Newey and West (1987). To facilitate the interpretation of the estimates, all regressors are standardized to have a mean of zero and a standard deviation of one in each quarter. We run both contemporaneous regressions, in which fund herding and other characteristics are measured in the same quarter, and predictive regressions, with fund characteristics measured in the previous quarter. The results in Column 1 show that older funds have a higher tendency to herd. Our regression estimates also show that funds with lower portfolio turnover, i.e., funds that are less active, tend to herd more. Moreover, funds experiencing outflows in the past show a

[14] In the Appendix we show that the forecasting power of fund herding remains significant even after we remove the top and bottom decile of herding and anti-herding funds.

higher tendency to herd in the future. We also test the association between herding behavior and managerial experience.[15] The results in Column 2 show that funds with less experienced managers tend to herd more, both in contemporaneous and in predictive regressions. Finally, we find that other fund characteristics such as expense ratios and past performance do not play a significant role in explaining or predicting mutual fund herding.

We then compute a transition matrix of the frequency that a fund belonging to a given decile in quarter $t$ remains in the same decile or moves to a different portfolio in the subsequent quarter. The results, presented in Panel C of Table 4, indicate a fair degree of persistence in fund herding. On average, more than 44% (45%) of antiherding funds in Decile 1 (herding funds in Decile 10) remain in the same group in the subsequent quarter.

We next investigate how the predictability of fund herding varies across fund characteristics. At the end of each quarter, we double-sort funds independently into four groups based on fund herding and a given characteristic, obtaining sixteen portfolios. For each portfolio, we compute average net returns as well as intercepts from the four-factor model of Carhart (1997). The results for these double sorts are shown in Table 5. The sort on fund size (Panel A) shows that herding funds significantly underperform their antiherding peers across all but the smallest funds, with a performance gap ranging from 11 to 18 basis points per month as measured by Carhart (1997) four-factor alphas. The sort on fund age (Panel B) shows that the performance differential between herding and antiherding funds varies between $-12$ and $-16$ basis points per month for funds in the first three age groups, and is not significantly different from zero for the oldest funds. Fund herding is also a stronger predictor of performance for funds whose managers have the shortest experience in the industry (Panel C), with a performance gap between herding and antiherding funds of 20 basis points per month. These findings indicate that fund herding provides more information on skill for funds or managers with a shorter record. Panel D shows that the performance of herding funds is negative and significant, on a risk-adjusted basis, irrespective of the net inflows that funds have received in the previous quarter. However, the performance differential between herding and antiherding funds is significant only for funds experiencing moderate and large net inflows. Finally, we ask whether the link between fund herding and future performance varies with a fund's past

[15] We measure manager experience as the number of years in which a fund manager appears in the CRSP mutual fund database. For this analysis we exclude funds that are managed by a team and focus on those with an individual manager only; this data requirement considerably reduces our sample from about 160,000 observations to about 70,000.

performance.[16] Panel E shows that the performance gap between herding and antiherding funds is particularly strong among past winners, at 24 basis points per month. Furthermore, antiherding winners achieve the highest future returns, whereas herding losers experience the lowest future returns; the performance gap reaches 33 basis points per month, corresponding to an annualized return of 3.96% ($t$-statistic of 3.19). This finding indicates that we can combine the information contained in past performance with our measure of herding to obtain a sharper signal about mutual fund skill.

# 4 Fund herding, future performance, and skill

A natural interpretation of the results presented in Section 3 is that herding behavior reveals skill: unskilled fund managers may exhibit a stronger tendency to follow past institutional trades, thus experiencing underperformance in the future.

In this section we provide a number of tests to better understand the link between fund herding and future performance. First, we show that fund herding is related to recently developed measures of mutual fund skill, while providing distinct information for the predictability of mutual fund performance. Second, we show that the performance gap between herding and antiherding funds is persistent over different horizons. Third, we show that this performance gap is particularly strong in times of greater investment opportunities in the mutual fund industry. Overall, our tests suggest that the predictive power of fund herding for mutual fund performance is associated with cross-sectional differences in skill.

## 4.1 Other measures of skill

The results presented in Panel E of Table 5 offer suggestive evidence of a link between herding behavior and skill. The large differential in future performance between herding losers and antiherding winners (3.96% per year) indicates that the interaction between fund herding and a traditional measure of fund skill, such as past performance, can enhance the predictability of mutual fund performance and thus improve the identification of skilled and unskilled funds.

In this subsection we directly relate fund herding to three recently developed measures of fund

[16] We measure past performance as the intercept from the three-factor model of Fama and French (1993) estimated over the previous three years. Varying the estimation window of fund alpha between one and three years or replacing the Fama-French alpha with the Carhart alpha yield very similar results.

skill: active share (Cremers and Petajisto (2009)), similarity in funds' investment decisions (Cohen, Coval, and Pástor (2005)), and reliance on public information (Kacperczyk and Seru (2007)). We first check the relation between fund herding and these measures of skill, by adding them to the cross-sectional regressions presented in Table 4. We find that fund herding is related to these three measures of skill in an intuitive way. When we estimate predictive regressions of mutual fund performance controlling for these measures, we find that fund herding retains its predictive ability. We present these results in Table 6.

The first measure we consider is active share. We have carefully excluded from our sample all index funds, so that our measure of herding is not affected by commonalities in trading patterns due to tracking a market index. However, Cremers and Petajisto (2009) show that many active funds are closet indexers, having portfolios that overlap with those of their benchmark index, and achieve poor performance.[17] To the extent that herding funds are less active funds or closet indexers, they are likely to exhibit inferior performance. Panel A shows that fund herding is negatively related to active share, controlling for other fund characteristics and measures of skill. To disentangle the herding effect from the closet indexer effect, we re-estimate our predictive panel regressions including a control for active share. The first two columns of Panel B present the estimated regression coefficients. Consistent with Cremers and Petajisto (2009), active share has predictive power for mutual fund performance. However, its inclusion in the regression specification does not erode the importance of our herding measure: the slope coefficient on fund herding is significantly negative and very similar to our baseline case estimate. This evidence suggests that the performance predictability associated with our measure of fund herding is distinct from the information contained in active share.[18]

As a second measure of skill we consider the variable developed by Cohen, Coval, and Pástor (2005), who show that funds whose portfolio holdings or trading decisions are similar to those of managers with distinguished performance records achieve superior performance in the future.[19] Following Cohen, Coval, and Pástor (2005), we compute a performance metric (CCP) that measures

[17] Active Share is computed as the fraction of the fund's portfolio holdings that differs from its benchmark index holdings.

[18] Our study is also related to Cohen, Polk, and Silli (2010), who establish a link between the concentration of a portfolio on its manager's best ideas and mutual fund performance. They show that best ideas that are unpopular perform better than best ideas that are popular.

[19] In a similar spirit, Pomorski (2009) shows that funds that mimic the trades of successful funds exhibit superior performance in the future.

the extent to which a manager's trades resemble those of managers with high performance records.[20] Panel A shows that CCP is negatively related to fund herding, suggesting that funds whose trades resemble those of successful funds tend to herd less. When we include CCP in our predictive regressions in Panel B we find that, while the similarity measure positively predicts mutual fund performance, fund herding retains its predictive ability. The two metrics therefore provide distinct information on mutual fund skill.

The third measure of skill that we consider is mutual funds' reliance on public information. Kacperczyk and Seru (2007) provide evidence of underperformance by funds whose trades rely heavily on revisions in analysts' stock recommendations. We estimate funds' reliance on public information using two different variables: (i) the $R^2$ obtained from our baseline trade regression (1), and (ii) the $R^2$ of a regression of fund trades on changes in analyst stock recommendations, as in Kacperczyk and Seru (2007). We report the coefficients obtained using the latter variable, but the two measures yield very similar results. Panel A shows that fund herding is higher for funds whose trading decisions rely more strongly on public information. However, the last two columns of Panel B show that the predictive power of fund herding is not affected by $R^2$, confirming our baseline results.

In summary, the analysis in this subsection uniformly shows that, while fund herding is negatively related to other known measures of skill, it retains its ability to predict mutual fund performance after controlling for these measures. We conclude that fund herding provides investors with valuable and distinct information on the cross-sectional distribution of fund skill.

### 4.2 Persistence in performance

The literature on mutual fund performance has long recognized the difficulty of separating mutual fund skill from the effect of chance. One cynical view of our results is that herding funds may underperform due primarily to their bad luck. Although it is difficult to entirely rule out this possibility, we tackle this problem by looking at the persistence in the performance differential between herding and antiherding funds. Each quarter we group funds into decile portfolios on the

[20] Specifically, in each quarter we first construct a proxy for the quality of a given stock based on the average skill of all managers trading the stock, weighted by the portfolio weights they place on the stock. Managerial skill is measured using Fama and French (1993) alphas estimated over the previous three years. We then obtain a quarterly fund-level measure of quality by aggregating the quality of all stocks traded by a given manager, based on the manager's portfolio composition. The results from this test are very similar if we use the holdings-based measure of similarity of Cohen, Coval, and Pastor (2005) rather than their trade-based measure.

basis of their herding tendency and track the performance of these portfolios in the subsequent 6, 9, and 12 months. Since these portfolios are characterized by overlapping holding periods, we estimate their performance following Jegadeesh and Titman (1993). If the underperformance of herding funds was random, we would expect it to weaken and revert to zero as we extend the holding horizon. On the contrary, under the hypothesis that performance is related to skill, we would expect persistence in the performance gap between herding and antiherding funds.

The results of this analysis are presented in Table 7. We present only net returns for brevity, but the results for gross returns are similar. The results reveal that the underperformance of herding funds tends to be persistent. For example, considering four-factor alphas, herding funds underperform their antiherding peers by 11 basis points per month in the subsequent 6 months. This return differential persists when we extend the holding period to 9 months and 12 months (the $t$-statistics based on Newey-West (1987) standard errors are respectively 2.63, 3.37, and 2.92). This high degree of persistence lends support to the hypothesis that the association between fund herding and future performance is related to skill.

### 4.3 Time-varying investment opportunities

If the performance gap between herding and antiherding funds is a result of differences in skill, we would expect this gap to increase in times of greater investment opportunities in the mutual fund industry. During these times skilled managers may benefit more from their stock-picking skills, whereas unskilled managers may suffer greater losses from their informational disadvantages. Previous papers use the cross-sectional dispersion in stock returns to capture investment opportunities in the mutual fund industry. For example, Ankrim and Ding (2002) find that the dispersion in stock returns is positively related to the dispersion in mutual fund returns, and Petajisto (2010) finds that it is positively related to the performance of stock pickers over time. As in previous literature, we measure return dispersion using the Russell-Parametric Cross-Sectional Volatility Index for US equities, which is defined as follows:

$$CrossVol_t = \sqrt{\sum_{i=1}^{N} w_{i,t-1}(R_{i,t} - R_{m,t})^2},$$

where $R_{i,t}$ is the return on stock $i$ in month $t$, $R_{m,t}$ is the return on the market portfolio in month $t$, and $w_{i,t-1}$ is the beginning of period, float-adjusted capitalization weight of stock $i$.[21] As the cross-sectional dispersion in stock returns around the market increases, both the potential gain from outperforming the market and the potential loss from underperforming it increase. As a result, the spread in performance between skilled and unskilled managers is likely to widen.

We examine the return differential between herding and antiherding funds by regressing it on $CrossVol$, measured either contemporaneously or with a lag of one month. We report the results from these time-series regressions in Panel A of Table 8. The estimates show that the difference in performance between herding and antiherding funds widens both during and after periods with high dispersion in stock returns, supporting our conjecture.

We then use our panel regression framework to test whether the cross-sectional differences in performance predicted by fund herding are linked to variations in $CrossVol$. As with the previous analysis, the dependent variable is mutual fund performance measured by the Carhart (1997) four-factor net fund alpha. We control for fund size, age, expense ratio, turnover, flows, and past alpha. We include an interaction term between $CrossVol$ and fund herding to test whether the association between herding and future performance varies with return dispersion. $CrossVol$ is measured both in month $t$ (i.e. contemporaneous to fund performance) and in month $t-1$. The results from the panel regressions are reported in Panel B of Table 8. The coefficient estimates on fund herding are negative and significant, and of similar magnitude to our baseline results in Table 3. The estimated coefficient on the interaction term is $-0.32$ for both contemporaneous and lagged $CrossVol$, suggesting that the underperformance of herding funds is significantly greater during and after periods of high dispersion in stock returns.

Our analysis of the time-varying performance of herding funds complements the recent work by Kacperczyk, Van Nieuwerburgh, and Velkamp (2012), who show that mutual funds exhibit stock picking skill in booms and market timing ability in recessions. Our results suggest that the dispersion in mutual fund performance associated with their tendency to herd is particularly large during and after periods in which firm-specific information is more valuable. Therefore, mutual fund investors could potentially benefit from a dynamic strategy that discriminates between herding and antiherding managers.

[21] We obtain the index from the Frank Russell Company.

# 5 Robustness tests

In this section we perform a number of robustness tests to further corroborate our results on the ability of herding to predict mutual fund performance. First, we test the robustness of the association between herding and fund performance using two alternative measures of performance. Next, we estimate fund herding using four alternative regression specifications. In particular, we control for the potential serial dependence in a fund's own trades, we consider the association between a fund's trades and contemporaneous aggregate institutional trades, we estimate a fund's tendency to follow persistent institutional trades, and we orthogonalize aggregate institutional trades with respect to a wide variety of other stock characteristics that may affect the trading decisions of a fund. Finally, we show that the underperformance of herding funds is not driven by the price impact of aggregate institutional trades.

## 5.1 Alternative measures of mutual fund performance

The measures of mutual fund performance used in Section 3 are based on net fund returns delivered to investors and gross returns that add back fees and expenses. In this subsection we re-estimate the baseline predictive panel regressions of Table 3 by replacing Carhart 4-factor alphas with alternative measures of performance based on mutual funds' stock holdings and trades. The use of these alternative measures is important to gain a more complete understanding of the sources of cross-sectional differences in performance between herding and antiherding funds. We show that the negative relation between fund herding and future performance is significant even if we measure performance using equity holdings or trades. The results are presented in Table 9.

Our first alternative measure of performance is the holdings-based Characteristic-Selectivity measure (CS) developed by Daniel, Grinblatt, Titman, and Wermers (1997):

$$CS_{t+1} = \sum_{i=1}^{N} w_{i,t}(R_{i,t+1} - R^b_{i,t+1}),$$

where $w_{i,t}$ is the weight of stock $i$ in the portfolio of a fund at the end of quarter $t$, $R_{i,t+1}$ is the monthly return of stock $i$ during quarter $t+1$, and $R^b_{i,t+1}$ is the corresponding monthly return on the characteristic-based benchmark portfolio for stock $i$. The benchmark portfolios are formed on the basis of size, industry-adjusted book-to-market, and momentum. The first two columns of

Table 9 present the estimated coefficients from predictive panel regressions of fund performance on fund herding and other fund characteristics measured in the previous quarter. The results show that herding funds exhibit inferior stock-picking ability than their antiherding peers, suggesting that they are less skilled.

As a second alternative measure of performance we use the trade-based measure of Grinblatt and Titman (1993) (GT):

$$GT_{t+1} = \sum_{i=1}^{N} (w_{i,t} - w_{i,t-4}) R_{i,t+1},$$

where $w_{i,t}$ and $w_{i,t-4}$ are the weights of stock $i$ in the fund's portfolio at the end of quarters $t$ and $t-4$, and $R_{i,t+1}$ is the monthly return of stock $i$ during quarter $t+1$. This measure reflects the covariance between the change in the portfolio weights of a stock and its subsequent return. Following Grinblatt and Titman (1993), we compute the change in weights over the year that precedes the measurement of returns. Columns 3 and 4 of Table 9 show that fund herding negatively predicts performance as captured by the GT measure.

Finally, we compute the GT measure with respect to the future trades of a fund. We ask whether the trading decisions that mutual funds make *after* we measure their herding behavior yield different returns for herding and antiherding funds. Specifically, we look at the trades that the fund implements over the year that follows the measurement of fund herding, i.e., during quarters $t+1$ to $t+4$, and we compute the monthly returns to these trades in the subsequent quarter, $t+5$:

$$GT_{t+5} = \sum_{i=1}^{N} (w_{i,t+4} - w_{i,t}) R_{i,t+5},$$

where $w_{i,t+4}$ and $w_{i,t}$ are the weights of stock $i$ in the fund's portfolio at the end of quarters $t+4$ and $t$, and $R_{i,t+5}$ is the monthly return of stock $i$ during quarter $t+5$. The last two columns of Table 9 show that fund herding predicts the returns deriving from the trading decisions that funds make over the subsequent year. In particular, herding funds tend to make trading decisions that result in future inferior returns, whereas the trading decisions of antiherding funds tend to yield superior performance. This result lends further support to the skill channel in explaining the link between herding and future performance. Differences in herding behavior identify differences in the subsequent trading decisions of mutual funds, which lead to differences in performance.

Overall, these robustness tests corroborate our evidence from Section 3, and further reinforce the link between fund herding, future performance, and mutual fund skill.

## 5.2 Alternative measures of fund herding

### 5.2.1 Own trades

One could argue that our measure of fund herding may capture a mechanical correlation in the trades of a given fund over time, for example due to persistent fund flows or to stealth trading.[22] This could potentially affect our performance results, if persistent flows were inducing price pressure and subsequent reversals in returns.[23] To control for this possibility, and to ensure that fund herding captures imitation in sequential trading decisions, we re-estimate our baseline fund trade regression (1) after including the fund's own past trades in a given stock, $Trade_{i,j,t-1}$:

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

As with our baseline regression we then compute the inverse-time-weighted average of $\beta_{j,t}$ for each fund in each quarter, obtaining an alternative measure of herding, and estimate its association with future fund performance. The results, presented in Panel A of Table 10, confirm the strong negative relation between fund herding and future performance, after controlling for the effects of other fund characteristics.

### 5.2.2 Contemporaneous institutional trades

If aggregate institutional trades are persistent over time, the correlation between the current trades of a mutual fund and past institutional trades may be driven by the contemporaneous correlation between the fund's trades and those of other institutional investors. To control for this possibility we re-construct our measure of herding from a trade regression that includes the current change in institutional ownership for stock $i$, $\Delta IO_{i,t}$:

$$Trade_{i,j,t} = \alpha_{j,t}+\beta_{j,t}\Delta IO_{i,t-1}+\gamma_{j,t}Mom_{i,t-1}+\delta_{1,j,t}MC_{i,t-1}+\delta_{2,j,t}BM_{i,t-1}+\delta_{3,j,t}\Delta IO_{i,t}+\varepsilon_{i,j,t}. \quad (4)$$

[22] For example, see Sirri and Tufano (1998) and Chevalier and Ellison (1997) for evidence of persistent mutual fund flows. Mutual funds could also split their trades over time to reduce their price impact.

[23] Coval and Stafford (2007) and Lou (2012) investigate the impact of mutual fund flows on stock returns and fund performance, documenting initial price pressure and subsequent reversals.

The performance regressions obtained with the new measure of fund herding are shown in Panel B of Table 10. Even controlling for the influence of contemporaneous institutional trades, the tendency of mutual funds to follow past institutional trades is negatively associated with their future performance.

#### 5.2.3 Institutional trade persistence

So far we have defined fund herding as the correlation between a fund's trades and past aggregate institutional trades over two adjacent quarters. We now modify our measure of fund herding to capture the behavior of mutual funds following buy or sell herds that have developed over several quarters in the past. Specifically, for any given stock, we construct a measure of persistence in past institutional trading by counting the number of consecutive quarters in which the stock is bought or sold by institutional investors, attributing positive values to buy decisions and negative values to sell decisions.[24]

At the end of each quarter $t$ we re-estimate our basic trade regression using this new measure of past institutional trades, $Pers_{i,t-1}$, measured at the end of quarter $t-1$, including in the regression the usual stock characteristics to control for style:

$$Trade_{i,j,t} = \alpha_{j,t} + \beta_{j,t} Pers_{i,t-1} + \gamma_{j,t} Mom_{i,t-1} + \delta_{1,j,t} MC_{i,t-1} + \delta_{2,j,t} BM_{i,t-1} + \varepsilon_{i,j,t}. \quad (5)$$

The coefficient $\beta_{j,t}$ now represents the responsiveness of the trades of mutual fund $j$ to different degrees of persistence in buying or selling by institutional investors, measured over horizons of several quarters in the past. We then use these quarterly coefficients to construct a new measure of herding, as in our baseline case.

The results from panel regressions of fund performance on this new measure of herding are reported in Panel C of Table 10. They indicate that the tendency of mutual funds to follow past institutional trading patterns negatively predicts their future performance, irrespective of the

[24] A stock is bought (sold) if the change in institutional ownership in a given quarter is above (below) the cross-sectional median. For example, for a stock bought in quarter $t$ and sold in quarter $t-1$ trade persistence equals +1, while for a stock bought in quarters $t$ and $t-1$ and sold in $t-2$ trade persistence equals +2. Stocks that are bought or sold for at least 4 consecutive quarters have a trade persistence value of +4 and -4, respectively. Dasgupta, Prat, and Verardo (2011a) document empirically that stocks persistently bought or sold by institutional investors experience return reversals in the long run (see also Dasgupta, Prat, and Verardo (2011b) for a theoretical model of short- and long-term associations between herding and stock returns in the presence of career-concerned money managers).

horizon over which we measure past aggregate institutional trades.

### 5.2.4 Residual institutional trades

The baseline specification used to estimate fund herding controls for the three main variables capturing the style of a given fund: momentum, market capitalization, and book-to-market. Here we consider five additional stock characteristics that might influence both aggregate institutional trades and a fund manager's trading decisions: stock turnover, idiosyncratic volatility, analyst forecast revisions, share issuance, and industry. We include stock turnover because institutions exhibit a preference for liquid stocks, as documented in Gompers and Metrick (2001). Therefore, a similar preference by a mutual fund manager may induce a mechanical correlation between the manager's trade and past institutional trades. Similarly, idiosyncratic volatility (Bennett, Sias, and Starks (2003)), revisions in analyst earnings forecasts (Kacperczyk and Seru (2007)), and past share issuance (Jiang (2010)) could play a role in generating a correlation between the trades of a given fund and past institutional trades. Finally, we include industry controls because prior research shows evidence of industry herding (Choi and Sias (2009)) and also documents a link between mutual fund performance and the industry concentration of mutual fund portfolios (Kacperczyk, Sialm, and Zheng (2005)).

Since these stock characteristics have been shown to predict returns, they may affect future fund performance.[25] Therefore, we orthogonalize aggregate institutional trades with respect to these characteristics by estimating the following cross-sectional regression in each quarter $t$ for all the stocks in our sample:

$$\begin{aligned} \Delta IO_{i,t} &= \gamma_{0t} + \gamma_{1t} Mom_{i,t} + \gamma_{2t} MC_{i,t} + \gamma_{3t} BM_{i,t} + \gamma_{4t} Turn_{i,t} + \gamma_{5t} IVol_{i,t} + \\ &\quad \gamma_{6t} FRev_{i,t} + \gamma_{7t} Issue_{i,t} + \sum_{k=1}^{9} \gamma_{7+k,t} IND_k + \varepsilon_{i,t}, \end{aligned} \tag{6}$$

where $Turn_{i,t}$ is the number of shares traded for stock $i$ in quarter $t$ scaled by shares outstanding; $IVol_{i,t}$ is the standard deviation of the residuals from a regression of the daily excess returns of stock $i$ on the Fama and French three factors in quarter $t$; $FRev_{i,t}$ is the change in consensus analyst earnings forecasts scaled by stock price at the end of the pervious period; $Issue_{i,t}$ is the

[25] See, for example, Kaniel, Gervais, and Mingelgrin (2001) on trading volume; Ang et al. (2006) on idiosyncratic volatility; Gleason and Lee (2003) on analyst earnings forecast revisions; Daniel and Titman (2006) on share issuance; Kacperczyk, Sialm, and Zheng (2005) on industry concentration.

share issuance for firm $i$ in the previous year (the natural log of the ratio of the split-adjusted shares outstanding at the end of quarter $t$ divided by the split-adjusted shares outstanding at the end of quarter $t-4$); and $IND_k$ is a dummy variable indicating industry membership based on the Fama and French 10-industry classification. We then compute cross-sectional regressions of fund trades on past residual institutional trades, by fund and by quarter, obtaining new quarterly estimates of fund herding.

As in our baseline procedure, we average these quarterly estimates of herding over the lifetime of a fund using a rank-inverse weighting scheme that assigns higher weights to more recent observations. We use this new measure of herding to estimate performance panel regressions and report the results in Panel D of Table 10. The estimated coefficients on our herding variable clearly show that the tendency of mutual funds to follow past aggregate trades negatively predicts their performance. The magnitudes and significance of the coefficients are similar to those obtained from our baseline specification.

To summarize, this subsection shows that the performance forecasting power of herding is robust to different ways of estimating the tendency of a mutual fund to follow past institutional trades. Furthermore, it does not depend on the horizon over which past aggregate trades are measured or on the stock characteristics that we control for when estimating the correlation between fund trades and past aggregate trades.

### 5.3 Price impact of aggregate institutional trades

One possible driver of the link between herding and future performance might be the price impact of aggregate institutional trades. If institutional trades exert a destabilizing pressure on prices, fund managers who follow these trades may "buy high and sell low," thus achieving on average an inferior performance. This hypothesis relies crucially on the premise that aggregate institutional trades predict reversals in stock returns and, additionally, that such return reversals occur in the period in which we evaluate mutual fund performance.

To examine this premise, we investigate the relation between aggregate institutional trades and future stock returns. In particular, for each month from January 1990 to December 2009, we estimate the ability of changes in aggregate institutional ownership to predict monthly stock returns measured in the subsequent four quarters, after controlling for a variety of stock characteristics. Table 11 presents the results. In the first specification we include firm size, book-to-market, stock returns in the previous quarter, and stock returns in the previous year. In the second specification we add stock turnover, idiosyncratic volatility, share issuance, and analyst earnings forecast revisions. We use the Fama and MacBeth (1973) procedure to conduct statistical inference.

Aggregate institutional trades are measured in quarter $t$. The results from the predictive regressions show that the slope coefficients on institutional trades are statistically indistinguishable from zero for all forecasting horizons $t+1$ to $t+4$ and for both regression specifications. To map the forecasting horizon of this regression to our investigation of mutual fund herding and performance we note that, if quarter $t$ is the period in which we measure aggregate institutional trades, then individual mutual fund trades are measured in quarter $t+1$ and mutual fund performance is measured over quarter $t+2$. The results suggest that, at least for the sample period that we consider, aggregate institutional trades have no predictive power for the cross-section of stock returns. Based on this evidence, we can rule out the possibility that the underperformance of herding funds arises mainly from price pressure caused by aggregate institutional trades.[26]

### 5.4 Do investors use information on fund herding?

In this subsection we ask whether mutual fund investors are aware of the predictability of fund performance associated with herding. In other words, we ask whether investors switch money out of herding funds with lower expected future performance and into antiherding funds with higher expected future performance. To address this question we regress the percentage fund flows in quarter $t+1$ on a fund's herding tendency and a number of fund characteristics measured in quarter $t$.

The results, as reported in Table 12, indicate a generally negative but statistically insignificant relation between mutual fund herding and future fund flows. These findings suggest that herding funds may be perceived by some investors as relatively inferior. However, on average, mutual fund

[26] We also perform a further test to rule out the possibility that reversals in stock returns (and hence underperformance) may derive from price pressure induced by institutional trades. Dasgupta, Prat, and Verardo (2011a) show that stocks bought or sold after institutional herds lasting several quarters exhibit return reversals in the future. Each quarter we eliminate from our sample those stocks that have been persistently bought or sold by institutional investors over the previous four or more quarters. We then estimate fund herding using this new sample of stocks, compute holdings- and trade-based measures of mutual fund performance (CS and GT), and re-estimate panel regressions of future performance on fund herding and other fund characteristics. Our results (unreported) are similar to those obtained in Table 9, suggesting that the predictive power of fund herding for mutual fund performance is not driven by the price impact of persistent institutional trades. These results are not inconsistent with the findings of Dasgupta, Prat, and Verardo (2011a), who show evidence of reversals for long-term returns measured over periods of about two years.

investors do not respond aggressively to the information about future performance that is captured by our measure of fund herding.

## 6 Conclusions

This paper asks whether the tendency of mutual funds to follow the collective trading decisions of other institutional investors can predict their performance, thus revealing information about their skill. We create a fund-level measure of herding to capture the intertemporal correlation between a managers' trades and past institutional trades, after accounting for the tendency of funds to invest in the same styles or engage in momentum trading. We then test whether this measure of fund herding can predict cross-sectional differences in mutual fund performance.

We find that herding behavior strongly and negatively predicts the cross-section of mutual fund returns. The top decile portfolio of funds with the highest herding tendency underperforms the bottom decile portfolio of antiherding funds by about 2.28% on an annualized basis, both before and after expenses. We obtain similar results when we adjust the fund returns to account for their risk exposures: the underperformance of herding funds is 1.92% based on Carhart (1997) four-factor alphas. Our regression results show that the predictive ability of fund herding is distinct from the effect of past performance and other fund characteristics such as size, age, turnover, expense ratio, and net flows.

We then provide suggestive evidence that the negative association between fund herding and future performance is related to managerial skill. First, while being negatively related to several recently developed measures of skill, fund herding contains distinct information for the predictability of mutual fund performance. Second, the inferior performance of herding funds is persistent over a horizon of one to four quarters. Third, the performance gap between herding and antiherding funds is stronger in periods of greater investment opportunities in the mutual fund industry.

Overall, these results establish a strong link between the tendency of mutual fund managers to trade in herds and their future performance, suggesting that the herding behavior of mutual fund managers reveals information about their skill. Although existing theoretical models do not explicitly examine the relation between herding behavior and ability, our findings are broadly consistent with some features of sequential decision making models. For example, our evidence on the outperformance of antiherding funds could be related to features of the reputational model of

Avery and Chevalier (1999), in which skilled managers exhibit antiherding behavior if they have precise information on their ability. Our findings could also be related to models of informational cascades, in which agents with high ability are more likely to deviate from the consensus (Bikhchandani, Hirshleifer, and Welch (1992) and Trueman (1994)). Finally, our results might be consistent with a scenario in which some managers receive common private information later than others, generating intertemporal correlation in trades (Hirshleifer, Subrahmanyam, and Titman (1994)).[27] In these models, the tendency to trade in a correlated manner or to deviate from past collective actions is not explicitly related to managerial ability. Our findings indicate that exploring the link between ability and herding in both theoretical and empirical research could shed further light on the motives and consequences of herding behavior.

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## Table 1

## Descriptive Statistics

This table presents descriptive statistics for our sample of mutual funds and the stocks they trade. The sample consists of 2,255 distinct mutual funds from the 4th quarter of 1989 to the 3rd quarter of 2009, in total 56,116 fund-quarters. Panel A presents summary statistics on fund characteristics. Fund size is the quarter-end total net fund assets in millions of dollars, Fund age is the fund age in years, Exp ratio is the fund expense ratio, Turnover is the turnover ratio of the fund, Quarterly Flow is the quarterly growth rate of assets under management after adjusting for the appreciation of the fund's assets, and Quarterly Return is the quarterly net fund return. Panel B presents summary statistics for $\beta$ and *FH*. $\beta$ is the slope coefficient from fund-specific quarterly regressions of mutual fund trades on past aggregate institutional trades measured in the previous quarter, controlling for past stock returns, firm size, and the book-to-market ratio. Both the dependent and independent variables are cross-sectionally standardized to have means of zero and standard deviations of one for each fund in each quarter. We use this quarterly coefficients $\beta$ to construct our measure of fund-level herding, *FH*, through a rank inverse-weighting scheme, assigning higher weights to more recent quarters. The statistics are computed across funds in each quarter and then averaged over time (*Cross-section*), or over time for each individual fund and then averaged across funds (*Time-series*).

### Panel A: Summary Statistics of Fund Characteristics

| *Fund Characteristics* | Mean | Std Dev | $5^{th}$ Pctl | $25^{th}$ Pctl | Median | $75^{th}$ Pctl | $95^{th}$ Pctl |
|---|---|---|---|---|---|---|---|
| Fund size | 1605.29 | 5602.45 | 18.07 | 94.80 | 322.60 | 1093.25 | 6380.60 |
| Fund age | 17.63 | 14.56 | 5.00 | 8.00 | 12.50 | 21.00 | 51.00 |
| Exp ratio | 0.0127 | 0.0045 | 0.0065 | 0.0099 | 0.0122 | 0.0150 | 0.0202 |
| Turnover | 0.8510 | 0.8581 | 0.1100 | 0.3400 | 0.6461 | 1.1000 | 2.2300 |
| Quarterly flow | 0.0132 | 1.5830 | -0.1209 | -0.0441 | -0.0141 | 0.0234 | 0.1692 |
| Quarterly return | 0.0155 | 0.1052 | -0.1769 | -0.0361 | 0.0205 | 0.0739 | 0.1764 |

### Panel B: Estimates of β and Fund Herding (%)

*Cross-sectional statistics (averaged over time, 80 quarters)*

| | Mean | Std Dev | $5^{th}$ Pctl | $25^{th}$ Pctl | Median | $75^{th}$ Pctl | $95^{th}$ Pctl |
|---|---|---|---|---|---|---|---|
| β | 2.30 | 18.73 | -27.84 | -7.83 | 2.15 | 12.62 | 32.63 |
| Fund Herding | 2.42 | 7.12 | -8.81 | -1.51 | 2.35 | 6.39 | 13.86 |

*Time-series statistics (averaged across funds, 2255 funds)*

| | Mean | Std Dev | $5^{th}$ Pctl | $25^{th}$ Pctl | Median | $75^{th}$ Pctl | $95^{th}$ Pctl |
|---|---|---|---|---|---|---|---|
| β | 1.50 | 17.43 | -25.41 | -9.17 | 1.44 | 12.15 | 28.61 |
| Fund Herding | 1.80 | 5.72 | -6.91 | -1.86 | 1.77 | 5.43 | 10.58 |

## Table 2
## Fund Herding and Future Performance: Decile Portfolios

This table presents the performance of decile portfolios formed on the basis of the average tendency of mutual funds to follow past institutional trades. Fund-level herding *FH* is defined as the slope coefficient from cross-sectional regressions of mutual fund trades on past aggregate institutional trades measured in the past quarter, controlling for past stock returns, firm size, and the book-to-market ratio. These regressions are estimated per fund-quarter with both dependent and independent variables cross-sectionally standardized to have means of zero and standard deviations of one. We average these quarterly slope coefficients through a rank inverse-weighting scheme, assigning higher weights to more recent quarters. The decile portfolios are formed and rebalanced at the end of each quarter from 1989Q4 to 2009Q3 and the return series range from January 1990 to December 2009. Decile 10 is the portfolio of funds with the highest average herding measure. We compute monthly equally weighted percentage net and gross (net plus expense ratio) returns on the portfolios, as well as risk-adjusted returns based on the CAPM, the Fama and French (1993) three-factor model, the Carhart (1997) four-factor model, the Pastor and Stambaugh (PS, 2003) five-factor model, and the Ferson and Schadt (FS, 1996) conditional model. We report the alphas in monthly percentages. The *t*-statistics are shown in parentheses. ***, **, * denote statistical significance at the 1%, 5%, and 10% level, respectively.

| | **1** | **2** | **3** | **4** | **5** | **6** | **7** | **8** | **9** | **10** | **D10-D1** |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | *Net Return* | | | | | |
| Average | 0.84 | 0.8 | 0.8 | 0.79 | 0.78 | 0.74 | 0.75 | 0.77 | 0.69 | 0.65 | -0.19*** |
| | (2.91) | (2.76) | (2.78) | (2.76) | (2.69) | (2.55) | (2.55) | (2.60) | (2.30) | (2.18) | (-3.37) |
| CAPM α | 0.07 | 0.03 | 0.03 | 0.02 | 0.01 | -0.04 | -0.03 | -0.01 | -0.1 | -0.14 | -0.21*** |
| | (1.07) | (0.48) | (0.52) | (0.37) | (0.10) | (-0.69) | (-0.65) | (-0.27) | (-1.76) | (-2.58) | (-3.71) |
| FF α | 0.02 | -0.02 | -0.02 | -0.03 | -0.04 | -0.08 | -0.06 | -0.04 | -0.11 | -0.15 | -0.17*** |
| | (0.31) | (-0.4) | (-0.46) | (-0.67) | (-0.96) | (-1.85) | (-1.46) | (-0.81) | (-2.21) | (-3.06) | (-3.26) |
| Carhart α | 0.01 | -0.03 | -0.02 | -0.05 | -0.05 | -0.07 | -0.06 | -0.03 | -0.12 | -0.14 | -0.16*** |
| | (0.20) | (-0.5) | (-0.42) | (-0.92) | (-1.2) | (-1.55) | (-1.33) | (-0.57) | (-2.34) | (-2.59) | (-2.93) |
| PS α | 0.00 | -0.04 | -0.03 | -0.06 | -0.05 | -0.07 | -0.06 | -0.02 | -0.12 | -0.14 | -0.14*** |
| | (0.02) | (-0.73) | (-0.56) | (-1.12) | (-1.18) | (-1.48) | (-1.22) | (-0.41) | (-2.23) | (-2.58) | (-2.67) |
| FS α | -0.02 | -0.09 | -0.05 | -0.08 | -0.07 | -0.11 | -0.09 | -0.07 | -0.14 | -0.19 | -0.17*** |
| | (-0.34) | (-1.88) | (-1.24) | (-1.64) | (-2.02) | (-3.03) | (-2.12) | (-1.63) | (-3.2) | (-4.18) | (-3.18) |
| | | | | | | *Gross Return* | | | | | |
| Average | 0.95 | 0.91 | 0.9 | 0.89 | 0.88 | 0.84 | 0.85 | 0.87 | 0.79 | 0.76 | -0.19*** |
| | (3.31) | (3.12) | (3.14) | (3.10) | (3.02) | (2.89) | (2.90) | (2.94) | (2.65) | (2.56) | (-3.38) |
| CAPM α | 0.19 | 0.13 | 0.13 | 0.12 | 0.1 | 0.06 | 0.07 | 0.09 | 0 | -0.02 | -0.21*** |
| | (2.74) | (2.10) | (2.24) | (1.93) | (2.02) | (1.24) | (1.36) | (1.65) | (0.07) | (-0.47) | (-3.72) |
| FF α | 0.13 | 0.08 | 0.08 | 0.07 | 0.06 | 0.02 | 0.04 | 0.06 | -0.01 | -0.04 | -0.17*** |
| | (2.37) | (1.59) | (1.60) | (1.37) | (1.63) | (0.50) | (0.83) | (1.29) | (-0.19) | (-0.79) | (-3.27) |
| Carhart α | 0.12 | 0.08 | 0.08 | 0.05 | 0.05 | 0.03 | 0.04 | 0.07 | -0.02 | -0.03 | -0.16*** |
| | (2.08) | (1.41) | (1.52) | (1.03) | (1.25) | (0.77) | (0.82) | (1.44) | (-0.37) | (-0.59) | (-2.95) |
| PS α | 0.11 | 0.06 | 0.07 | 0.04 | 0.05 | 0.03 | 0.04 | 0.08 | -0.02 | -0.03 | -0.14*** |
| | (1.93) | (1.16) | (1.32) | (0.83) | (1.18) | (0.75) | (0.89) | (1.52) | (-0.33) | (-0.55) | (-2.69) |
| FS α | 0.1 | 0.01 | 0.05 | 0.02 | 0.03 | -0.01 | 0.01 | 0.03 | -0.04 | -0.08 | -0.17*** |
| | (2.02) | (0.31) | (1.12) | (0.32) | (0.71) | (-0.2) | (0.21) | (0.70) | (-0.81) | (-1.71) | (-3.23) |

## Table 3

## Fund Herding and Future Performance: Predictive Regressions

This table presents coefficient estimates from predictive panel regressions estimating the association between herding and future fund performance. Fund Herding (*FH*) is defined as the slope coefficient from cross-sectional regressions of mutual fund trades on past aggregate institutional trades measured in the past quarter, controlling for past stock returns, firm size, and the book-to-market ratio. These regressions are estimated per fund-quarter with both dependent and independent variables cross-sectionally standardized to have means of zero and standard deviations of one. We average these quarterly slope coefficients through a rank inverse-weighting scheme, assigning higher weights to more recent quarters. Future mutual fund performance is measured using Carhart (1997) four-factor alpha (both net and gross, in monthly percentages), where factor loadings are estimated using rolling-window regressions in the past three years. The panel regressions control for fund size, fund age, expense ratio (in percent), fund turnover, fund percentage flow in the past quarter, and fund alpha (in percent) estimated in the past three years. The regressions include fixed time effects and the standard errors are clustered by fund. The *t*-statistics are presented in parentheses. ***, **, * denote statistical significance at the 1%, 5%, and 10% level, respectively.

| | 4-factor Net α *(t+1)* | | 4-factor Gross α *(t+1)* | |
|---|---|---|---|---|
| | 1 | 2 | 1 | 2 |
| Fund Herding | -0.466*** | -0.438*** | -0.469*** | -0.437*** |
| | (-5.16) | (-4.83) | (-5.18) | (-4.82) |
| Log(TNA) | | -0.007** | | -0.008** |
| | | (-2.01) | | (-2.41) |
| Log(Age) | | 0.015* | | 0.016* |
| | | (1.79) | | (1.87) |
| Expense | | -0.076*** | | -0.005 |
| | | (-4.66) | | (-0.28) |
| Turnover | | -0.026*** | | -0.025*** |
| | | (-3.49) | | (-3.40) |
| PastFlow | | 0.002*** | | 0.002*** |
| | | (2.59) | | (2.73) |
| PastAlpha | | 0.014 | | 0.011 |
| | | (0.63) | | (0.46) |
| *Adjusted* $R^2$ | 0.059 | 0.060 | 0.059 | 0.060 |
| *N* | 167,854 | 160,067 | 167,854 | 160,067 |

## Table 4

## Herding and Fund Characteristics

This table presents statistics for decile portfolios of funds sorted on the basis of their average fund-level herding, *FH*. FH is the average of quarterly slope coefficients from cross-sectional regressions of individual mutual fund trades on past aggregate institutional trades measured in the past quarter, controlling for past stock returns, firm size, and the book-to-market ratio. The average uses a rank inverse-weighting scheme, assigning higher weights to more recent quarters. Panel A shows average values of fund characteristics for decile portfolios of funds sorted on FH. Fund size is the quarter-end total net fund assets, Fund age is the fund age in years, Exp ratio is the fund expense ratio, Turnover is the turnover ratio of the fund, Quarterly Flow is the growth rate of money in the previous quarter, and Quarterly Return is the net fund return. Fund flows and returns are cross-sectionally demeaned. Bold face denotes statistical significance at the 5% level, based on Newey-West (1987) standard errors. Panel B shows the estimated coefficients from Fama-MacBeth (1973) regressions of Fund Herding on fund characteristics. The regressors are measured either contemporaneously or with one quarter lag, and they are standardized to have a mean of zero and a standard deviation of one in each quarter. *t*-statistics are based on Newey-West (1987) standard errors. Panel C shows the average transition frequency of funds across deciles of FH, from quarter *t* to quarter *t+1*.

### Panel A: Characteristics of Funds Sorted on the basis of Fund Herding

| Decile | 1: L | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10: H | H-L |
|---|---|---|---|---|---|---|---|---|---|---|---|
| *Fund Characteristics* | | | | | | | | | | | |
| FH | -0.1037 | -0.0408 | -0.0156 | 0.0019 | 0.0166 | 0.0305 | 0.0460 | 0.0641 | 0.0894 | 0.1525 | **0.2561** |
| Fund Size | 796.95 | 1347.14 | 1645.41 | 1815.11 | 1901.57 | 1829.00 | 1819.90 | 1477.64 | 1263.84 | 775.78 | -21.17 |
| Fund age | 15.51 | 17.50 | 18.88 | 19.39 | 19.79 | 20.48 | 20.22 | 19.98 | 20.15 | 17.82 | **2.31** |
| Exp ratio | 0.0136 | 0.0126 | 0.0122 | 0.0120 | 0.0119 | 0.0120 | 0.0121 | 0.0123 | 0.0124 | 0.0132 | **-0.0004** |
| Turnover | 0.9568 | 0.8406 | 0.7971 | 0.7940 | 0.8029 | 0.8012 | 0.7992 | 0.7973 | 0.8187 | 0.8284 | **-0.1283** |
| Quarterly return | 0.0018 | 0.0005 | 0.0008 | 0.0013 | 0.0001 | 0.0002 | -0.0005 | -0.0026 | 0.0008 | -0.0025 | **-0.0043** |
| Quarterly flow | 0.0370 | -0.0047 | -0.0023 | -0.0033 | -0.0041 | -0.0084 | -0.0078 | -0.0071 | -0.0024 | 0.0031 | -0.0339 |

**Panel B: Cross-sectional Regressions of Fund Herding on Fund Characteristics**

| Dependent variable: Fund Herding | | | | |
|---|---|---|---|---|
| | Contemporaneous | | Predictive | |
| | 1 | 2 | 1 | 2 |
| Log(TNA) | -0.081 | -0.189*** | -0.024 | -0.193*** |
| | (-1.09) | (-2.81) | (-0.30) | (-3.31) |
| Log(Age) | 0.250*** | 0.241** | 0.271*** | 0.249** |
| | (3.22) | (2.50) | (3.22) | (2.29) |
| Log(Exp) | | -0.168** | | -0.150* |
| | | (-2.21) | | (-1.68) |
| Expense | -0.050 | -0.071 | -0.047 | -0.132 |
| | (-1.02) | (-0.85) | (-0.86) | (-1.59) |
| Turnover | -0.256** | -0.245** | -0.128 | -0.128 |
| | (-2.51) | (-2.35) | (-1.07) | (-1.02) |
| Past Flow | -0.008 | 0.097 | -0.162** | -0.045 |
| | (-0.10) | (1.17) | (-1.99) | (-0.47) |
| Past Alpha | 0.133 | 0.146 | 0.182 | 0.331* |
| | (1.11) | (0.97) | (1.39) | (1.92) |
| *Adjusted* $R^2$ | 0.010 | 0.010 | 0.011 | 0.015 |

**Panel C: Transition Matrix for Funds sorted on Fund Herding**

| | Transition probabilities (%), Quarters *t* to *t*+1 | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| **FH Deciles (t)** | **1** | **2** | **3** | **4** | **5** | **6** | **7** | **8** | **9** | **10** |
| FH Deciles (t+1) | | | | | | | | | | |
| 1 | 43.69 | 18.69 | 10.05 | 6.34 | 4.09 | 3.41 | 2.34 | 1.96 | 1.91 | 1.28 |
| 2 | 22.87 | 23.76 | 16.54 | 10.88 | 7.9 | 5.83 | 4.72 | 3.22 | 2.84 | 1.45 |
| 3 | 11.58 | 17.91 | 19.66 | 15.63 | 11.61 | 8.16 | 6.01 | 4.71 | 4.06 | 1.8 |
| 4 | 6.49 | 12.52 | 16.21 | 18.11 | 14.44 | 11.52 | 8.19 | 6.33 | 4.86 | 2.3 |
| 5 | 4.34 | 8.26 | 11.6 | 14.7 | 17.37 | 15.99 | 11.39 | 9.26 | 6.04 | 2.8 |
| 6 | 3.35 | 6.24 | 8.31 | 11.97 | 15.23 | 17.33 | 15.26 | 11.72 | 8.01 | 4.12 |
| 7 | 2.8 | 4.47 | 6.76 | 8.63 | 11.32 | 14.55 | 17.89 | 16.16 | 12.8 | 6.68 |
| 8 | 1.95 | 3.73 | 4.75 | 6.79 | 8.59 | 11.5 | 16.09 | 18.52 | 17.98 | 11.77 |
| 9 | 1.52 | 2.42 | 4.25 | 4.52 | 5.96 | 7.78 | 11.59 | 17.69 | 23.29 | 22.36 |
| 10 | 1.4 | 2 | 1.88 | 2.41 | 3.49 | 3.92 | 6.52 | 10.43 | 18.21 | 45.44 |

## Table 5
## Herding, Fund Characteristics, and Future Performance: Double Sorts

This table presents the performance of 16 portfolios formed on the basis of the average tendency of mutual funds to follow past institutional trades, *FH*, and a battery of fund characteristics. We sort funds independently into four groups based on fund herding and into four groups based on the following fund characteristics: fund size (Panel A), fund age (Panel B), manager experience (Panel C), net fund inflows (Panel D), and past performance measured by three-factor alphas estimated in the previous three years (Panel E). We compute the average monthly net return and the Carhart (1997) four-factor α for each of the 16 portfolios. The *t*-statistics are shown in parentheses. ***, **, * denote statistical significance at the 1%, 5%, and 10% level, respectively.

**Panel A: Fund Size**

| | Net Return | | | | | 4-Factor Net α | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Herding | Low | 2 | 3 | High | High-Low | Low | 2 | 3 | High | High-Low |
| Small | 0.99 | 0.95 | 0.98 | 0.89 | -0.09 | -0.05 | -0.05 | -0.01 | -0.10 | -0.05 |
| | (3.48) | (3.46) | (3.49) | (3.19) | (-1.58) | (-0.71) | (-0.8) | (-0.23) | (-1.73) | (-0.9) |
| 2 | 1.00 | 1.00 | 0.96 | 0.83 | -0.18*** | -0.05 | -0.05 | -0.02 | -0.15 | -0.11* |
| | (3.45) | (3.46) | (3.35) | (2.77) | (-2.72) | (-0.65) | (-0.84) | (-0.38) | (-2.14) | (-1.65) |
| 3 | 0.99 | 0.97 | 0.93 | 0.82 | -0.17*** | -0.02 | -0.10 | -0.08 | -0.20 | -0.18*** |
| | (3.42) | (3.25) | (3.12) | (2.64) | (-2.69) | (-0.3) | (-1.42) | (-1.14) | (-2.71) | (-2.84) |
| Large | 0.98 | 0.89 | 0.83 | 0.83 | -0.15** | -0.01 | -0.10 | -0.10 | -0.13 | -0.12** |
| | (3.56) | (3.21) | (2.90) | (2.76) | (-2.33) | (-0.17) | (-2.47) | (-2.25) | (-2.63) | (-2.39) |
| Large-Small | -0.01 | -0.06 | -0.14** | -0.06 | -0.05 | 0.04 | -0.05 | -0.09* | -0.03 | -0.07 |
| | (-0.08) | (-0.99) | (-2.46) | (-0.95) | (-0.81) | (0.63) | (-0.84) | (-1.67) | (-0.54) | (-0.96) |

**Panel B: Fund Age**

| | Net Return | | | | | 4-Factor Net α | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Herding | Low | 2 | 3 | High | High-Low | Low | 2 | 3 | High | High-Low |
| Young | 1.02 | 1.03 | 1 | 0.84 | -0.18*** | -0.03 | -0.01 | -0.02 | -0.18 | -0.16** |
| | (3.46) | (3.47) | (3.39) | (2.78) | (-2.86) | (-0.49) | (-0.21) | (-0.27) | (-2.70) | (-2.21) |
| 2 | 0.98 | 0.88 | 0.91 | 0.8 | -0.19*** | -0.06 | -0.14 | -0.06 | -0.18 | -0.12** |
| | (3.47) | (3.22) | (3.25) | (2.70) | (-3.13) | (-0.99) | (-2.11) | (-0.93) | (-2.55) | (-2.06) |
| 3 | 1.03 | 0.94 | 0.95 | 0.87 | -0.16** | 0.01 | -0.11 | -0.03 | -0.13 | -0.14** |
| | (3.62) | (3.27) | (3.27) | (2.90) | (-2.18) | (0.16) | (-2.10) | (-0.48) | (-1.82) | (-2.09) |
| Old | 0.90 | 0.93 | 0.82 | 0.87 | -0.03 | -0.08 | -0.06 | -0.12 | -0.09 | -0.02 |
| | (3.31) | (3.31) | (2.88) | (2.99) | (-0.5) | (-1.34) | (-0.99) | (-2.56) | (-1.69) | (-0.29) |
| Old-Young | -0.12* | -0.1 | -0.17*** | 0.03 | 0.15** | -0.05 | -0.04 | -0.10** | 0.09* | 0.14** |
| | (-1.85) | (-1.29) | (-2.93) | (0.62) | (2.12) | (-0.95) | (-0.61) | (-2.09) | (1.66) | (1.97) |

**Panel C: Manager Experience**

| | Net Return | | | | | 4-Factor Net α | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Herding | Low | 2 | 3 | High | High-Low | Low | 2 | 3 | High | High-Low |
| Low exp | 0.83 | 0.77 | 0.75 | 0.64 | -0.19*** | 0.02 | -0.07 | -0.05 | -0.18 | -0.20*** |
| | (2.51) | (2.29) | (2.26) | (1.88) | (-2.67) | (0.21) | (-1.02) | (-0.68) | (-2.50) | (-2.73) |
| 2 | 0.78 | 0.73 | 0.74 | 0.64 | -0.13** | 0.00 | -0.06 | -0.03 | -0.13 | -0.13* |
| | (2.48) | (2.35) | (2.29) | (1.99) | (-2.00) | (0.03) | (-0.89) | (-0.47) | (-1.70) | (-1.89) |
| 3 | 0.78 | 0.7 | 0.69 | 0.66 | -0.12* | -0.03 | -0.12 | -0.08 | -0.11 | -0.08 |
| | (2.47) | (2.17) | (2.09) | (1.99) | (-1.78) | (-0.42) | (-1.65) | (-1.22) | (-1.46) | (-1.42) |
| High exp | 0.81 | 0.77 | 0.69 | 0.7 | -0.11 | 0.01 | -0.03 | -0.07 | -0.06 | -0.07 |
| | (2.64) | (2.57) | (2.19) | (2.20) | (-1.31) | (0.14) | (-0.60) | (-1.01) | (-0.9) | (-0.83) |
| High-Low exp | -0.01 | -0.01 | -0.06 | 0.07 | 0.08 | -0.01 | 0.03 | -0.02 | 0.12* | 0.13 |
| | (-0.19) | (-0.08) | (-0.63) | (0.79) | (0.74) | (-0.08) | (0.50) | (-0.32) | (1.78) | (1.23) |

**Panel D: Past Flows**

| | Net Return | | | | | 4-Factor Net α | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Herding | Low | 2 | 3 | High | High-Low | Low | 2 | 3 | High | High-Low |
| Outflow | 0.93 | 0.86 | 0.92 | 0.79 | -0.14** | -0.08 | -0.13 | -0.03 | -0.18 | -0.10 |
| | (3.23) | (3.00) | (3.14) | (2.71) | (-2.2) | (-0.85) | (-1.46) | (-0.37) | (-2.04) | (-1.51) |
| 2 | 1.00 | 0.94 | 0.84 | 0.81 | -0.20*** | 0.03 | -0.06 | -0.10 | -0.14 | -0.17*** |
| | (3.60) | (3.42) | (3.01) | (2.82) | (-3.41) | (0.44) | (-1.02) | (-1.74) | (-1.96) | (-2.89) |
| 3 | 0.94 | 0.90 | 0.92 | 0.86 | -0.08 | -0.07 | -0.09 | -0.06 | -0.13 | -0.05 |
| | (3.32) | (3.23) | (3.15) | (2.88) | (-1.14) | (-1.14) | (-2.08) | (-1.19) | (-1.96) | (-0.83) |
| Inflow | 1.09 | 1.09 | 1.00 | 0.93 | -0.16** | 0.00 | 0.00 | -0.04 | -0.13 | -0.13* |
| | (3.62) | (3.61) | (3.36) | (2.92) | (-2.42) | (-0.05) | (-0.04) | (-0.69) | (-2.05) | (-1.94) |
| Inflow-outflow | 0.16 | 0.23** | 0.08 | 0.14 | -0.02 | 0.08 | 0.13 | -0.01 | 0.05 | -0.03 |
| | (1.29) | (2.08) | (0.79) | (1.22) | (-0.32) | (0.76) | (1.19) | (-0.07) | (0.53) | (-0.35) |

**Panel E: Past Performance**

| | Net Return | | | | | 4-Factor Net α | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Herding | Low | 2 | 3 | High | High-Low | Low | 2 | 3 | High | High-Low |
| Low Past α | 0.93 | 0.89 | 0.92 | 0.81 | -0.12** | -0.12 | -0.15 | -0.09 | -0.23 | -0.11* |
| | (3.34) | (3.23) | (3.29) | (2.82) | (-2.08) | (-1.33) | (-1.8) | (-1.12) | (-2.82) | (-1.79) |
| 2 | 0.95 | 0.95 | 0.91 | 0.88 | -0.07 | -0.06 | -0.06 | -0.07 | -0.08 | -0.03 |
| | (3.52) | (3.58) | (3.37) | (3.24) | (-1.23) | (-0.92) | (-1.19) | (-1.41) | (-1.21) | (-0.57) |
| 3 | 0.94 | 0.95 | 0.92 | 0.89 | -0.05 | -0.07 | -0.04 | -0.03 | -0.07 | 0.00 |
| | (3.39) | (3.42) | (3.29) | (3.12) | (-0.89) | (-1.3) | (-0.87) | (-0.71) | (-1.19) | -0.08 |
| High Past α | 1.12 | 0.95 | 0.94 | 0.87 | -0.26*** | 0.10 | -0.08 | -0.05 | -0.15 | -0.24*** |
| | (3.34) | (2.86) | (2.74) | (2.44) | (-3.73) | (1.23) | (-0.89) | (-0.57) | (-1.49) | (-3.29) |
| High-Low α | 0.20 | 0.06 | 0.02 | 0.06 | -0.14* | 0.22* | 0.07 | 0.04 | 0.08 | -0.14* |
| | (1.24) | (0.41) | (0.12) | (0.39) | (-1.83) | (1.84) | (0.55) | (0.31) | (0.66) | (-1.73) |

## Table 6

## Fund Herding and Future Performance: Other Measures of Skill

This table presents estimates of the relation between fund herding and other measures of skill (Panel A) and the association between fund herding and future fund performance (Panel B). Fund Herding (*FH*) is defined as the slope coefficient from cross-sectional regressions of mutual fund trades on past aggregate institutional trades measured in the past quarter, controlling for past stock returns, firm size, and the book-to-market ratio. See Table 2 for a description of the variables. The three measures of skill are Active Share (Cremers and Petajisto, 2009), similarity in trades (CCP similarity) constructed as in Cohen, Coval, and Pastor (2005), and the $R^2$ from regressions of fund trades on revisions in analyst recommendations as in Kacperczyk and Seru (2007). Panel A: Fama-MacBeth (1973) cross-sectional regressions of Fund Herding, with *t*-statistics based on Newey-West (1987) standard errors. Panel B: Panel regressions of mutual fund performance, measured using Carhart (1997) four-factor alpha (both net and gross in monthly percentages), where factor loadings are estimated using rolling-window regressions in the past three years. The regressions include fixed time effects and the standard errors are clustered by fund. *t*-statistics are presented in parentheses. ***, **, * denote statistical significance at the 1%, 5%, and 10% level, respectively.

### Panel A

### Fund Herding and Other Measures of Skill

| Dependent variable: Fund Herding | | | | |
|---|---|---|---|---|
| | Contemporaneous | | Predictive | |
| | 1 | 2 | 1 | 2 |
| Active Share | -0.543*** | -0.388*** | -0.484*** | -0.420*** |
| | (-5.94) | (-4.28) | (-4.37) | (-2.78) |
| $R^2$ | 0.586*** | 0.665*** | 0.630*** | 0.726*** |
| | (4.59) | (6.12) | (4.86) | (5.72) |
| CCP similarity | -0.213** | -0.150 | -0.099 | -0.055 |
| | (-2.42) | (-1.46) | (-1.20) | (-0.55) |
| Log(TNA) | -0.092 | -0.054 | -0.022 | -0.107 |
| | (-1.09) | (-0.49) | (-0.26) | (-1.44) |
| Log(Age) | 0.381*** | 0.296*** | 0.389*** | 0.258*** |
| | (3.63) | (4.02) | (3.24) | (2.83) |
| Log(Exp) | | -0.149** | | -0.139** |
| | | (-2.31) | | (-2.04) |
| Expense | -0.010 | -0.106 | -0.064 | -0.274** |
| | (-0.18) | (-0.91) | (-0.99) | (-2.46) |
| Turnover | -0.378*** | -0.332*** | -0.227* | -0.206* |
| | (-3.10) | (-2.87) | (-1.75) | (-1.64) |
| Past Flow | -0.123 | -0.043 | -0.213* | -0.064 |
| | (-1.18) | (-0.33) | (-1.93) | (-0.41) |
| Past Alpha | 0.245** | 0.099 | 0.200 | 0.250 |
| | (2.13) | (0.63) | (1.51) | (1.37) |
| | (-2.42) | (-1.46) | (-1.20) | (-0.55) |
| *Adjusted $R^2$* | 0.036 | 0.032 | 0.035 | 0.029 |

**Panel B**
**Predictive Regressions of Fund Performance**

| | Dependent variable: 4-factor Net α (t+1) | | | | | |
|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 | 6 |
| Fund Herding | -0.532*** | -0.538*** | -0.470*** | -0.442*** | -0.494*** | -0.474*** |
| | (-4.57) | (-4.57) | (-5.18) | (-4.85) | (-5.01) | (-4.74) |
| Active Share | 0.127** | 0.199*** | | | | |
| | (2.79) | (4.45) | | | | |
| CCP similarity | | | 0.059** | 0.038 | | |
| | | | (2.08) | (1.30) | | |
| $R^2$ | | | | | 0.075 | 0.077 |
| | | | | | (0.82) | (0.84) |
| Log(TNA) | | -0.008* | | -0.007* | | -0.010*** |
| | | (-1.74) | | (-1.90) | | (-2.67) |
| Log(Age) | | -0.004 | | 0.016* | | 0.028*** |
| | | (-0.40) | | (1.83) | | (3.17) |
| Expense | | -0.103*** | | -0.074*** | | -0.069*** |
| | | (-5.00) | | (-4.53) | | (-3.98) |
| Turnover | | -0.041*** | | -0.024*** | | -0.024*** |
| | | (-3.93) | | (-3.30) | | (-3.14) |
| Past Flow | | 0.023 | | 0.002*** | | 0.002*** |
| | | (1.53) | | (2.62) | | (3.27) |
| Past Alpha | | 0.037 | | | | 0.025 |
| | | (1.34) | | | | (1.15) |
| *Adjusted $R^2$* | 0.081 | 0.084 | 0.059 | 0.060 | 0.062 | 0.063 |
| *N* | 98,386 | 92,962 | 166,525 | 158,771 | 150,177 | 143,876 |

## Table 7
## Fund Herding and Persistence in Performance

This table presents the performance of decile portfolios formed on the basis of the average tendency of mutual funds to follow past institutional trades. Fund Herding (*FH*) is defined as the slope coefficient from cross-sectional regressions of mutual fund trades on past aggregate institutional trades measured in the past quarter, controlling for past stock returns, firm size, and the book-to-market ratio. These regressions are estimated per fund-quarter with both dependent and independent variables cross-sectionally standardized to have means of zero and standard deviations of one. We average these quarterly slope coefficients through a rank inverse-weighting scheme, assigning higher weights to more recent quarters. The decile portfolios are formed at the end of each quarter from 1989Q4 to 2009Q3 and the return series ranges from January 1990 to December 2009. The holding period for each portfolio varies from 6 to 12 months. Decile 10 is the portfolio of funds with the highest average herding measure. We compute monthly equally weighted percentage net and gross (net plus expense ratio) returns on the portfolios, as well as risk-adjusted returns based on the CAPM, the Fama and French (FF, 1993) three-factor model, the Carhart (1997) four-factor model, the Pastor and Stambaugh (PS, 2003) five-factor model, and the Ferson and Schadt (FS, 1996) conditional model. Alphas are in monthly percentages. The Newey-West (1987) *t*-statistics are shown in parentheses. ***, **, * denote statistical significance at the 1%, 5%, and 10% level, respectively.

### Panel A: 6-Month Holding Period

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | D10-D1 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | *Net Return* | | | | | |
| Average | 0.82 | 0.81 | 0.8 | 0.76 | 0.77 | 0.76 | 0.75 | 0.77 | 0.71 | 0.67 | -0.15*** |
| | (2.56) | (2.51) | (2.53) | (2.40) | (2.41) | (2.39) | (2.36) | (2.35) | (2.16) | (2.02) | (-2.81) |
| CAPM α | 0.05 | 0.03 | 0.04 | -0.01 | -0.01 | -0.02 | -0.03 | -0.02 | -0.08 | -0.12 | -0.17*** |
| | (0.70) | (0.50) | (0.53) | (-0.11) | (-0.12) | (-0.27) | (-0.55) | (-0.37) | (-1.49) | (-2.1) | (-3.12) |
| FF α | 0.00 | -0.02 | -0.02 | -0.06 | -0.05 | -0.06 | -0.06 | -0.04 | -0.10 | -0.13 | -0.13*** |
| | (-0.02) | (-0.33) | (-0.34) | (-1.13) | (-1.21) | (-1.37) | (-1.39) | (-0.93) | (-2.01) | (-2.59) | (-3.04) |
| Carhart α | -0.01 | -0.02 | -0.02 | -0.07 | -0.06 | -0.05 | -0.06 | -0.03 | -0.10 | -0.12 | -0.11*** |
| | (-0.18) | (-0.39) | (-0.33) | (-1.24) | (-1.36) | (-1.09) | (-1.29) | (-0.65) | (-1.91) | (-2.13) | (-2.63) |
| PS α | -0.02 | -0.03 | -0.03 | -0.08 | -0.07 | -0.05 | -0.06 | -0.03 | -0.10 | -0.12 | -0.10** |
| | (-0.35) | (-0.58) | (-0.44) | (-1.42) | (-1.38) | (-1.04) | (-1.25) | (-0.55) | (-1.87) | (-2.06) | (-2.34) |
| FS α | -0.05 | -0.07 | -0.06 | -0.11 | -0.10 | -0.09 | -0.10 | -0.07 | -0.11 | -0.16 | -0.11** |
| | (-1.11) | (-1.56) | (-1.39) | (-2.11) | (-2.75) | (-2.3) | (-2.8) | (-1.78) | (-2.69) | (-3.95) | (-2.57) |

**Panel B: 9-Month Holding Period**

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | D10-D1 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | *Net Return* | | | | | |
| Average | 0.83 | 0.80 | 0.80 | 0.75 | 0.77 | 0.76 | 0.75 | 0.76 | 0.71 | 0.68 | -0.15*** |
| | (2.62) | (2.52) | (2.53) | (2.40) | (2.42) | (2.39) | (2.34) | (2.34) | (2.18) | (2.04) | (-3.05) |
| CAPM α | 0.06 | 0.03 | 0.03 | -0.02 | -0.01 | -0.01 | -0.03 | -0.02 | -0.08 | -0.11 | -0.17*** |
| | (0.76) | (0.40) | (0.41) | (-0.22) | (-0.16) | (-0.23) | (-0.57) | (-0.41) | (-1.5) | (-2.01) | (-3.38) |
| FF α | 0.01 | -0.02 | -0.02 | -0.07 | -0.05 | -0.06 | -0.06 | -0.05 | -0.09 | -0.13 | -0.14*** |
| | (0.13) | (-0.47) | (-0.39) | (-1.36) | (-1.33) | (-1.32) | (-1.49) | (-1.05) | (-2.05) | (-2.7) | (-3.55) |
| Carhart α | 0.00 | -0.03 | -0.03 | -0.08 | -0.07 | -0.05 | -0.07 | -0.04 | -0.09 | -0.12 | -0.12*** |
| | (-0.01) | (-0.51) | (-0.48) | (-1.45) | (-1.47) | (-1.04) | (-1.45) | (-0.74) | (-1.91) | (-2.21) | (-3.37) |
| PS α | -0.01 | -0.04 | -0.03 | -0.09 | -0.07 | -0.05 | -0.07 | -0.03 | -0.09 | -0.12 | -0.11*** |
| | (-0.15) | (-0.65) | (-0.57) | (-1.6) | (-1.47) | (-0.97) | (-1.4) | (-0.65) | (-1.84) | (-2.17) | (-2.96) |
| FS α | -0.05 | -0.08 | -0.07 | -0.11 | -0.09 | -0.09 | -0.11 | -0.07 | -0.12 | -0.16 | -0.11*** |
| | (-0.96) | (-1.65) | (-1.42) | (-2.12) | (-2.61) | (-2.06) | (-2.86) | (-1.78) | (-3.01) | (-4.05) | (-2.84) |

**Panel C: 12-Month Holding Period**

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | D10-D1 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | *Net Return* | | | | | |
| Average | 0.83 | 0.79 | 0.79 | 0.75 | 0.76 | 0.77 | 0.75 | 0.76 | 0.71 | 0.68 | -0.15*** |
| | (2.61) | (2.48) | (2.48) | (2.37) | (2.39) | (2.39) | (2.30) | (2.32) | (2.17) | (2.03) | (-2.6) |
| CAPM α | 0.06 | 0.02 | 0.02 | -0.02 | -0.01 | -0.01 | -0.04 | -0.02 | -0.07 | -0.11 | -0.17*** |
| | (0.67) | (0.22) | (0.20) | (-0.29) | (-0.19) | (-0.15) | (-0.62) | (-0.39) | (-1.52) | (-1.94) | (-2.93) |
| FF α | 0.01 | -0.03 | -0.03 | -0.07 | -0.05 | -0.05 | -0.06 | -0.05 | -0.09 | -0.12 | -0.13*** |
| | (0.12) | (-0.63) | (-0.67) | (-1.46) | (-1.28) | (-1.19) | (-1.55) | (-1.05) | (-2.04) | (-2.59) | (-3.15) |
| Carhart α | 0.00 | -0.04 | -0.04 | -0.08 | -0.06 | -0.05 | -0.07 | -0.04 | -0.09 | -0.11 | -0.11*** |
| | (-0.07) | (-0.66) | (-0.75) | (-1.49) | (-1.38) | (-1.01) | (-1.52) | (-0.79) | (-1.91) | (-2.07) | (-2.92) |
| PS α | -0.01 | -0.05 | -0.05 | -0.09 | -0.07 | -0.05 | -0.07 | -0.04 | -0.09 | -0.11 | -0.10** |
| | (-0.21) | (-0.75) | (-0.84) | (-1.62) | (-1.37) | (-0.93) | (-1.44) | (-0.68) | (-1.82) | (-2.04) | (-2.56) |
| FS α | -0.06 | -0.08 | -0.08 | -0.11 | -0.10 | -0.08 | -0.11 | -0.07 | -0.12 | -0.15 | -0.10** |
| | (-0.97) | (-1.6) | (-1.8) | (-2.47) | (-2.45) | (-1.91) | (-2.8) | (-1.7) | (-3.16) | (-3.85) | (-2.31) |

## Table 8
## Fund Herding, Future Performance, and Investment Opportunities

This table presents results from time-series and panel regressions of mutual fund performance on the dispersion in stock returns and fund characteristics. Panel A shows the time series regressions. At the end of each quarter from 1989Q4 to 2009Q3, we form ten portfolios on the basis of Fund Herding and compute their monthly equally weighted net and gross (plus expense ratio) returns (in percent). The return series ranges from January 1990 to December 2009. We compute the difference in returns between Decile 10, with the highest *FH*, and Decile 1, with the lowest *FH*. We then run time-series regressions of this return differencial on the dispersion in stock returns as measured by the Russell-Parametric Cross-Sectional Volatility Index for US equities (CrossVol) from July 1996 to December 2009. To facilitate interpretation, the cross-sectional volatility index is standardized to have a mean of zero and a standard deviation of one. Specifications 1 and 2 use the contemporaneous and one-month lagged CrossVol, respectively. Panel B presents the results of panel regressions of mutual fund performance as measured by the Carhart (1997) four-factor net fund alpha (in percent) on *FH*, fund characteristics, and an interaction term between *FH* and CrossVol. The panel regressions control for fund size, fund age, expense ratio (in percent), fund turnover, fund percentage flows in the past quarter, and fund alpha (in percent) in the past three years. The regressions include fixed time effects and the standard errors are clustered by fund. In specification 1 CrossVol is measured in the same month as fund performance; in specification 2 it is measured with one-month lag. The *t*-statistics are shown in parentheses. ***, **, * denote statistical significance at the 1%, 5%, and 10% level, respectively.

### Panel A: Time-Series Regression

| Dependent Variable | Return Differential between Herding and Anti-Herding Funds | | | |
|---|---|---|---|---|
| | Net Return | | Gross Return | |
| | 1 | 2 | 1 | 2 |
| Intercept | -0.254*** | -0.253*** | -0.255*** | -0.253*** |
| | (-3.70) | (-3.67) | (-3.70) | (-3.68) |
| CrossVol | -0.197*** | | -0.198*** | |
| | (-2.86) | | (-2.87) | |
| $\text{CrossVol}_{-1}$ | | -0.217*** | | -0.218*** |
| | | (-3.14) | | (-3.15) |
| *Adjusted* $R^2$ | 0.043 | 0.053 | 0.043 | 0.053 |
| *N* | 162 | 161 | 162 | 161 |

### Panel B: Panel Regression

| Dependent Variable | Fund-Level 4-Factor Net α | | Fund-Level 4-Factor Gross α | |
|---|---|---|---|---|
| | 1 | 2 | 1 | 2 |
| Fund Herding | -0.528*** | -0.535*** | -0.529*** | -0.535*** |
| | (-4.76) | (-4.92) | (4.77) | (4.93) |
| CrossVol× FH | -0.321** | | -0.321** | |
| | (-2.14) | | (-2.14) | |
| $\text{CrossVol}_{-1}$×FH | | -0.323** | | -0.323** |
| | | (-2.51) | | (-2.52) |
| Log(TNA) | -0.0101*** | -0.0102*** | -0.011*** | -0.011*** |
| | (-2.76) | (-2.79) | (3.07) | (3.11) |
| Log(Age) | 0.030*** | 0.030*** | 0.031*** | 0.031*** |
| | (3.39) | (3.38) | (3.50) | (3.49) |
| Expense | -0.067*** | -0.067*** | 0.007 | 0.006 |
| | (-3.78) | (-3.82) | (0.41) | (0.37) |
| Turnover | -0.023*** | -0.023*** | -0.022*** | -0.022*** |
| | (-3.01) | (-3.02) | (2.95) | (2.95) |
| PastFlow | 0.002*** | 0.002*** | 0.002*** | 0.002*** |
| | (3.41) | (3.44) | (3.70) | (3.74) |
| PastAlpha | 0.025 | 0.024 | 0.021 | 0.020 |
| | (1.12) | (1.09) | (0.94) | (0.91) |
| *Adjusted* $R^2$ | 0.06 | 0.06 | 0.06 | 0.06 |
| *N* | 140,041 | 139,837 | 140,041 | 139,837 |

## Table 9
## Alternative Measures of Fund Performance

This table presents coefficient estimates from predictive panel regressions testing the association between fund-level herding and future mutual fund performance. Fund performance is computed from fund stock holdings using two measures: the Daniel, Grinblatt, Titman, and Wermers (DGTW 1997) Characteristic Selectivity (CS) measure (columns 1 and 2), and the Grinblatt and Titman (1993) (GT) measure (columns 3-6). Performance is measured in monthly percentages. Columns 3-4 report the monthly GT measure computed over quarter *t+1* and columns 5-6 report the monthly GT measure computed over quarter *t+5*. The panel regressions control for fund size (TNA), fund age, expense ratio (in percent), and fund turnover measured in quarter t, as well as fund percentage flow in the previous quarter and fund alpha (percent) in the previous three years. The regressions include fixed time effects and the standard errors are clustered by fund. The *t*-statistics are shown in parentheses. ***, **, * denote statistical significance at the 1%, 5%, and 10% level, respectively.

| | DGTW measure (CS) | | Grinblatt-Titman Measure (GT) | | | |
|---|---|---|---|---|---|---|
| | *t+1* | | *t+1* | | *t+5* | |
| | 1 | 2 | 3 | 4 | 5 | 6 |
| Fund Herding | -0.251** | -0.276*** | -0.208** | -0.244** | -0.173** | -0.197** |
| | (-2.39) | (-2.63) | (-2.10) | (-2.54) | (-2.10) | (-2.30) |
| Log(TNA) | | -0.006* | | -0.007* | | -0.004 |
| | | (-1.64) | | (-1.88) | | (-1.17) |
| Log(Age) | | 0.015 | | -0.002 | | -0.003 |
| | | (1.56) | | (-0.25) | | (-0.40) |
| Expense | | -0.018 | | 0.011 | | 0.010 |
| | | (-1.14) | | (0.82) | | (0.82) |
| Turnover | | -0.008 | | -0.007 | | 0.007 |
| | | (-0.92) | | (-1.01) | | (0.95) |
| PastFlow | | 0.005 | | 0.005*** | | -0.023 |
| | | (0.32) | | (13.12) | | (-1.38) |
| PastAlpha | | 0.022 | | 0.049*** | | -0.013 |
| | | (0.96) | | (2.63) | | (-0.84) |
| *Adjusted $R^2$* | 0.054 | 0.056 | 0.209 | 0.206 | 0.241 | 0.237 |
| *N* | 136,742 | 129,596 | 155,083 | 147,358 | 132,347 | 125,104 |

## Table 10
## Alternative Measures of Fund Herding

This table presents coefficient estimates from predictive panel regressions testing the association between four alternative measures of fund-level herding and mutual fund performance (four-factor net and gross fund α). The four alternative measures of fund-level herding are constructed as follows: (1) the slope coefficient from regressions of mutual fund trades on past aggregate institutional trades, controlling for the fund's own past trades, past stock returns, firm size, and the book-to-market ratio; (2) the slope coefficient from regressions of mutual fund trades on past aggregate institutional trades, controlling for contemporaneous aggregate institutional trades, past stock returns, firm size, and the book-to-market ratio; (3) the slope coefficient from regressions of mutual fund trades on the trading persistence of past aggregate institutional trades (Dasgupta, Prat, and Verardo, 2011), controlling for past stock returns, firm size, and the book-to-market ratio; and (4) the correlation coefficients between mutual fund trades and past aggregate institutional trades, ortogonalized with respect to past stock returns, firm size, the book-to-market ratio, turnover, idiosyncratic volatility, analyst earnings forecast revisions, firm share issuance, and industry dummies. The regressions are estimated per fund-quarter with both dependent and independent variables cross-sectionally standardized to have means of zero and standard deviations of one. The quarterly measures of fund-level herding (regression and correlation coefficients) are averaged over time for each fund, using an inverse-time-weighted average that gives a higher weight to the most recent quarters. Future mutual fund performance is measured using Carhart (1997) four-factor alpha (in percent), where fund betas are estimated using rolling-window regressions in the past three years. The panel regressions control for fund size, fund age, expense ratio, fund turnover, fund percentage flow in the past quarter, and fund alpha in the past three years. The regressions include fixed time effects and the standard errors are clustered by fund. The *t*-statistics are shown in parentheses.

| | Panel A: Controlling for past own trades | | | | Panel B: Controlling for contemporaneous aggregate institutional trades | | | |
|---|---|---|---|---|---|---|---|---|
| | 4-factor Net α | | 4-factor Gross α | | 4-factor Net α | | 4-factor Gross α | |
| | 1 | 2 | 3 | 4 | 1 | 2 | 3 | 4 |
| Fund Herding | -0.377*** | -0.356*** | -0.381*** | -0.357*** | -0.330*** | -0.340*** | -0.335*** | -0.340*** |
| | (-4.21) | (-3.87) | (-4.23) | (-3.87) | (-3.70) | (-3.70) | (-3.76) | (-3.70) |
| Log(TNA) | | -0.007** | | -0.009** | | -0.006 | | -0.007* |
| | | (-2.08) | | (-2.48) | | (-1.38) | | (-1.67) |
| Log(Age) | | 0.015* | | 0.016* | | 0.020** | | 0.020** |
| | | (1.78) | | (1.87) | | (1.99) | | (2.03) |
| Expense | | -0.076*** | | -0.005 | | -0.044** | | 0.026 |
| | | (-4.68) | | (-0.33) | | (-2.30) | | (1.34) |
| Turnover | | -0.025*** | | -0.024*** | | -0.018** | | -0.017* |
| | | (-3.42) | | (-3.33) | | (-2.00) | | (-1.92) |
| PastFlow | | 0.002*** | | 0.002*** | | 0.012 | | 0.009 |
| | | (2.59) | | (2.73) | | (0.84) | | (0.66) |
| PastAlpha | | 0.013 | | 0.010 | | 0.016 | | 0.012 |
| | | (0.58) | | (0.42) | | (0.51) | | (0.40) |
| *Adjusted $R^2$* | 0.059 | 0.060 | 0.059 | 0.060 | 0.055 | 0.056 | 0.055 | 0.056 |
| *N* | 167,653 | 159,866 | 167,653 | 159,866 | 107,629 | 104,055 | 107,629 | 104,055 |

| | Panel C: Following persistent institutional trades | | | | Panel D: Controlling for other stock characteristics | | | |
|---|---|---|---|---|---|---|---|---|
| | 4-factor Net α | | 4-factor Gross α | | 4-factor Net α | | 4-factor Gross α | |
| | 1 | 2 | 3 | 4 | 1 | 2 | 3 | 4 |
| Fund Herding | -0.333*** | -0.329*** | -0.333*** | -0.328*** | -0.473*** | -0.486*** | -0.484*** | -0.486*** |
| | (-3.13) | (-3.20) | (-3.15) | (-3.19) | (-4.85) | (-4.92) | (-4.96) | (-4.91) |
| Log(TNA) | | -0.007** | | -0.008** | | -0.007** | | -0.008** |
| | | (-2.05) | | (-2.45) | | (-1.98) | | (-2.38) |
| Log(Age) | | 0.015* | | 0.016* | | 0.016* | | 0.017* |
| | | (1.76) | | (1.85) | | (1.86) | | (1.94) |
| Expense | | -0.076*** | | -0.005 | | -0.068*** | | 0.003 |
| | | (-4.66) | | (-0.28) | | (-4.22) | | (0.19) |
| Turnover | | -0.025*** | | -0.024*** | | -0.025*** | | -0.025*** |
| | | (-3.36) | | (-3.27) | | (-3.40) | | (-3.31) |
| PastFlow | | 0.002*** | | 0.002*** | | 0.002*** | | 0.002*** |
| | | (2.64) | | (2.78) | | (2.92) | | (3.09) |
| PastAlpha | | 0.015 | | 0.011 | | 0.009 | | 0.006 |
| | | (0.65) | | (0.49) | | (0.40) | | (0.24) |
| *Adjusted* $R^2$ | 0.059 | 0.060 | 0.059 | 0.060 | 0.060 | 0.061 | 0.060 | 0.060 |
| *N* | 167,854 | 160,067 | 167,854 | 160,067 | 160,987 | 153,530 | 160,987 | 153,530 |

## Table 11
## Price Impact of Aggregate Institutional Trades

This table presents estimates of the relation between aggregate institutional trades and future stock returns. For each month from January 1990 to December 2009, we regress monthly stock returns in excess of the one-month Treasury bill rate, measured in quarters *t+1* to *t+4*, on aggregate institutional trades and stock characteristics measured in quarter *t*. Size is the natural log of stock market cap in millions of dollars. BM is the natural log of the book-to-market ratio. MOM3 is the stock return in quarter *t*. MOM12 is the stock return in the previous year. Turnover is trading volume in quarter *t* divided by the number of shares outstanding. Idiosyncratic volatility is the standard deviation of the residuals from a regression of daily stock returns on the Fama and French (1993) three factors, measured in quarter *t*. Share Issuance is the natural log of the ratio of the split-adjusted shares outstanding at the end of quarter *t* divided by the split-adjusted shares outstanding at the end of quarter *t*-4. Analyst earnings forecast revision is the quarterly change in consensus analyst earnings forecasts scaled by the stock price at the end of the previous period. The coefficients reported in the table are time-series averages of monthly regression coefficients, following Fama and MacBeth (1973). The *t*-statistics are shown in parentheses. ***, **, * denote statistical significance at the 1%, 5%, and 10% level, respectively.

| Dep variable: Excess returns (%) | Quarter *t*+1 | | Quarter *t*+2 | | Quarter *t*+3 | | Quarter *t*+4 | |
|---|---|---|---|---|---|---|---|---|
| | 1 | 2 | 1 | 2 | 1 | 2 | 1 | 2 |
| ΔIO | 0.006 | -0.014 | 0.006 | 0.012 | -0.027 | -0.038 | -0.002 | 0.010 |
| | (0.24) | (-0.57) | (0.22) | (0.51) | (-0.90) | (-1.44) | (-0.09) | (0.40) |
| Size | 0.027 | -0.148** | 0.032 | -0.029 | -0.008 | -0.024 | -0.010 | 0.018 |
| | (0.28) | (-1.97) | (0.32) | (-0.39) | (-0.08) | (-0.31) | (-0.10) | (0.23) |
| BM | 0.198* | 0.082 | 0.211* | 0.124 | 0.137 | 0.078 | 0.162 | 0.123 |
| | (1.78) | (0.99) | (1.89) | (1.60) | (1.23) | (0.99) | (1.47) | (1.56) |
| MOM3 | 0.006 | 0.002 | 0.184* | 0.190** | 0.194** | 0.189*** | 0.111 | 0.135** |
| | (0.06) | (0.03) | (1.84) | (2.47) | (2.06) | (2.66) | (1.30) | (2.14) |
| MOM12 | 0.290*** | 0.318*** | -0.003 | 0.033 | -0.168** | -0.117** | -0.134* | -0.116* |
| | (3.12) | (3.90) | (-0.04) | (0.49) | (-2.37) | (-1.96) | (-1.71) | (-1.77) |
| Turnover | | -0.003 | | -0.034 | | -0.014 | | -0.013 |
| | | (-0.04) | | (-0.43) | | (-0.17) | | (-0.16) |
| Idiosyncratic Vol | | -0.286*** | | -0.075 | | 0.006 | | 0.116 |
| | | (-2.67) | | (-0.64) | | (0.05) | | (1.02) |
| Share Issuance | | -0.169*** | | -0.178*** | | -0.181*** | | -0.158*** |
| | | (-5.48) | | (-5.14) | | (-5.00) | | (-4.53) |
| Forecast Revision | | 0.224*** | | -0.051 | | 0.062* | | 0.029 |
| | | (5.17) | | (-1.61) | | (1.90) | | (0.80) |
| *Adjusted* $R^2$ | 0.043 | 0.066 | 0.038 | 0.057 | 0.034 | 0.053 | 0.031 | 0.048 |

## Table 12
## Fund Herding and Future Fund Flows

This table presents coefficient estimates for the association between fund-level herding and future fund flows. All variables are described in Table 2. All independent variables are measured at the end of quarter *t*. The dependent variable is the net flow of a given fund during quarter *t+1*. Net flow is the growth rate of assets under management after adjusting for the appreciation of the fund's assets. Fund flows are winsorized at 0.05% and 99.95%. The regressions include fixed time effects and the standard errors are clustered by fund. The *t*-statistics are shown in parentheses. ***, **, * denote statistical significance at the 1%, 5%, and 10% level, respectively.

| | 1 | 2 |
|---|---|---|
| Fund Herding | -0.033** | -0.019 |
| | (-2.34) | (-1.58) |
| Log(TNA) | | -0.003*** |
| | | (-5.85) |
| Log(Age) | | -0.009*** |
| | | (-7.58) |
| Expense | | 0.131 |
| | | (0.60) |
| Turnover | | 0.002 |
| | | (0.99) |
| PastFlow | | 0.192*** |
| | | (11.13) |
| PastAlpha | | 5.758*** |
| | | (19.67) |
| *Adjusted* $R^2$ | 0.010 | 0.084 |
| *N* | 55,595 | 53,002 |

## Appendix

## Fund Herding and Future Performance: Removing Top and Bottom Deciles of Fund Herding

This table presents coefficient estimates from predictive panel regressions estimating the association between fund-level herding and future fund performance. Fund Herding (*FH*) is defined as the slope coefficient from cross-sectional regressions of mutual fund trades on past aggregate institutional trades measured in the past quarter, controlling for past stock returns, firm size, and the book-to-market ratio. These regressions are estimated per fund-quarter with both dependent and independent variables cross-sectionally standardized to have means of zero and standard deviations of one. We average these quarterly slope coefficients through a rank inverse-weighting scheme, assigning higher weights to more recent quarters. Future mutual fund performance is measured using Carhart (1997) four-factor alpha (both net and gross in monthly percentages), where factor loadings are estimated using rolling-window regressions in the past three years. The panel regressions control for fund size, fund age, expense ratio (in percent), fund turnover, fund percentage flow in the past quarter, and fund alpha (in percent) in the past three years. The regressions include fixed time effects and the standard errors are clustered by fund. We remove the top10% herding funds and the bottom 10% anti-herding funds from the regressions. The *t*-statistics are presented in parentheses. ***, **, * denote statistical significance at the 1%, 5%, and 10% level, respectively.

| | 4-factor Net α | | 4-factor Gross α | |
|---|---|---|---|---|
| | 1 | 2 | 1 | 2 |
| *FH* | -0.424*** | -0.487*** | -0.421*** | -0.485*** |
| | (-2.62) | (-2.94) | (-2.60) | (-2.92) |
| Log(TNA) | | -0.009** | | -0.010*** |
| | | (-2.31) | | (-2.68) |
| Log(Age) | | 0.018* | | 0.018** |
| | | (1.93) | | (2.01) |
| Expense | | -0.090*** | | -0.019 |
| | | (-5.12) | | (-1.07) |
| Turnover | | -0.022*** | | -0.022*** |
| | | (-3.01) | | (-2.91) |
| Past Flow | | 0.033* | | 0.030* |
| | | (1.77) | | (1.65) |
| Past Alpha | | 0.005 | | 0.002 |
| | | (0.20) | | (0.07) |
| *Adjusted* $R^2$ | 0.061 | 0.062 | 0.061 | 0.062 |
| *N* | 134,460 | 128,308 | 134,460 | 128,308 |

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# Does herding behavior reveal skill? An analysis of mutual fund performance

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