Best Predictors: Mutual Fund Specialization and Institutional Herding

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Abstract

This paper develops an empirical measure for a portfolio manager's informational advantage in trading an individual stock. Such a metric allows for the identification of each public company's *Best Predictors*: the decile of equity mutual funds with the strongest informational edge over the stock. Out-of-sample tests show that the aggregate behavior of a company's *Best Predictors* is a robust predictor of future abnormal returns on its stock. At the fund level, averaging a fund's informational advantage across all the stocks held into the fund's own portfolio yields a robust predictor for future fund performance and flow. These findings suggest a relevant degree of specialization amongst institutional investors: portfolio managers tend to specialize in (and become particularly good at) trading a small set of stocks. Also, when the average *Best Predictor* of a public firm buys (sells) its shares, such a move anticipates subsequent increases (decreases) in the stock's overall level of institutional ownership – suggesting that such specialization is known by the community of money managers and plays a central role in the formation of institutional herds.

1 Introduction

This paper documents evidence of the existence and persistence of mutual fund managers' ability to anticipate individual stocks' short-term returns. Using a comprehensive sample of active U.S. equity funds' holdings from 1997 to 2012, our analysis starts with the identification of each stock's *Best Predictors*: the subset of fund managers who display the strongest informational advantage towards a particular stock. Stocks heavily bought by their *Best Predictors* outperform stocks heavily sold by their *Best Predictors* by 0.176% per month (2.135% per year) on an equal weighted-basis, after adjustments for loadings on market, size, value, momentum, and liquidity factors. Nieuwerburgh and Veldkamp (2010) provide a theoretical explanation for this sort of specialization amongst portfolio managers by modeling the joint choice of a manager for asset-specific information acquisition and portfolio optimization. Our paper offers empirical support for some of their predictions and sheds light on an unexploited aspect of portfolio managers' stock-picking skills.

Also, the community of mutual fund managers seem to be (at least partially) aware of such cross-sectional differences in terms of funds' ability to make trading decisions on individual stocks. Changes in the level of ownership of a given stocks by its *Best Predictors* positively predict subsequent changes in the stock's overall level of institutional ownership (by the broader universe of 13F institutions). This finding suggests that such informational specialization might contribute to the formation of herds (Sias (2004), Dasgupta, Prat, and Verardo (2011a)).

At the fund level, we unveil a new dimension of mutual fund skill. Aggregating *Predictive Power* across all stocks held into a given fund's portfolio (weighted by their respective portfolio weights) provides a metric for the manager's average informational advantage in trading each of the very stocks she holds – we will refer to such a metric as a fund's *Trade Precision.* Out-of-sample tests show that the decile of mutual funds with the greatest *Trade Precision* outperforms the decile of funds with the lowest *Trade Precision* by 0.115% on a monthly basis (1.389% yearly) after adjusting for loadings on market, size, value, momentum, and liquidity factors. This performance gap is statistically and economically significant and lasts around 14 quarters. Through regression analysis, we find the connection between *Trade Precision* and future fund performance to be robust to the inclusion of other measures of mutual fund skill. These results demonstrate MF managers' superior ability to trade a particular subset of stocks and suggest that such managers are informed investors – even though their informational advantage seems to be concentrated in a small number of their holdings. The standard approach to measure portfolio managers' stock-picking skills oversees this aspect because managers let their portfolios grow and include stocks towards which they do not have a strong informational edge. This dynamic is well explained by Berk and Green (2004).

There is a fairly extensive body of research focused on the determinants of mutual funds' performance. Yet, most studies in this area have attempted to measure (and find the antecedents of) individual portfolio managers' skills in picking stocks and/or timing the market [1]. This paper departs from this traditional approach and takes the fund-stock dyad as the primary focus of analysis. The basic idea is that the same portfolio manager might have an informational edge towards a few stocks that allows her to outperform her peers when trading these very stocks. The same fund manager, however, might not display the same performance when trading stocks of other companies. A portfolio manager who is quite successful in anticipating the right time to buy (or to sell) shares of company ABC might make very poor calls about the prospects of investing in a different firm XYZ.

Recent empirical findings suggest that fund managers' ability to generate profits is enhanced when they focus on a specific subset of companies. For instance, Kacperczyk, Sialm, and Zheng (2005) show that funds that concentrate their trading activity into one industry tend to achieve superior performance. Also, funds place larger bets – and achieve superior performance – when they trade stocks of companies to which they are somehow connected through educational networks (Cohen, Frazzini, and Malloy (2008)) or geographical proximity (Coval and Moskowitz (2001)). Antón, Cohen, and Polk (2021) and Jiang, Verbeek, and Wang (2014) report evidence supporting the notion that active mutual funds invest only a small portion of their assets in high alpha stocks (their best investment ideas, stock towards which the portfolio manager is likely to possess some informational edge in comparison to other investors), but overdiversify in order to smooth their portfolio's overall volatility, price impact and liquidity risk. One potential explanation for all these empirical findings is that funds might specialize in – and then become comparatively better than their peers at – anticipating price moves of a small group of individual stocks, as opposed to the whole universe of public firms.

There are many potential explanations for differences in the same fund's predictive power over future short-term abnormal returns on different stocks. A portfolio manager might have

[1] See Fama and French (2010) for a great review of the vast literature on the existence of skill (as opposed to luck) in the cross-section of mutual fund managers. This debate can be traced back to Jensen (1968) and the very measurement of alphas.

acquired a deeper level of knowledge and familiarity with a specific firm than the average investor by many different reasons. For instance, it might be due to a long time of deep and diligent research focused on a specific industry or company [2] – or even on the typical ways investors react to corporate announcements. Alternatively, the manager could have a social tie to one (or more) insider(s) (Cohen et al. (2008)). Another less likely possibility is that the fund manager him/herself might have worked at the company (or with a competitor, supplier or client) in the past, which yields him/her knowledge about reliable informational sources and/or a more accurate assessment of the impact of specific news on company fundamentals, for example. Regardless of the source of such an informational edge, it is likely to persist over the course of some months, quarters, or perhaps even years. We exploit the hypothesis that such informational edges not only exist and have some persistence, but also that such specialization might be (at least partially) known by the community of mutual fund managers.

The identification of individual stocks' *Best Predictors* allows for another interesting test. We ask whether the larger crowd of 13F institutions deliberately follow the moves of those portfolio managers regarded as the *Best Predictors* of each stock individually. We do so by regressing changes in the level of institutional ownership of a given stock (measured as the percentage of its shares outstanding held by 13F institutions) on the average behavior of the stock's very own *Best Predictors* over the preceding quarter and year. We find that an increase (decrease) in the average number of shares held by a stock's *Best Predictors* is followed by a subsequent increase (decrease) in the stock's overall level of Institutional Ownership over the next quarter and year. The robustness of this relationship suggests that the community of portfolio managers is somehow aware of this specialization amongst mutual fund managers. In fact, managers seem to mimic the behavior of each stock's very own *Best Predictors* – buying or selling individual stocks after their respective *Best Predictors* do so.

In summary, evidence collected and documented in this paper reveals that institutional investors display substantial cross-sectional differences in their levels of expertise in trading the average individual stock. This variability has important consequences for the cross-section of mutual fund returns, for the predictability of short-term stock returns and for the formation of institutional herds amongst mutual fund managers.

The remaining of this paper is organized as follows. Section 2 describes the nature and

[2] The usual structure of buy-side research into the asset management industry induces industry and firm specialization on the part of the analysts.

sources of the data used in our empirical analysis. Section 3 describes the procedure we employ in order to measure a fund's informational edge towards an individual stock. This metric is the main building block of our empirical analysis. At the stock level, we use it to find each stock's *Best Predictors* (the top decile o funds with the greatest level of *Predictive Power*). At the fund level, we use it to estimate a fund's *Trade Precision* (as the fund's *Predictie Power* averaged across all stocks into the fund's own portfolio). In section 4 we use cross-sectional differences in funds' *Trade Precision* to predict future fund performance. In section 5 we relate funds' *Trade Precision* to several fund characteristics and to other measures of mutual funds' stock picking skills. In section 6, we document evidence of time persistence in the performance gap between the top and bottom deciles of funds ranked by *Trade Precision.* In section 7, we show that *Trade Precision*'s predictive power over future performance of individual mutual is robust to the inclusion of controls for several relevant fund characteristics and for other measures of mutual funds' skills. Section 8 brings the level of analysis to the stock level and documents that changes in the levels of ownership of a stock by its *Best Predictors* (the top decile of funds with the greatest *Predictive Power* over the stock) anticipates changes in the stock's total ownership by the broader set of 13F institutions – highlighting that specialization might lead to the formation of herds among institutional investors. Section 9 documents that stocks more heavily bought (sold) by its own *Best Predictors* outperform (underperform) other stocks. Section 10 concludes the paper.

2 Data

Our sample consists of all actively managed U.S. equity funds from 1997 to 2012. Data on stock prices, returns, shares outstanding and turnover comes from the Center for Research on Security Prices' (CRSP) monthly and daily files. Data on mutual fund returns, assets under management, expenses ratio, turnover ratio and other fund characteristics come from CRSP mutual funds database. Data on mutual fund holdings comes from Thomson Reuters' CDA/Spectrum. Since we intenct to capture active mutual funds that invest primarily in U.S. equities, we exclude index funds from our sample. We then follow Kacperczyk, Sialm, and Zheng (2008) and eliminate balanced, bond, money market, sector, and international funds. We also exlude funds with any of the following investment objectives as provided by Thomson Reuters: 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. Our sample starts in 1997 due to scarcity of fund-stock dyads with frequent data on fund holdings[3]. In order to address the incubation bias documented by Elton, Gruber, and Blake (2001) and Evans (2010), we further exclude observations prior to the reported fund inception date, and funds whose net assets fall below $5 million. After all the cleaning, we get a final sample with 2,417 distinct mutual funds.

Table 1 reports descriptive statistics for some funds characteristis. An average fund in our sample manages $1.3 billion dollars, is 14 years old, has an annual expense ratio equal to 1.29%, an annual turnover ratio equal to 87%, achieves an average net return of 1.94% per quarter (7.98% per year) and attracts 4.32% in net money flow per quarter. These numbers are failry close to those typically reported in the empirical literature on actively managed equity mutual funds.

[Insert table 1 around here]

3 Predictive Power

We define the $Preditive\ Power_{i,j,t}$ of fund j over stock i at quarter t as the level of skill with which the fund's portfolio manager is able to predict the stock's future short-term abnormal returns. This measure has important characteristics worth highlighting. First, it is defined at the fund-stock dyad level. This contrasts with the most common perspective into the literature on stock-picking skills (which is to center on fund-level measures). This allows us to draw conclusions for both the stock and the fund's future performance. Second, it is a dynamic measure allowing for time-variation in a portfolio manager's informational edge towards a given stock – while there is some continuation in such an informational advantage, it is likely to display relevant shifts over longer periods of time.

Empirically, we can measure a portfolio manager's informational advantage towards an individual stock by computing the intertemporal correlation across two hidden variables: (1) shifts in the funds' preferences for the stock, and (2) subsequent abnormal returns on the stock. Unfortunately, we cannot directly observe the funds' preference shifts. We argue, though, that

[3] For the computation of our measure for a fund's *Predictive Power* over the future abnormal returns on an individual stock, we require at least three observation for the funds' holdings on the stock over the last four quarters. The number of stock-fund dyads that satisfy this condition per quarter dramatically increases after the late 1990's.

a good proxy for such preference changes can be obtained by observing changes in portfolio weights given to the stock. But we do need to control for the fund's preferences related to style. In order to do so, we run the regression described in equation 1 for each quarter-fund. We interpret the residuals of this regression as a component of the fund's preference for the stock that cannot be explained away by the manager's preference for (or against) momentum, small, or value stocks. Additionally, we include a control for changes in the stock's overall level of institutional ownership as a way to control for the fund's tendency to herd and follow other institutional investors (Sias (2004), Dasgupta, Prat, and Verardo (2011b), Jiang and Verardo (2018)). Finally, we use these residuals to rank stocks into deciles ranging from the more heavily purchased (the most preferred stocks) to the more heavily sold (the least preferred ones) by the fund. Accordingly, $rank(UnexplainedTrade_{i,j,t})$ assumes a value ranging from one to ten according to this ranking system. This is our main metric for a fund's inclination to increase its exposition to a stock, regardless of its style-related preferences and its herding inclination.

$$\begin{aligned} \Delta PortfolioWeight_{i,j,t} = \alpha_{j,t} + \delta 1_{j,t} * MC_{i,t-1} + \delta 2_{j,t} * BM_{i,t-1} + \delta 3_{j,t} * Mom_{i,t-1} + \\ + \delta 4_{j,t} * \Delta IO_{i,t} + \delta 5_{j,t} * \Delta IO_{i,t-1} + \varepsilon_{i,j,t} \end{aligned} \tag{1}$$

The dependent variable in equation 1 is the change in the weight of stock i into the portfolio of fund j over quarter t: $\Delta PortfolioWeight_{i,j,t} = (Shares_{i,j,t} * StockPrice_{i,t})/TotalAssets_{j,t}$- $(Shares_{i,j,(t-1)} * StockPrice_{i,(t-1)})/TotalAssets_{j,(t-1)}$. The independent variables are the natural log of the market capitalization of stock i at the end of quarter $(t-1)$, $MC_{i,t-1}$; the log of book-to-market ratio of stock i at the end of quarter $(t-1)$, $BM_{i,t-1}$; the cumulated return on stock i measured over quarter $(t-1)$, $Mom_{i,t-1}$; and the changes in the percentage of the outstanding shares of stock i held by the aggregate portfolio of all 13F Institutions over the current quarter t, $\Delta IO_{i,t}$, and over the previous quarter, $\Delta IO_{i,(t-1)}$. All the independent variables are intended to capture fund preferences for specific stock features and styles, as well as the fund's tendency to trade in the same direction as other institutions. Therefore, the residuals of these regressions represent a component of the fund's willingness to increase (or to decrease) its exposure to a stock that cannot be attributed to such preferences. Also, the choice to use changes in portfolio weights as opposed to percentage changes in the number of split-adjusted shares held by the fund rules out the need to otherwise account for the effect of fund flows on its trades. For example, if a manager is keeping constant the number of split-adjusted shares of a company held in its portfolio in face of fund outflows, such behavior tells us something about her preferences for that stock – she is in fact resisting to liquidate such a position even under the need to liquidate some of the funds' assets to allow for fund investors' redemptions (Alexander, Cici, and Gibson (2007)).

Our next step is to use Carhart (1997)'s four-factor model to find abnormal returns on individual stocks. We run intra-quarter regressions for daily returns on individual stocks, and then compute cumulative abnormal return for the whole quarter: $CAR_{i,t}$. We sort and rank stocks according to their $CAR_{i,t}$ into ten deciles: from the winners (the ten percent stocks with the greatest $CAR_{i,t}$) to the losers (the ten percent stocks with the worse $CAR_{i,t}$). Therefore, we have a variable $rank(CAR_{i,t})$ for each stock-quarter that ranges from one to ten according to the component of the cumulative return on the stock that cannot be explained by its loading on market, size, value and momentum factors.

Finally, for each stock-fund-quarter, we define the fund's $Predictive\ Power_{i,j,t}$ over the stock's performance in the near future as the correlation across $rank(UnexplainedTrade_{i,j,t})$ and $rank(CAR_{i,t})$ computed over the last four quarters – ranging from $(t-4)$ to $(t-1)$[4].

$$\begin{aligned} &PredictivePower_{i,j,t} = \\ &\qquad correlation(rank(\Delta PortfolioWeight_{i,j,\tau}), rank(CAR_{i,(\tau+1)})) \qquad (2) \\ &\qquad \tau = (t-4), ..., (t-1) \end{aligned}$$

By computing the intertemporal correlations across ranks for a funds' portfolio shifts towards a stock and the stock's subsequent abnormal returns, we capture the degree of accuracy with which such a fund has been able to predict the performance of the stock over the last year. A higher level of $Predictive\ Power_{i,j,t}$ is an indication that fund j has been very skillful in adjusting her portfolio in aticipation of abnormal performance of the stock i in the recent past. In turn, we claim that this imlpy a likely informational edge over other institutions regarding factors specifically important for predicting returns on stock i. Such an advantage has many potential causes: she might have researched the company comparatively better than her peers; she might have social ties to one or more insiders – allowing for greater and/or faster access to firm-specific information; she might even have worked in the company in the past – or with a

[4]We exclude any observation for which we have less than three data points (out of the last four quarters) in order to compute this corrleation

close customer, competitor or supplier; etc. Regardless of the source of such an informational advantage, its existence might have sensible consequences – for both the company and the fund – that will be further explored in the next sections.

4 Predicting Fund Performance

In this section we turn our focus to consequences of *Predictive Power* for future mutual fund performance. Aggregating a fund's *Predictive Power* across all stocks held in its own portfolio allows us to have a measure for the portfolio manager's average informational edge over the very stock she holds. See equation 3.

$$TradePrecision_{j,t} = \sum_{i=1}^{I}(PredictivePower_{i,j,t} * PortfoltioWeight_{i,j,t}) \tag{3}$$

Through this aggregation, we develop a fund-level measure that can be used to predict future mutual fund perfomance. Table 2 presents summary statistics for $Trade\ Precision_{j,t}$.

[Insert table 2 around here]

Using cross-sectional differences in funds' $Trade\ Precision_{j,t}$, we study its effects on fund performance. We examine both net and gross returns – which add back fees and expenses. We start from univariate portfolio tests. At the end of each quarter, we sort mutual funds into ten portfolios based on $TradePrecision_{j,t}$. We then compute equally weighted returns for each decile over the subsequent quarter. W ealso 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 Pastor and Stambaugh (2003). Table 3 presents results.

[Insert table 3 around here]

Funds in the top (bottom) decile of Table 3 exhibit the greatest (lowest) levels of *Trade Precision.* Fund returns are measured in each month of quarter $(t + 1)$. The panel for net returns shows that, in the quarter following portfolio formation, funds in the top decile of *Trade Precision* outperform the funds in the bottom decile by 11.7 bps per month, which implies a return differential of 1.41% per year. The performance differential between funds into the top and bottom deciles of *Trade Precision* cannot be attributed to differences in risk loadings or investment styles, as the differences in alphas from the CAPM, Fama and French (1993), Carhart (1997), and Pastor and Stambaugh (2003) models are 11.9, 10.6, 10.6 and 11.5 bps per month respectively, all statistically significant. If we consider gross fund returns, results point in the same direction: funds in the top *Trade Precision* decile strongly outperform their peers in the bottom *Trade Precision* decile. Overall, the performance differential between funds in the top and bottom deciles ranges between 1.28% and 1.44% on an annualized basis.

This evidence shows that cross-sectional differences in *Trade Precision* can significantly predict differences in mutual fund performance, which suggests that *Trade Precision* is informative about mutual fund skill. The performance differential between funds in the top and bottom deciles of *Trade Precision* is economically important, especially when considered in light of existing evidence on cross-sectional dispersion in mutual fund performance.

5 Trade Precision and Other Measures of Mutual Fund Skill

In this section, we investigate the relation between funds' *Trade Precision* and several fund characteristics. Table 4 reports the results of regressions that have *Trade Precision* as the dependent variable. The first column presents coefficient estimates from a cross-sectional regression of *Trade Precision* on fund size, age, expense ratio, turnover, net flows, and performance (measured by a fund's Fama-French alpha estimated over the previous three years). Results show that none of the variables tested is a statistically significant antecedent of *Trade Precision.* In the second specification, we include two other measures that have been shown to capture dimensions of stock picking skill. First, Cremers and Petajisto (2009) show that funds with higher degrees of active share – whose portfolios overlap less with their benchmarks – outperform their peers. Second, Cohen, Coval, and Pastor (2005) show that funds whose portfolio holdings resemble the holdings of funds with the greatest performance record in the past tend to outperform. There is no statistically significant association between none of these skill measures and *Trade Precision.* Indeed, it seems that *Trade Precision* captures a different dimension of managerial stock picking ability.

[Insert table 4 around here]

6 Persistence in Mutual Fund Performance Differences

We also test for persistence in the return differential between funds in the top and bottom deciles of *Trade Precision.* Tables 5 and 6 present statistics for the return gap when the holding period (after portfolio formation) is enhanced from one through sixteen quarters.

[Insert table 5 around here]

[Insert table 6 around here]

The return differential persists over the course of many quarters and is statistically significant up to the fourteenth quarter after portfolio formation. Such a lasting difference indicates that the performance gap is likely due to relatively stable differences across funds. Also, figure 1 shows the behavior of such performance defferences (in gross and net returns) as it slowly dissipates over time.

[Insert Figure 1 around here]

7 Predicting Mutual Fund Performance With Regressions

In this section, we link cross-sectional differences in mutual funds' $Trade\ Precision_{j,t}$ to subsequent fund performance. We regress individual fund performance (measured by Carhart (1997)'s four-factor alphas for individual fund returns) on funds' level of *Trade Precision*, measured in the previous quarter. We control for several relevant fund characteristics and for two measures of mutual funds' portfolio management skills: *Active Share* (Cremers and Petajisto (2009)) and *Similarity* (Cohen et al. (2005)). Table 7 reports the main results of these regressions.

[Insert table 7 around here]

Thsi evidence shows a strong and statistically significant relationship between *Trade Precision* and future fund performance (measured by both net and gross fund returns), which is consistent with the notion that *Trade Precision* captures some degree of the fund manager's average informational edge towards the very stocks she holds. Also, the statistical significance of this association is robust to the inclusion of controls for other measures of stock-picking skills. This suggests that *Trade Precision* captures a different dimension of such skill by portfolio managers.

8 Guiding Other Institutions

In this section, we consider the possibility of a gradual information acquisition framework. Investors who acquire information earlier than others – which is likely the case of money managers that have superior *Predictive Power* over the performance of individual stocks – might be followed by others, and then unwinding their positions when the trades of the broader range of investors move prices to more fully reflect information about fundamental values (Froot, Scharfstein, and Stein (1992), and Hirshleifer, Subrahmanyam, and Titman (1994)). An implication of this theoretical construction is that the *Best Predictors* of the behavior of a given stock might anticipate the trades of the broader crowd of 13F Institutions.

In order to empirically test this prediction, we define the group of *Best Predictors* for the performance of a given stock over quarter $(t + 1)$ as the top decile of funds with the greatest *Predictive Power* over the stock, as measured over quarter t. In turn, we define $OwnershipbyBestPredictors_{i,t}$ as the percentage of outstanding shares of stock i held by its *Best Predictors*. We then use panel data to regress changes in $InstitutionalOwnership$ – defined as the percentage of total outstanding shares of company i held by the aggregate portfolio of all 13F institutions – during quarter $(t+1)$ and from quarter $(t+1)$ through quarter $(t+4)$ on changes in $OwnershipbyBestPredictors_{i,t}$. We control for size, book-to-market, and momentum at the end of quarter t. We also control for the change in the level of *Institutional Ownership* for the stock over quarter t. Results presented in table 8 show a statistically significant association between $OwnershipbyBestPredictors_{i,t}$ and $InstitutionalOwnership_{i,(t+1)}$.

$$\begin{aligned} \Delta IO_{i,(t+1)} = \alpha + \Delta OwnershipbyBestPredictors_{i,t} + \\ + \delta 1 * MC_{i,t} + \delta 2 * BM_{i,t} + \delta 3 * Mom_{i,t} + \delta 4_{j,t} * \Delta IO_{i,t} + \varepsilon_{i,j,t} \end{aligned} \tag{4}$$

Table 8 presents results for these regressions. It can be observed that increases (decreases) in ownership by individual stocks' *Best Predictors* lead to increases (decreases) in institutional ownership by the larger crowd of 13F Institutions. These are statistically significant effects.

[Insert table 8 around here]

These results might help explain the formation of herds amongst mutual funds. If the community of money managers is aware of cross-sectional differences in terms of funds' ability to anticipate the performance of individual stocks, they might deliberatively decide to follow the moves of each stock's very own *Best Predictors*.

9 Stock Returns

Another important test for the existence of an actual informational advantage displayed by some funds about the prospects of investing in a given firm is to check whether stocks actually offer superior (inferior) returns after their *Best Predictors* collectively buy (sell) their shares. This is the main test we conduct in this section.

Each quarter, we sort stocks according to the average trade of its *Best Predictors*. We follow Jiang and Verardo (2018) and define $Trade_{i,j,t}$ as the percentage change in the number of split-adjusted shares of stock i held by fund j over quarter t. We choose to use the average $Trade_{i,j,t}$ by a stock's *Best Predictors* as opposed to the change in the level of $OwnershipbyBestPredictors_{i,t}$ to avoid the problem of dealing with differences in terms of fund size amongst the *Best Predictors*. Computing the average $Trade$ across all funds considered to be a stock's *Best Predictor* allows us to give the same importance for each of these fund's signal (in terms of increasing or decreasing the share of their AUM given to the stock), whereas using the overall level of ownerhip by a stock's *Best Predictors* would give more importance to the largest funds. Indeed, by forming stock quintiles based on the average $Trade$ by each individual stock's *Best Predictors*, we find statistically significant differences in terms of future stock returns (and alphas). Again, we use 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 Pastor and Stambaugh (2003). Table 9 presents results for this analysis based on stock quintiles.

[Insert table 9 around here]

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Results displayed in table 9 show that, in the quarter following portfolio formation, stocks more heavily bought by their respective *Best Predictors* outperform those more heavily sold by their *Best Predictors* by 16.3 bps per month, which implies a return differential of 1.97% per year. These differences in performance cannot be attributed to differences in stocks' risk loadings, as the differences in alphas from the CAPM, Fama and French (1993), Carhart (1997), and Pastor and Stambaugh (2003) models are equal to 14.0, 13.1, 18.4 and 17.6 bps per month respectively, all statistically significant. These findings are consistent with the existence of informational edges that persist over time. Mutual funds managers who have been able to accurately predict the behavior of an individual stock in the recent past are likely to continue doing so in the near future.

10 Conclusion

The most common approach in the empirical literature on mutual funds' performance focuses on identifying (and looking for antecedents of) fund level measures of stock picking skills. Few studies take into consideration that the same portfolio manager might have (and often does have) substantially different degrees of proficiency when it comes to trading two different stocks. A fund that consistently buys (sells) stocks of a fixed company in anticipation of a price rise (fall) might make substantially poorer trading decisions regarding stocks of other public companies. This paper takes the fund-stock dyad as the central focus of its analysis and builds an empirical dynamic measure for an institution's informational edge towards a given stock. Such a perspective allows us to derive important consequences for implications for individual stocks, for mutual fund managers, and for the broader community of professional money managers.

A fund's superior ability to generate positive performance when trading the stocks of a given company has many potential causes. It could derive from a deep understanding of the business (due to a diligent research on the industry and/or company fundamentals), or from a close connection to an insider, for instance. Regardless of its source, however, such a comparative informational edge is likely to persist over the course of some months, quarters, or even years.

To develop a way to measure a portfolio manager's informational edge towards a given stock, we start by estimating funds dynamic stock preferences. For each fund-quarter, we sort stocks according to their change in portfolio weight. We then independently rank individual stocks according their five-factors abnormal returns over the subsequent quarter. The correlation across these two rankings (measured over four-quarter rolling windows) yields our dynamic measure for a portfolio managers *Predictive Power* towards an individual stock.

At the stock level, we are able to identify some mutual fund managers (to which we refer as the stock's *Best Predictors*) that display a specially accurate capacity to trade the stock – buying (selling) shares in anticipation of positive (negative) abnormal returns. Out-of-sample tests then show that increases (decreases) in demand for the stock by its own *Best Predictors* predict superior (inferior) stock performance in the future. Also, increases (decreases) in the ownership of a stock by its own *Best Predictors* are followed by subsequent increases (decreases) in its overall institutional ownership by the whole universe of 13F institutions over the next year.

At the fund level, we are able to compute a fund's average *Predictive Power* towards the stocks held in its own portfolio (weighted by their respective portfolio weights). This yields a measure of the funds' average ability to predict future abnormal returns on the stocks it is invested in: the fund's *Trade Precision*. Out-of-sample tests show that *Trade Precision* turns out to be a robust predictor of future mutual fund performance and flow. The return gap between funds into the top and bottom deciles of *Trade Precisions* is statistically and economically significant, and lasts over 14 quarters. Also, *Trade Precisions* is unrelated to other fund characteristics (such as fund size, expense ratio or age) and its predictive power over future fund returns is robust to controls for other measures of stock picking skills.

The evidence reported in this study shows that the average equity mutual fund displays a relevant level of specialization in trading some stocks particularly well (as opposed to researching the whole universe of public companies). Yet, fund managers let their assets grow by including stocks towards which they have no strong informational advantage – a dynamic fully consistent with and very well explained theoretically by Berk and Green (2004). Finally, portfolio managers seem to be well aware of such specializations: they actually mimic the buying and selling decisions undertaken by each individual stock's own *Best Predictors* – which in turn contributes to the formation of herds amongst institutional investors.

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Table 1. Summary Statistics for Fund Characteristics.

This table presents descriptive statistics for the sample of actively managed mutual funds analyzed in this paper. The sample consists of 2,417 distinct mutual funds over the period 1997 to 2012. Fund Size is quarter-end total net fund assets in millions of dollars; Fund Age is the number of years a fund is present in the CRSP mutual fund database; Expense is the fund's 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.

Fund Characteristics								
Variable	**Obs**	**Mean**	**SD**	**Pctl 5**	**Pctl 25**	**Pctl 50**	**Pctl 75**	**Pctl 95**
Fund Size	52,826	1316.42	4527.61	20.1	88.22	280.6	925.0	4967.3
Fund Age	52,826	13.63	10.17	3.08	65.00	10.67	17.25	37.67
Expense Ratio (%)	49,024	1.294	0.435	0.69	1.00	1.24	1.53	2.05
Turnover (%)	48,095	86.961	100.022	12.0	36.1	65.0	110.0	218.0
Quarterly Flow (%)	52,826	0.432	23.873	-12.784	-5.044	-1.794	2.326	18.842
Quarterly Return (%)	52,826	1.937	10.776	-18.470	-3.441	3.061	8.487	17.504

Table 2. Summary Statistics for Trade Precision.

This table presents descriptive statistics for the sample of actively managed mutual funds analyzed in this paper. The sample consists of 2,147 distinct mutual funds over the period 1997 to 2012. For fund j and stock i at quarter t, $PredictivePower_{i,j,t}$ is computed as the correlation across two different ranks in which stock i is classified. First, for each of the last four quarters, stocks are sorted according to the unexplained component of the net change in portfolio weight (this unexpected component is estimated as the residual of a regression in which the portfolio change is the dependent variable and independent variables include stock size, momentum, book-to-market ratio and changes in institutional ownership over the current and the previous one). Second, stocks are independently sorted according to their cumulated abnormal returns over each of the quarters subsequent to the portfolio changes (using Carhart (1997)). The correlation across the positions of stock i in each of these two rankings provides the estimation of $PredictivePower_{i,j,t}$. At the fund level, the overal $TradePrecision_{j,t}$ is defined as the weighted average of its $PredictivePower_{i,j,t}$ over each of the stocks held in its own portfolio – weighted by portfolio weights.

Panel A: Trade Precision (Cross-sectional statistics averaged over time)

Variable	Quarters	Mean	SD	Pctl 5	Pctl 25	Pctl 50	Pctl 75	Pctl 95
Trade Precision (%)	61	-0.11	3.04	-5.34	-1.89	-0.08	1.69	5.05

Panel B: Trade Precision (Time-series statistics averaged across funds)

Variable	Funds	Mean	SD	Pctl 5	Pctl 25	Pctl 50	Pctl 75	Pctl 95
Trade Precision (%)	2,417	-0.17	2.61	-4.18	-1.90	-0.17	1.56	3.81

Table 3. Funds' Trade Precision and Future Performance: Portfolios.

This table presents the performance of decile portfolios formed based on $TradePrecision_{j,t}$, which is the average $PredictivePower_{i,j,t}$ a fund has over each stock included in its own portfolio (weighted by portfolio weights). In turn, the $PredictivePower_{i,j,t}$ of fund j over stock i at quarter t is computed as the intertemporal correlation (calculated from $(t-4)$ through $(t-1)$) across the cross-sectional rank for the cumulated abnormal return on stock i (using the four-factor model of Carhart (1997)) and the cross-sectional rank for the unexplained component of the change in weight of stock i on the portfolio of fund j over the previous quarter – stocks size, book-to-market ratio, momentum and changes in institutional ownership are used as independent variables in such regressions. The decile portfolios are formed at the end of each quarter from 1996Q4 to 2012Q1 and held for one quarter. The resulting monthly return series span from January 1997 to June 2012. Decile 10 is the portfolio of funds with the highest $TradePrecision_{j,t}$. I compute equally weighted net and gross (net plus expense ratio) returns on the portfolios, as well as risk-adjusted returns based on the CAPM, Fama and French (1993)'s four-factor model (FF), and Pastor and Stambaugh (2003) five-factor model (PS). I report average returns and alphas in monthly percentages. Newey and West (1987)'s t-statistics are shown in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively, for the return differentials between deciles 1 and 10.

Panel A: Gross Return											
Portfolio	**D1**	**D2**	**D3**	**D4**	**D5**	**D6**	**D7**	**D8**	**D9**	**D10**	**(D10-D1)**
Average	0.444	0.490	0.479	0.473	0.449	0.491	0.509	0.530	0.547	0.561	0.117**
	(1.267)	(1.344)	(1.294)	(1.228)	(1.152)	(1.265)	(1.323)	(1.429)	(1.495)	(1.602)	(2.279)
CAPM	0.070	0.098	0.080	0.057	0.031	0.077	0.096	0.131	0.153**	0.188**	0.119**
	(0.822)	(1.258)	(1.047)	(0.752)	(0.352)	(0.796)	(1.137)	(1.634)	(2.017)	(2.101)	(2.301)
FF	-0.007	0.027	0.011	-0.002	-0.033	0.005	0.028	0.056	0.083	0.099	0.106**
	(-.106)	(0.401)	(0.178)	(-.042)	(-.544)	(0.075)	(0.472)	(0.888)	(1.281)	(1.470)	(2.100)
Carhart	0.015	0.039	0.025	-0.009	-0.040	-0.009	0.016	0.060	0.104	0.121*	0.106**
	(0.219)	(0.585)	(0.394)	(-.151)	(-.637)	(-.127)	(0.273)	(0.952)	(1.623)	(1.819)	(2.067)
PS	-0.041	-0.001	-0.018	-0.047	-0.065	-0.041	-0.012	0.028	0.070	0.074	0.115**
	(-.610)	(-.009)	(-.292)	(-.796)	(-1.05)	(-.586)	(-.200)	(0.441)	(1.092)	(1.126)	(2.202)
Panel B: Net Return											
Portfolio	**D1**	**D2**	**D3**	**D4**	**D5**	**D6**	**D7**	**D8**	**D9**	**D10**	**(D10-D1)**
Average	0.345	0.391	0.380	0.372	0.348	0.389	0.407	0.429	0.447	0.462	0.117**
	(0.984)	(1.070)	(1.024)	(0.967)	(0.893)	(1.004)	(1.058)	(1.157)	(1.222)	(1.319)	(2.277)
CAPM	-0.030	-0.002	-0.020	-0.043	-0.070	-0.024	-0.006	0.030	0.053	0.089	0.119**
	(-.349)	(-.026)	(-.256)	(-.571)	(-.811)	(-.246)	(-.076)	(0.380)	(0.702)	(0.995)	(2.299)
FF	-0.106	-0.073	-0.088	-0.102*	-0.134**	-0.096	-0.073	-0.045	-0.016	-0.000	0.106**
	(-1.52)	(-1.09)	(-1.39)	(-1.73)	(-2.18)	(-1.39)	(-1.24)	(-.713)	(-.252)	(-.002)	(2.098)
Carhart	-0.084	-0.060	-0.074	-0.109*	-0.140**	-0.109	-0.085	-0.040	0.005	0.022	0.106**
	(-1.21)	(-.904)	(-1.17)	(-1.83)	(-2.26)	(-1.59)	(-1.43)	(-.633)	(0.073)	(0.330)	(2.067)
PS	-0.139**	-0.099	-0.117*	-0.146**	-0.165***	-0.140**	-0.112*	-0.071	-0.029	-0.024	0.115**
	(-2.07)	(-1.49)	(-1.86)	(-2.47)	(-2.64)	(-2.03)	(-1.88)	(-1.13)	(-.445)	(-.375)	(2.204)

Table 4. Funds' Trade Precision and Fund Characteristics.

This table shows the estimated coefficients from panel regressions of $TradePrecision_{j,t}$ on fund characteristics. $TradePrecision_{j,t}$ is the average $PredictivePower_{i,j,t}$ a fund has over each stock included in its own portfolio (weighted by portfolio weights). In turn, the $PredictivePower_{i,j,t}$ of fund j over stock i at quarter t is computed as the intertemporal correlation (calculated from $(t-4)$ through $(t-1)$) across the cross-sectional rank for the cumulated abnormal return on stock i (using the four-factor model of Carhart (1997) and the cross-sectional rank for the unexplained component of the change in weight of stock i on the portfolio of fund j over the previous quarter – stocks size, book-to-market ratio, momentum and changes in institutional ownership are used as independent variables in such regressions. Fund Size is the natural log of the quarter-end total net fund assets; Fund Age is the natural log of fund age in years; Expense Ratio is the fund expense ratio; Turnover is the turnover ratio of the fund; Quarterly Flow is the fund flow in the previous quarter; Alpha is the fund's four-factor alpha estimated over the previous three years; Active Share (AS) is the share of a fund's holdings that differ from the benchmark index holdings, as in Cremers and Petajisto (2009); and Fund Similarity is the degree to which a fund's investment decisions resemble those of successful funds, as in Cohen et al. (2005). Regressions include time fixed effects and the standard errors are clustered by fund. t-statistics are shown in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Determinants of Funds' Trade Precision		
Model	**(1)**	**(2)**
Intercept	0.000	0.000
	(-0.718)	(-0.082)
Fund Age	0.000	0.000
	(-0.751)	(-0.408)
Fund Alpha	0.002	0.109
	(0.568)	(0.311)
Expense Ratio	-0.064	0.025
	(1.005)	(0.316)
Fund Size	0.000	0.000
	(1.075)	(0.920)
Quarterly Flow	0.000	0.000
	(-0.184)	(0.570)
Turnover Ratio	0.000	0.001*
	(0.774)	(1.673)
Fund Similarity		0.019
		(1.065)
Active Share		-0.003
		(-1.501)
Degrees of Freedom	2,347	1,807

Table 5. Persistence in the Return Gap. Gross Returns.

This table presents long-term differences in performance between funds in the top and bottom deciles of Trade Precision. Mutual funds are sorted into 10 portfolios based on Trade Precision, as described in table 3. The return series span January 1997 to June 2012. The holding period for each portfolio, indicated by K, varies from one to 16 quarters. The table reports differences in returns between Decile 10 (highest Trade Precision) and Decile 1 (lowest Trade Precision). I compute monthly equally-weighted gross returns (net plus expense ratio) on the portfolios, as well as risk-adjusted returns based on the CAPM, the Fama and French (1993) (FF) three-factor model, the Carhart (1997) four-factor model, and the Pastor and Stambaugh (2003) (PS) five-factor model. Returns and alphas are in monthly percentages. Newey and West (1987)'s t-statistics are shown in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	Gross Returns														
Holding Period	**K=2**	**K=3**	**K=4**	**K=5**	**K=6**	**K=7**	**K=8**	**K=9**	**K=10**	**K=11**	**K=12**	**K=13**	**K=14**	**K=15**	**K=16**
Average	0.097**	0.087**	0.101***	0.087***	0.076**	0.079***	0.076***	0.068**	0.073***	0.070***	0.061**	0.056**	0.047**	0.034	0.027
	(2.467)	(2.432)	(2.863)	(2.679)	(2.491)	(2.680)	(2.661)	(2.462)	(2.741)	(2.723)	(2.432)	(2.344)	(2.030)	(1.487)	(1.200)
CAPM	0.101**	0.089**	0.102***	0.086***	0.073**	0.074**	0.069**	0.062**	0.067**	0.064**	0.056**	0.051**	0.042*	0.028	0.021
	(2.572)	(2.462)	(2.861)	(2.638)	(2.396)	(2.522)	(2.464)	(2.261)	(2.541)	(2.525)	(2.233)	(2.137)	(1.823)	(1.252)	(0.945)
FF	0.082**	0.073**	0.089**	0.074**	0.063**	0.068**	0.065**	0.058**	0.065**	0.065**	0.056**	0.052**	0.042*	0.029	0.023
	(2.162)	(2.068)	(2.521)	(2.291)	(2.092)	(2.290)	(2.289)	(2.103)	(2.452)	(2.516)	(2.242)	(2.158)	(1.846)	(1.326)	(1.069)
Carhart	0.078**	0.061*	0.073**	0.056*	0.045	0.050*	0.048*	0.043	0.052**	0.052**	0.044*	0.038*	0.029	0.017	0.011
	(2.039)	(1.764)	(2.134)	(1.821)	(1.579)	(1.801)	(1.800)	(1.636)	(2.032)	(2.091)	(1.803)	(1.680)	(1.321)	(0.814)	(0.529)
PS	0.087**	0.072**	0.088**	0.071**	0.062**	0.068**	0.067**	0.061**	0.069***	0.065***	0.056**	0.051**	0.038*	0.026	0.018
	(2.230)	(2.052)	(2.549)	(2.310)	(2.180)	(2.481)	(2.547)	(2.357)	(2.698)	(2.622)	(2.300)	(2.230)	(1.754)	(1.221)	(0.880)

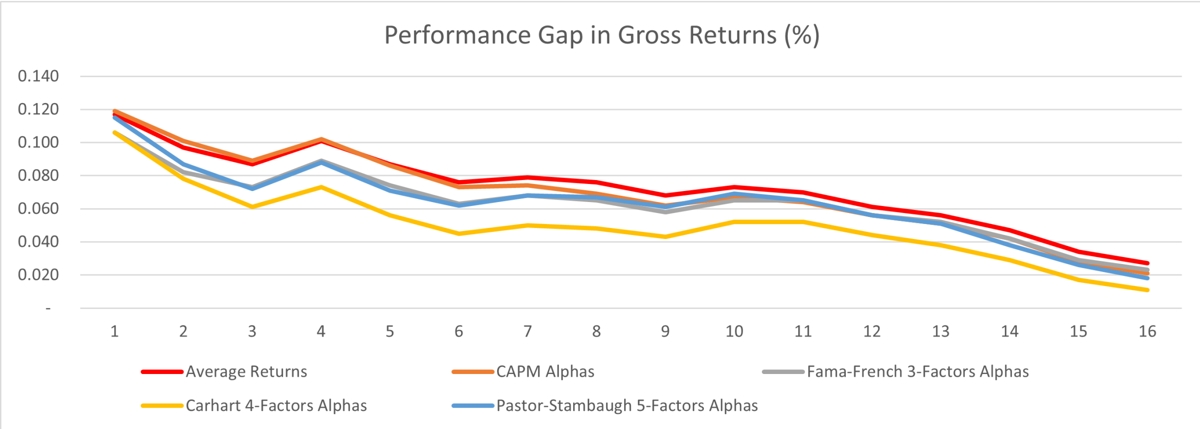
Table 6. Persistence in the Return Gap. Net Returns.

This table presents long-term differences in performance between funds in the top and bottom deciles of Trade Precision. Mutual funds are sorted into 10 portfolios based on Trade Precision, as described in table 3. The return series span January 1997 to June 2012. The holding period for each portfolio, indicated by K, varies from one to 16 quarters. The table reports differences in returns between Decile 10 (highest Trade Precision) and Decile 1 (lowest Trade Precision). I compute monthly equally-weighted net returns on the portfolios, as well as risk-adjusted returns based on the CAPM, the Fama and French (1993) (FF) three-factor model, the Carhart (1997) four-factor model, and the Pastor and Stambaugh (2003) (PS) five-factor model. Returns and alphas are in monthly percentages. Newey and West (1987)'s t-statistics are shown in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	Net Returns														
Holding Period	**K=2**	**K=3**	**K=4**	**K=5**	**K=6**	**K=7**	**K=8**	**K=9**	**K=10**	**K=11**	**K=12**	**K=13**	**K=14**	**K=15**	**K=16**
Average	0.097**	0.087**	0.101***	0.086***	0.075**	0.079***	0.075***	0.068**	0.073***	0.070***	0.061**	0.056**	0.047**	0.033	0.026
	(2.464)	(2.424)	(2.858)	(2.672)	(2.484)	(2.674)	(2.658)	(2.461)	(2.743)	(2.727)	(2.434)	(2.344)	(2.028)	(1.481)	(1.190)
CAPM	0.101**	0.088**	0.101***	0.086***	0.073**	0.074**	0.069**	0.062**	0.067**	0.064**	0.056**	0.051**	0.042*	0.028	0.020
	(2.569)	(2.455)	(2.856)	(2.633)	(2.389)	(2.517)	(2.461)	(2.261)	(2.544)	(2.529)	(2.236)	(2.138)	(1.822)	(1.247)	(0.936)
FF	0.082**	0.073**	0.088**	0.074**	0.063**	0.067**	0.065**	0.058**	0.065**	0.065**	0.056**	0.052**	0.042*	0.029	0.022
	(2.159)	(2.061)	(2.516)	(2.286)	(2.085)	(2.284)	(2.285)	(2.101)	(2.454)	(2.518)	(2.241)	(2.156)	(1.842)	(1.318)	(1.058)
Carhart	0.078**	0.061*	0.073**	0.055*	0.045	0.050*	0.048*	0.043	0.052**	0.052**	0.043*	0.038*	0.028	0.017	0.010
	(2.036)	(1.757)	(2.130)	(1.815)	(1.572)	(1.794)	(1.794)	(1.633)	(2.033)	(2.092)	(1.803)	(1.678)	(1.317)	(0.807)	(0.518)
PS	0.087**	0.072**	0.088**	0.071**	0.061**	0.068**	0.066**	0.061**	0.069***	0.065***	0.056**	0.050**	0.038*	0.025	0.018
	(2.227)	(2.046)	(2.547)	(2.307)	(2.176)	(2.478)	(2.546)	(2.358)	(2.702)	(2.626)	(2.301)	(2.228)	(1.749)	(1.213)	(0.869)

Figure 1. Performance Gap Over Time.

These figures show persistence in the return gap between mutual funds in the top and bottom deciles of *Trade Precision*. The return series span January 1997 to June 2012. The holding period for each portfolio, indicated by K, varies from one to 16 quarters. I compute monthly equally-weighted net returns on the portfolios, as well as risk-adjusted returns based on the CAPM, the Fama and French (1993) (FF) three-factor model, the Carhart (1997) four-factor model, and the Pastor and Stambaugh (2003) (PS) five-factor model. Returns and alphas are in monthly percentages.



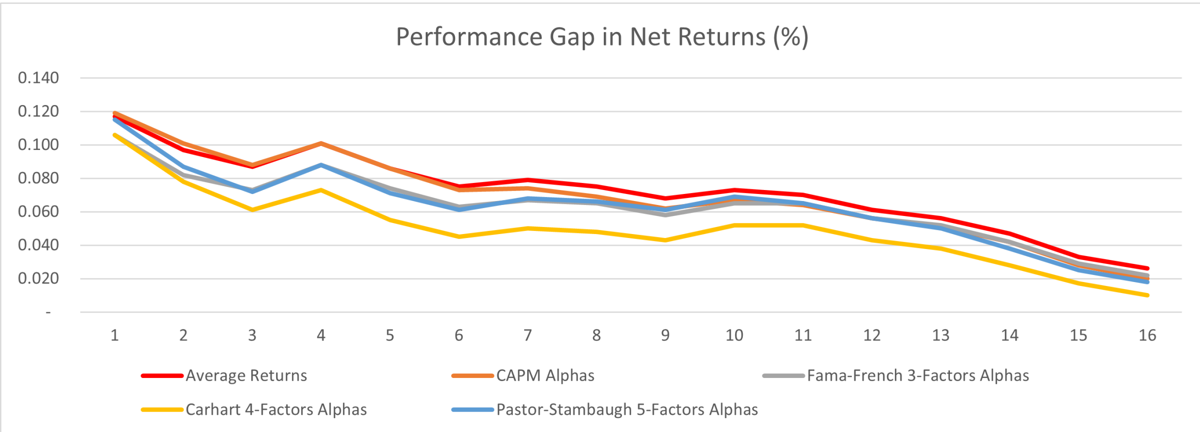


Table 7. Trade Precision and Future Performance: Predictive Regressions.

This table presents coefficient estimates from predictive panel regressions estimating the association between Funds' Trade Precision and future fund performance. $TradePrecision_{j,t}$ is constructed as the average $PredictivePower_{i,j,t}$ a fund has over each stock included in its own portfolio (weighted by portfolio weights). In turn, the $PredictivePower_{i,j,t}$ of fund j over stock i at quarter t is computed as the intertemporal correlation (calculated from $(t-4)$ through $(t-1)$) across the cross-sectional rank for the cumulated abnormal return on stock i (using the four-factor model of Carhart (1997)) and the cross-sectional rank for the unexplained component of the change in weight of stock i on the portfolio of fund j over the previous quarter – stocks size, book-to-market ratio, momentum and changes in institutional ownership are used as independent variables in such regressions. Future mutual fund performance is measured using Carhart (1997) four-factor alpha (both net and gross, in monthly percentages); factor loadings are estimated from rolling-window regressions over the previous three years. The panel regressions control for fund size; fund age; expense ratio; fund turnover; fund percentage flows in the previous quarter; fund alpha (in percent) estimated over the previous three years; active share (AS) is the share of a fund's holdings that differ from the benchmark index holdings, as in Cremers and Petajisto (2009); and fund Similarity is the degree to which a fund's investment decisions resemble those of successful funds, as in Cohen et al. (2005). The regressions include time fixed effects and the standard errors are clustered by fund. t-statistics are shown in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Dependent Variable	**Net Four-Factor Alphas**			**Gross Four-Factor Alphas**		
Model	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Intercept	0.001***	0.003***	0.001***	0.002***	0.003***	0.001***
	(16.34)	(9.938)	(3.657)	(31.81)	(9.986)	(3.693)
Trade Precision	0.006***	0.007***	0.005**	0.006***	0.007***	0.005**
	(3.075)	(3.024)	(2.279)	(3.041)	(3.030)	(2.286)
Fund Age		-0.000	-0.000*		-0.000*	-0.000*
		(-1.62)	(-1.69)		(-1.72)	(-1.70)
Expense Ratio		-0.062***	-0.102***		0.020	-0.020
		(-3.56)	(-5.65)		(1.121)	(-1.11)
Quaterly Flow		-0.001**	-0.001		-0.001**	-0.001
		(-1.98)	(-1.30)		(-2.00)	(-1.31)
Fund Size		-0.000	0.000		-0.000	0.000
		(-1.14)	(0.759)		(-1.13)	(0.735)
Turnover		-0.000***	-0.000***		-0.000***	-0.000***
		(-2.65)	(-2.80)		(-2.64)	(-2.80)
Previous Alpha		0.015***	0.016***		0.015***	0.016***
		(8.333)	(9.907)		(8.296)	(9.910)
Active Share			0.002***			0.002***
			(5.311)			(5.333)
Fund Similarity			0.012***			0.012***
			(6.607)			(6.584)
Degrees of Freedom	2,365	2,351	1,815	2,365	2,351	1,815

Table 8. Ownership by Best Predictors and Institutional Ownership.

This table presents coefficients from panel predictive regressions that use stocks' ownership by their respective Best Predictors (defined as the top decile of funds with the highest $PredictvePower_{i,j,t}$ over them) in quarter t to forecast aggregate institutional ownership changes in subsequent quarters. Control variables are past aggregate institutional ownership changes (lagged ΔIO), size, book-to-market ratio and momentum (cumulated return over past quarter), measured in quarter t. Regressions include time fixed effects and the standard errors are clustered by stock. t-statistics are shown in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Dependent Variable	$\Delta IO_{t;(t+1)}$		$\Delta IO_{t;(t+4)}$	
Intercept	0.013***	0.002***	0.065***	0.010***
	(6.732)	(12.04)	(10.05)	(14.11)
BPOwnDelta	0.003***	0.003**	0.004**	0.004**
	(2.601)	(2.174)	(2.518)	(2.066)
IODelta	-0.066***		-0.137***	
	(-8.70)		(-12.1)	
Mom	0.010***		0.021***	
	(7.037)		(8.486)	
BTM	-0.002***		-0.005***	
	(-5.43)		(-4.67)	
Size	-0.001***		-0.004***	
	(-5.99)		(-8.83)	
Degrees of Freedom	4,018	4,016	3,726	3,724

Table 9. Returns on Stocks Traded by their Most Precise Funds.

This table presents the performance of quintile portfolios formed based on the trading activity of each stock's Best Predict – defined as the funds in the top decile of $PredictivePower_{i,j,t}$ for each stock-quarter. For each stock-quarter, I compute the average trade (the percentage increase in the number of split-adjusted shares held by each fund) by its Best Predictors. Each quarter, I rank stocks cross-sectionally based on the average trade of their best predictors and sort them into stock quintiles that form portfolios to be held until the end of next quarter. Those stocks more heavily sold by their own Best Predictors are assigned to quintile Q1, while those more heavily bought by their own Best Predictors are assigned to quintile Q5. I compute equally weighted returns on the portfolios, as well as risk-adjusted returns based on the CAPM, the Fama and French (1993) (FF) three-factor model, the Carhart (1997) four-factor model, and Pastor and Stambaugh (2003) (PS) five-factor model. I report average returns and alphas in monthly percentages. Newey and West (1987)'s t-statistics are shown in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively, for the return differentials between quintiles 1 and 5.

Portfolio	**Q1**	**Q2**	**Q3**	**Q4**	**Q5**	**(Q5-Q1)**
Average	0.804**	0.735*	0.939**	1.017***	0.967**	0.163*
	(2.025)	(1.874)	(2.370)	(2.588)	(2.335)	(1.783)
CAPM	0.389**	0.334*	0.529***	0.607***	0.529***	0.140
	(2.172)	(1.740)	(2.849)	(3.408)	(2.973)	(1.557)
FF	0.225	0.162	0.313**	0.460***	0.356***	0.131
	(1.623)	(1.146)	(2.475)	(3.350)	(2.675)	(1.443)
Carhart	0.232*	0.192	0.347***	0.512***	0.416***	0.184**
	(1.665)	(1.368)	(2.769)	(3.836)	(3.268)	(2.189)
PS	0.151	0.099	0.267**	0.432***	0.327***	0.176**
	(1.082)	(0.708)	(2.136)	(3.238)	(2.594)	(2.049)