Why do funds make more when they trade more?

Jaden Jonghyuk Kim, Jung Hoon Lee, Shyam Venkatesan*

ABSTRACT

We introduce a conditional measure of skill, the correlation between a funds' residual trades, net of common trading motives, and future news about the stocks traded. Using this measure, we show that the average mutual fund manager in the cross-section has stock-picking skill. This result is robust to different benchmarks and is mainly driven by the manager's ability to predict a firm's cash-flow news. This skill has short-term persistence and is distinctly related to traditional measures of performance. Importantly, consistent with the Berk and Green (2004), fund flows are increasing with respect to managerial skill after controlling for fund performance.

JEL classification: G11, G20, G23.

Keywords: Mutual fund, performance, skill

*Kim is from the International Monetary Fund, Lee is from the Freeman School of Business at the Tulane University, and Venkatesan is from the Ivey Business School at the University of Western Ontario. We thank Azi Ben-Rephael, Matt Billett, Alan Crane, Kevin Crotty, Craig Holden, Ryan Israelsen, Dmitry Lubensky, Jeff Prince, Noah Stoffman, Luke Taylor, Charles Trzcinka, Jun Yang, and Scott Yonker for their valuable comments. We also benefited from the comments received during presentations at Indiana University, University of Connecticut, University of Wisconsin at Eau Claire, and Radford University. Send your correspondence to Jung Hoon Lee, Freeman School of Business, Tulane University, 7 McAlister Dr., New Orleans, 70118. Email: jlee39@tulane.edu. Shyam Venkatesan, Ivey Business School, University of Western Ontario, 1255 Western Road, London, Ontario, Canada. Email: svenkatesan@ivey.uwo.ca

With approximately $18 trillion invested with U.S. registered investment companies in 2017, the question of whether managers possess skill that guides their trades remains as salient as ever. Numerous researchers, starting with Jensen (1968), have examined the skill of a fund manager and have used a variety of empirical methodologies to do so.[1] Traditional tests use fund performance (e.g., α) to judge the skill of the manager. Berk and Green (2004) point out the fallacy of this approach. The question of whether mutual fund managers possess a scarce skill, stock picking, is different than the question of whether they add value to the individual investor. The primary objective of our paper is to take a new look at managerial skill that does not involve the return of a fund. When a portfolio manager generates private information about an asset, she trades based upon that information.[2] Knowing the manager's actions, when she has a private signal, and having the ability to observe those actions (portfolio changes) affords us an opportunity to ex-post assess the quality of her information. If skillful portfolio managers identify profitable investment opportunities and trade based on them, then changes in portfolio holdings and the innovation in the returns of the stocks they trade should be highly correlated.

A change in asset value has to do either with the discounted value of changes in expectation regarding future cash flows (cash-flow news) or with the discounted value of changes in expectation regarding the future expected return (discount-rate news). In this paper, we define managerial skill as the ability to generate private information about these unexpected changes in prices. The precision of the manager's information can be judged by studying how the changes in her portfolio covary with future changes in expectations about the value of the individual assets. In order to estimate the innovation in stock returns, we follow Vuolteenaho

[1] Jensen (1968), Carhart (1997), and Fama and French (2010) find little to no evidence to support the existence of skilled or informed managers. However, Daniel, Grinblatt, Titman and Wermers (1997), Chen, Jegadeesh and Wermers (2000), Kosowski et al. (2006), Kacperczyk, Sialm and Zheng (2008), Kacperczyk, Nieuwerburgh and Veldkamp (2014), and Pástor, Stambaugh and Taylor (2017) show evidence to support that there exist fund managers who make value-enhancing decisions.

[2] Using a rational expectations model of Grossman and Stiglitz (1980), Kacperczyk and Seru (2007) solve for the demand function (for risk assets) of an informed investor. They show that, on the arrival of a good (bad) private signal, the informed investor increases (decreases) her holdings relative to the uninformed investor. The key result of their model is the sensitivity of the demand function to changes in private information.

(2002) and Campbell and Vuolteenaho (2004) and fit a vector autoregression (VAR) model. Ferson and Schadt (1996) stress the importance of conditional performance evaluation in which the future expectations are conditioned on public information variables. The VAR methodology leads to a conditional expectation; using only publicly available information at time t to form an opinion on what the return should be at time $(t+1)$. This approach ensures that only innovation in returns is attributed to the manager's skill and not ex-post returns. Finally, we compute managerial skill by estimating the correlation between the unexpected changes in portfolio holdings and the future news about the firms.[3] As Kothari and Warner (2001) suggest, using fund trades to identify managerial skill mitigates criticism regarding the power of the statistical tests, which exists ubiquitously in return-based tests. The simultaneous use of innovation in returns and fund trades distinguishes our measure from other measures of managerial skill proposed in the recent literature and further enhances the inference on the extent of skill.

We use a large panel of 3,858 actively managed U.S. equity funds over the period from 1994 to 2017 and evaluate the skill at the fund-quarter level. The null hypothesis is that the *average* fund manager does not have any stock-picking skill, implying that the correlation between unexplained portfolio changes and future return innovation is zero. Aggregating skill at the fund level, we find evidence to reject the null hypothesis. The average fund manager in the cross-section has a positive and statistically significant stock-picking ability. For a robust examination of the null hypothesis, we benchmark our skill measure against a bootstraped "no skill" distribution. This test is in spirit similar to the distributional tests presented in Kosowski et al. (2006) and Fama and French (2010). The comparison against the simulated null helps us to clearly establish that there is considerable stock picking skill among mutual fund managers. Crane and Crotty (2018), somewhat surprisingly, show that index funds also exhibit skill and that this skill is persistent. Therefore, we use the distribution of

[3]We control for trades driven by reasons other than having private information (i.e., revisions in analyst recommendations (Brown, Wei and Wermers (2009)) or fund flows (Edelen (1999), Alexander, Cici and Gibson (2007) and Pástor, Stambaugh and Taylor (2017))).

skill exhibited by index fund managers as an additional benchmark and contrast our results against it. This comparison further highlights the ample evidence on the skill of active fund managers.

Next, we run regressions of traditional measures of future fund performance on both our skill measure and other skill proxies. The relationship between our skill measure and future performance is far from trivial, since the value of stocks traded accounts for less than 22% of the overall portfolio value in our sample. In our tests, we find a positive and significant relationship between skill and fund performance. One standard deviation increase in skill increases the quarterly risk-adjusted excess return by 0.35% per quarter when we use four-factor model. This finding clarifies that the traditional measures of performance actually capture some aspect of managerial skill. Importantly, the effect of our skill measure is not subsumed when we control for the return gap of Kacperczyk, Sialm and Zheng (2008) or reliance on public information (RPI) of Kacperczyk and Seru (2007) in the regression model. Thus, our measure captures a distinct aspect of the skill. A closer look at the manager's predictive ability suggests that the skill lies primarily in predicting the cash-flow news, as opposed to the discount-rate news, of the firm.[4]

Furthermore, we test for persistence in this skill and find evidence to support it. According to Berk and Green (2004), a fund manager's skill is implicitly assumed to be constant and the investors infer it over time. This implies that there should be some persistence in skill, at least in the short run. Over the long run, as investors update their beliefs about the manager's skill and invest more in the fund, it is hard to detect skill empirically. Our result suggests that although funds do not show nearly the same level of skills in consecutive periods, portfolio managers maintain their ordering; i.e., fund managers who are the most skilled in the current period continue to be the most skilled in the following periods and vice versa. This persistence in skill cannot be attributed to the momentum effect because the conditional measure of skill already accounts for the auto-correlation in returns in forming

[4] This is consistent with Vuolteenaho (2002) which shows that cash-flow component drives majority of the firm-level return variation.

expectations about future returns. Importantly, given the manner in which the skill measure is constructed, this persistence is based on the trades made by the fund manager.

Finally, and importantly, we also test whether investors respond to the observed skill. Berk and Green (2004), among others, assert that new money follows skill due to rational learning about the skill of managers. Therefore, the prediction is that, controlling for other factors, the market perceives skill differences among active fund managers and rewards more skilled managers with higher flows. We find empirical evidence to support this claim. When we perform quantile regression analysis that estimates the conditional distribution of quarterly flows given the skill and other variables, we observe a positive relationship between managerial skill and fund flows. In higher quantiles, this result is more pronounced, which indicates a convex flow-skill relationship.

In summary, through this paper, we contribute to the existing literature in three ways. First, prior research has been ambivalent about the extent of managerial skill because of serious concerns regarding a lack of power (Kothari and Warner (2001)), the inability to distinguish skill from luck (Fama and French (2010)), the appropriateness of a benchmark (Sensoy (2009)), and model misspecification (Pástor and Stambaugh (2002) and Kosowski et al. (2006)). We propose a new measure that relates changes in portfolio holdings to innovation in stock returns. A similar concept was proposed by Grinblatt and Titman (1993).[5] However, examining the ability of predicting a package of cash-flow news and discount-rate news (or equivalently just a return itself) provides only a blurry view on managerial skill as a high-volatility discount-rate component can unduly influence the inference. For instance, the estimation of discount rate news can be influenced by noise such as sentiment (Baker and Wurgler (2006)). Using the proposed measure of skill, we test a hypothesis that is central to mutual fund literature and demonstrate that even the *average* fund manager has stock-picking ability. This is in sharp contrast to the results in Fama and French (2010), who

[5] In a closely related setup, Pástor, Stambaugh and Taylor (2017) examine an idea that a fund trades more when it identifies great profit opportunities. They document a positive time-series relation between fund turnover and future fund performance. Kacperczyk, Nieuwerburgh and Veldkamp (2014) also find that funds with superior stock-picking skills have significantly higher average turnover.

find that only a small fraction, approximately 5%, of fund managers have the skill. Since our results are robust to multiple benchmarks such as bootstrapped no-skill distribution and index fund skill distribution, we attribute the difference to the drawback in using fund returns to assess managerial skill. The predictability of return innovation by mutual fund trades also asserts that fund managers are important agents in making markets efficient and challenges the notion that a majority of their trades are noise trades (see Dow and Gorton (1997)).[6] Thus, the results in this paper have implications for a long-running debate over whether managerial skill exists.

Second, Berk and Van Binsbergen (2016) and Barber, Huang and Odean (2016) examine which benchmark risk models investors use to evaluate fund performance and make their investment decisions. Our results establish a relationship between the skill of managers and fund flows even after controlling for the documented performance metrics that investors care about. Importantly, this relationship confirms the key premise of Berk and Green (2004): investors can identify skilled managers and compensate them by allocating capital accordingly. Furthermore, our results broaden understanding about investor sophistication by supporting the "smart money" hypothesis of Zheng (1999), and Keswani and Stolin (2008) and contradicting the "dumb money" effect suggested by Frazzini and Lamont (2008). Aggregate investors are not completely unsophisticated because they recognize managerial skill and channel their fund flows accordingly.

Finally, our skill measure can help in understanding managerial actions. Pástor, Stambaugh and Taylor (2017) show that a fund's turnover predicts the fund's subsequent performance positively. Our measure can explain this result because managers can predict innovation in returns of the stocks they trade. More generally, researchers are often interested in understanding why mutual funds would concentrate their holdings as opposed to holding a well-diversified portfolio (see Kacperczyk, Sialm and Zheng (2005)) or why would they

[6]Dow and Gorton (1997) argue that fund managers, due to their contracts, have an incentive to trade even when, despite their best efforts, they fail to discover profitable trading opportunities. As the principal cannot distinguish "actively doing nothing" from "simply doing nothing," managers trade to show that they have exerted effort.

deviate from their benchmarks (see Cremers and Petajisto (2009)). The information-based measure of skill introduced in this paper suggests that the managers have an informational advantage about certain stocks and seeks to exploit it.[7]

I. Related Literature

The literature pertaining to performance evaluation is vast and dates back to Jensen (1968). After controlling for risk, Jensen (1968) finds that mutual fund managers, on average, are unable to outperform the market and hence concludes that they are not skillful. Carhart (1997) also measures the performance of mutual fund managers and specifically focuses on the persistence of their performance. After controlling for the momentum factor, Carhart (1997) finds no persistence in the returns of mutual funds. Kosowski et al. (2006) point to the non-normality of an individual fund's return distribution and, hence, that of the cross-sectional distribution of the mutual fund alpha. Kosowski et al. (2006) introduce a new bootstrapping methodology to correct the empirical distribution and test whether there are any skilled managers in the entire cross-section. Fama and French (2010) use a similar methodology. They incorporate the cross-sectional covariance of fund returns in their bootstrap. These two studies reach different conclusions on the extent to which managerial skills exist and how they vary in the cross-section. Importantly, the methodology used in these two papers is designed only to test whether *any* manager in the cross-section is skilled. It cannot distinguish those who are skilled from those who are unskilled. Crane and Crotty (2018) apply distributional tests of skill versus luck to passive funds and find, somewhat surprisingly, that index fund have skill and that it is persistent.

Despite the widespread belief that managers do not possess skill, there exists some literature that finds evidence of skill. Grinblatt and Titman (1993) and Daniel et al. (1997) use a holdings-based measure of performance to examine evidence of managerial skill. Chen, Je-

[7] Alternatively, funds could deviate from their benchmarks due to agency issues such as the convex flow-performance relationship or the asymmetric compensation contracts awarded to portfolio managers.

gadeesh and Wermers (2000) find evidence that stocks that are purchased by mutual funds, overall, have higher returns than stocks that they sell.[8] Kacperczyk, Sialm and Zheng (2008) compare the reported fund performance with the performance of a hypothetical portfolio that invests in the previously disclosed holdings. This return gap predicts fund performance, which suggests that fund managers add value. Kacperczyk and Seru (2007) introduce a measure of managerial skill called *RPI.* Instead of looking at the ex-post effects of having private information, they argue that the extent to which mutual fund managers rely on public information determines the level of skill and that those managers who use lower amount of public information are better skilled. Cremers and Petajisto (2009) document that deviation from the prospectus benchmark is positively associated with better performance. Kacperczyk, Nieuwerburgh and Veldkamp (2014) show that managers display stock-picking ability during good economic conditions and time the market during bad economic conditions. Finally, instead of merely relying on the return measure, Berk and Van Binsbergen (2015) use the product of fund return and fund size to measure the value added by mutual fund managers and document the existence and persistence of managerial skill.

II. Data and Summary Statistics

We start with a sample of all mutual funds in the CRSP Survivorship Bias Free Mutual Fund Database. This database provides monthly information about all the fund-level variables that include return, total net assets, expenses, and turnover. In the empirical analysis, we focus exclusively on domestic equity mutual funds because the data on the holdings of these funds are most complete. To do so, we follow Kacperczyk, Sialm and Zheng (2008) and select funds based on their objective codes. Also, for a fund to be included in the sample, it must hold at least 80% of its wealth in stocks. Index funds are identified by their name using the CRSP mutual fund data set and are excluded from the sample. We then merge

[8]The focus of their paper is the overall mutual fund industry level, and it does not address whether the average mutual fund manager is skilled.

the holdings information with this file.

Although CRSP has data on holdings of mutual funds, this information is not reliable, and it does not go back in time. We use the Thompson Reuters CDA/Spectrum holdings database, which collects data from reports filed with the SEC and from voluntary reports by the funds. We exclude balanced, bond, money market, sector, and international funds. We also drop funds that hold fewer than 10 stocks in the portfolio and those that do not report their holdings on a calendar quarter basis. Following Evans (2010), we exclude funds that have less than $5 million under their management. We also exclude observations that pertain to a period prior to the fund's starting date. Quarterly holdings are not available for all the funds throughout the sample period. After 2004, the SEC mandated that all funds report their holdings on a quarterly basis. Prior to that, only semi-annual reporting was required. However, during those times, a large fraction of the funds voluntarily reported their holdings on a quarterly basis. For the missing quarters, we assume that the funds follow a buy-and-hold strategy, so we fill the holdings with the previous quarter's information.

Data regarding the price and returns of the individual firms in the portfolio are obtained from CRSP. We restrict our focus to ordinary common shares of firms incorporated in the United States (share codes 10 and 11). Since mutual funds have multiple share classes, we consolidate the data at the fund level. To consolidate the variables, we take the value-weighted average of individual classes, where the weight is determined by the proportionate share of TNA. We use the quarterly COMPUSTAT file for all the firm-level characteristics. In computing the skill of the fund manager, we use data regarding the analyst's past recommendations. For this purpose, we use the IBES stock analyst recommendation data. This database provides the consensus recommendations for different stocks over time using a scale of 1 to 5, where 1 represents a "strong buy" and 5 represents a "strong sell." We discuss the construction of consensus recommendations in greater detail below. The IBES database begins 1993, so a majority of the analysis presented here pertains to the period between January 1994 and December 2017.

Table I reports summary statistics about the fund characteristics in the sample. The sample has 3,858 unique active mutual funds and 110,567 fund-quarter observations. Statistics on expense ratio, turnover ratio, and age are also reported. Because there are no index funds in the sample, the expense ratio might be a little higher than that found in previous literature. The average fund in the sample trades close to 80% of their portfolio each year. Finally, consistent with prior research, the average mutual fund alpha in the sample is negative.

III. Skill Measure

As mentioned before, skill is measured by the correlation between changes in individual stocks in the manager's portfolio and the ex-post "news" regarding those stocks that were traded. Here, we discuss in detail how news is estimated and, subsequently, how the skill of the manager is calculated.

A. Estimating news

A.1. Components of stock return

The first step in computing the skill is to calculate the return innovation of all the stocks held in the manager's portfolio. Campbell (1996) extends the linear approximation of the present value relationship between current price and future dividends to a decomposition of returns and shows

$$\begin{aligned} r_{t+1} - E_t r_{t+1} &= (E_{t+1} - E_t)\sum_{j=0}^{\infty} \rho^j \Delta d_{t+1+j} - (E_{t+1} - E_t)\sum_{j=1}^{\infty} \rho^j r_{t+1+j} \\ &= N_{CF,t+1} - N_{DR,t+1}, \end{aligned} \tag{1}$$

where ρ is parameter of linearization, Δd represents the log dividend growth, r is the log return, N_{CF} is the cash-flow news or changes in expectations about the future cash flows of the firm, and N_{DR} represents the news about the future discount rates or expected returns. Equation (1) highlights that any unexpected return has only two sources; changes in expectations about future cash flows of the firm or changes in the expected returns. In other words, unexpected returns is the discounted effect of a current shock out to the infinite future. Although this shock is latent, its economic effects are captured by the cash-flow news and the discount-rate news. If a manager has private information about these shocks, then she should increase the holdings in the stock if it is a positive shock and decrease the holdings if it is a negative shock (Kacperczyk and Seru (2007)).

A.2. VAR methodology

The standard procedure to estimate the innovation in returns is to fit a vector autoregression (VAR). This approach was first adopted by Campbell (1991), which we closely follow. Return innovation can be further decomposed into cash-flow news and discount-rate news. It is common practice to first estimate the discount-rate news, $(E_{t+1} - E_t)\sum_{j=1}^{\infty} \rho^j r_{t+1+j}$, and then use the realized return, r_{t+1}, and equation (1) to back out the cash-flow news as the residual. We assume that the data is generated by a first-order VAR model:

$$z_{t+1} = \Gamma z_t + u_{t+1}, \tag{2}$$

where z_{t+1} is an $m \,\mathrm{x}\, 1$ vector of state variables with r_{t+1} as its first element, Γ is an $m \,\mathrm{x}\, m$ matrix of the parameters or the transition matrix, m is the number of state variables, and u_{t+1} is an i.i.d. vector of residuals or shocks. Then, following Campbell (1991), the cash-flow news and the discount-rate news are nothing but linear transformations of the shock vector (u_{t+1}) given by

$$\begin{aligned} N_{DR,t+1} &= e1'\lambda u_{t+1}, \\ N_{CF,t+1} &= (e1' + e1'\lambda)u_{t+1}. \end{aligned} \tag{3}$$

In the above formulation, e1 is an $m \,\text{x}\, 1$ vector that has one as the first element and zero for all remaining elements. λ is a $m \,\text{x}\, m$ matrix that maps the VAR shocks to the news. It is given by $\lambda \equiv \rho\Gamma(I - \rho\Gamma)^{-1}$, where I is an $m \,\text{x}\, m$ identity matrix. In equation (3), $e1'\lambda$ captures the long-run significance of the individual VAR shock to the expected discount rate. This formulation also suggests that the greater the value of the variable's coefficient in the return prediction equation of the VAR system, the greater the weight it receives in the discount-rate formula.[9] Campbell (1991) also points out that persistent variables receive more weight; this is captured by the term $(I - \rho\Gamma)^{-1}$.

A.3. State variables and firm-level VAR

Generally, the above decomposition is applied at the overall market level. However, Vuolteenaho (2002) presents a simple way to compute this at the firm level. A similar methodology is followed in Campbell, Polk and Vuolteenaho (2009). We follow the specification prescribed in Vuolteenaho (2002) and estimate a vector autoregression (VAR). Since the holdings data are in quarterly terms, the VAR is also estimated using quarterly data. We now present the state variables used in the VAR and discuss the estimation procedure.

The first state variable of the model is the firm's log stock returns (r_i). The common stock's quarterly returns are computed by compounding the monthly returns. If the returns are missing, we substitute a value of zero. Whenever there is delisiting, we substitute the delisting returns where available.[10] Vuolteenaho (2002) points out that log transformation of a firm's return may turn extreme values into influential observations and suggests that we can avoid this problem by unlevering the stocks by 10%. We implement this suggestion and treat the stock's returns as a portfolio with 90% invested in the stock and the remaining 10% invested in Treasury bills. Having past returns in the specification ensures that the effect of momentum in stock returns is captured.

[9] Given the above return generation process, it is easy to see that the two-period innovation in return, $(r_{t\to t+2} - E_t(r_{t\to t+2}))$, is given by $(r_{t\to t+2} - e1'\Gamma z_t - e1'\Gamma^2 z_t)$. Further, it can be shown that the two-period discount-rate news, $(E_{t+2} - E_t)\sum_{j=1}^{\infty}\rho^j r_{t+2+j}$, will then be $e1'\rho\Gamma(I-\rho\Gamma)^{-1}(u_{t+2} + \Gamma u_{t+1})$.

[10] Following Shumway (1997) we substitute a value of -30% as the delisting returns when they are missing.

The next state variable used in the model is the log book-to-market (BM) ratio. This is included in the state vector to capture the value effect in the stock's return. To compute the book value of equity (BE), we follow the method described in Campbell, Polk and Vuolteenaho (2009). The market value (ME) is the product of the number of shares outstanding and the price. Again, to avoid influential observations created by log transformations, the log book-to-market ratio is computed as $BM \equiv log[(0.9BE + 0.1ME)/ME]$.

The final state variable is the long-run profitability of the firm, $(\overline{ROE})$. Empirically, firms with higher profitability have earned higher returns, even after controlling for book-to-market ratio. The inclusion of firm profitability is also consistent with production-based models of asset pricing. This data is generated using the accounting clean-surplus relationship. The clean-surplus earnings (X_t) are computed after adjusting for equity offerings in the following manner:

$$X_t = [\frac{(1 + R_t)ME_{t-1} - D_t}{ME_t}] \ . \ BE_t - BE_{t-1} + D_t, \tag{4}$$

where R_t is the firm rate of return and D_t is the dividend, computed as the difference between returns including dividends (CRSP variable *ret*) and returns without dividends (CRSP variable *ret*x). The above relationship defines any change in the book value of a firm after adjusting for new stock issuance and dividends as profitability. We compute this measure for every quarter. The long-term profitability is then computed as the trailing twenty-quarter (or five-year) average of clean-surplus earnings divided by a similar trailing average of $(0.9\ BE + 0.1\ ME)$.

Before estimating the firm-level VAR, we subtract the log value-weight CRSP index returns from $r_{i,t}$. We also remove cross-sectional means from $BM_{i,t}$ and $\overline{ROE}_{i,t}$. Further, Vuolteenaho (2002) points out that relatively few firms will be in the sample for the entire time period and that conditioning on survival will bias the parameters. Therefore, Vuolteenaho (2002) suggests that the VAR parameters be estimated in a pooled regression, i.e., with all the firms at the same time. Under this specification, all the firms will share the same coefficient matrix. Adhering to these suggestions, we fit a panel VAR using a quarterly firm-level sample. The coefficients are estimated using the weighted least squares method. Because there are differences in the number of firms in each cross-section, we weight every cross-section by the inverse of the number of firms in that cross-section. Subsequently, the individual news terms (cash flow and discount rate) are calculated using the residuals in the manner described in equation (3). The above VAR specification and the news term computed are fairly robust.[11] An additional test to confirm the robustness is performed below.

B. *Estimating Skill*

We now discuss in detail the steps involved in computing the skill of the manager. Above, we propose that the manager's skill should be the correlation between the changes she makes to her portfolio and future news about the firms. Change in the holdings of an asset, i, at a time, t, is computed as the ratio of change in the number of shares of the stock held between the two quarters to the number of stocks held at the beginning of the quarter. The percentage change in the holdings is computed after adjusting for stock splits and stock dividends. Observing a change in the portfolio holdings does not necessarily imply that the manager has information. She could change her portfolio for reasons other than information.

Brown, Wei and Wermers (2009) show that mutual fund managers strongly follow consensus revisions in analyst recommendations and that they change their holdings based on these revisions. Therefore, we control for changes in consensus recommendations. Details about the consensus recommendations are provided in the IBES database. Multiple analysts report their recommendations on stocks. Analysts' recommendations are standardized to a five-point scale between 1 (strong buy) and 5 (strong sell). Using these recommendations, IBES reports a consensus recommendation number for each stock, which represents the collective opinion. As analysts update their reports or when new analysts submit their reports, it is obvious that there will be revisions to the consensus. Brown, Wei and Wermers (2009)

[11] Campbell, Polk and Vuolteenaho (2009) perform a variety of tests to confirm the robustness of this specification. Also see Vuolteenaho (2002) to note that the cash-flow news and discount-rate news estimated using only accounting variables are very similar to those estimated using the VAR.

show that a significant part of herding behavior is exhibited in the quarter after a recommendation change. Therefore, before the beginning of the current quarter, for each stock, we collect the previous two consensus recommendations ($\overline{rec}_{i,t-1}$ *and* $\overline{rec}_{i,t-2}$). We then refer to the difference between the last two consensus recommendations as *"herding,"* which represents the change in the consensus about a stock. Note that this variable is measured before the beginning of the quarter of trade. This avoids any endogeneity that might arise from an analyst changing his recommendations based on the changes in the holdings of the mutual fund manager.

Another reason that funds might change their holdings is flows to the funds. New money is an important aspect of the mutual fund industry and is in fact the core area of competition. Even fund managers who have no private information and want to maintain the same portfolio weights would have to change their holdings because of the inflows and outflows to the fund. Pástor, Stambaugh and Taylor (2017), who show that fund turnover is related to fund performance, modify the turnover measure in order to account for nondiscretionary fund flow-driven trades. In addition, Edelen (1999) and Alexander, Cici and Gibson (2007) highlight the level of liquidity-motivated trades and its implications for fund performance. To purge these flow-driven trades, we control for the net flows to the fund, j, for each quarter, t, computed as

$$Netflow_{j,t} = \frac{TNA_{j,t} - TNA_{j,t-1}(1 + R_{j,t})}{TNA_{j,t-1}}, \tag{5}$$

where *TNA* is the total net assets of the fund and $R_{j,t}$ is the cumulative net returns of the fund for the quarter, accumulated from the monthly returns.

Following the above discussion, we estimate the skill in two steps. We first fit the following regression:

$$\%change\ in\ holdings_{i,j,t} = \beta_{0,j} + \beta_1 * herding_{i,t-1} + \beta_2 * Netflow_{j,t} + \epsilon_{i,j,t} \tag{6}$$

where i represents the firm and j represents the fund. For the stocks that are newly added to the portfolio, we set the the value of percentage change (dependent variable) at 100% because it would be infinite otherwise. In the above specification, the intercept term is fund-specific and hence we control for any time invariant fund characteristics that influences changes in holdings.

We collect residuals, $\epsilon_{i,j,t}$, from (6). These $\epsilon_{i,j,t}$ represent the unexplained changes in holdings. In the second step, we compute the skill of the manager j at time t as

$$skill_{j,t} = corr(\epsilon_{i,j,t},\ news_{i,t+1}). \tag{7}$$

Correlation is computed using all the *traded* assets in the portfolio.[12] $news_{i,t+1}$ is the innovation in returns estimated earlier. In spirit, this approach is similar to the econometric approach used in Christoffersen, Evans and Musto (2013). In another specification, we also compute the correlation between unexplained changes in holdings and the news for two periods after the end of the quarter of trade.[13]

The issue of distinguishing between skill and luck is another challenge. An uninformed manager who is purely trading on noise could change her portfolio holdings and by sheer chance have her trades positively correlated to future news. To address this concern, we further require that, after the trade is made in a particular quarter, there are no trades in the opposite direction in the next period. For example, if the manager purchases a stock between $t-1$ and t, we include this particular stock in computing skill only if the holdings of this stock do not decrease in time t to $t+1$ ($t+2$ if two-period news is used). This filter helps in improving the identification of information-driven trades and reduces the probability of the results being driven by pure chance. In our subsequent analysis, to further differentiate skill

[12] Note that skill estimated using equations (6) and (7) is in spirit a partial correlation coefficient. This procedure nets out the effect of herding and net flows to the fund. As long as changes in consensus recommendations between quarter $(t-2)$ and $(t-1)$ and flows to the funds between $(t-1)$ and t do not affect the news in a stock for the period t to $(t+1)$, a reasonable assumption, skill is well identified (see the Frisch–Waugh–Lovell theorem).

[13] As a robustnesss check, we also value-weight the change in holdings when we compute the skill measure. See section V.A for the relevant result.

from luck, we also benchmark our skill measure against a bootstrapped "no skill" distribution. The speed of information gathering and processing is also an important aspect of managerial skill. However, given the limitation on data, the current design to evaluate skill does not the capture this dimension. Finally, fund managers are concerned about both the risk and return of the overall portfolio. Some managers might have private information but do not change their holdings because it might increase the overall portfolio risk. In this paper, we focus on the precision of a manager's private information. Because one cannot observe the private information the manager receives, one must rely on her actions from having private information. Therefore, we rely on observation of portfolio changes. However, this inaction (despite having information) will only impart a downward bias on the measure of skill.

IV. Empirical Analysis

A. Firm-level VAR Estimation

We start the estimation of skill by fitting a firm-level VAR. Log returns of the firm, log book-to-market ratio, and log profitability are the three state variables in the model. A detailed description regarding the construction of these variables is presented in section III.A.3. The results from the firm-level VAR are presented in Table II. Two sets of relevant standard errors are reported below the estimated coefficients. First, to account for any correlation in the error terms across all the firms in a given time, the standard errors are clustered cross-sectionally. Second, Shao and Rao (1993) show that their non-parametric jackknife method produces a consistent standard error estimate for ordinary least square and weighted least square models even in the presence of cross-sectional dependence amongst the error terms. We follow their re-sampling method and report the resulting standard errors also.

The parameter estimates imply that the expected returns are high when the past firm returns are high. Also, as expected, returns are high when the book-to-market ratio and past profitability are high. The most significant predictor of future book-to-market ratio is its own lagged value. The same is true of future firm profitability. The high persistence in these measures is the main reason that the R^2s of these regressions are so high. Since the current paper uses quarterly data, as opposed to annual data, the reported R^2s are a little higher than those found in earlier studies.

We collect the residuals from the above estimation, which are the innovation in returns. The parameters estimated in Table II, along with equation (3), are used to estimate the cash-flow news and the discount-rate news. It is also clear from comparing the magnitudes in the variance-covariance matrix of the cash-flow and discount-rate news that most firm-level stock returns are driven by cash-flow news. We then follow equations (6) and (7) above to estimate the skill for each fund-quarter and test the fundamental hypothesis of the paper. The null hypothesis here is that the average manager in the cross-section of U.S. equity mutual funds is unskilled. Figure 1 provides the distribution of skill. By definition, it should be clear that the values of skill lie strictly between -1 and 1. It is evident from the distribution that there are managers on both tails of the distribution. However, looking at Figure 1, it is not clear whether the average manager has any managerial skill.

Table III presents the numerical results. Panel A reports the distributional properties of the skill measure after aggregating it at the fund level across time. *skill* and *skill_2* are the skill measures computed using news from one and two quarters after the trade, respectively. We find evidence to reject the null hypothesis and report that there is considerable stock-picking ability among the fund managers. We use a standard t-test and a non-parametric bootstrapped test to test the significance of the mean. Both tests suggest that the average fund manager has a positive and statistically significant skill. These results support the model presented in Berk and Green (2004), who argue that a finding that an average manager has a negative risk-adjusted return does not imply a lack of skill. Although the average alpha in our sample is negative, consistent with the above argument, we find that the fund managers have skill and make informed trades. These results are also in line with the recent findings of Chen, Jegadeesh and Wermers (2000), Alexander, Cici and Gibson (2007), Baker et al. (2010), Kacperczyk, Nieuwerburgh and Veldkamp (2014) who also find evidence of stock picking skill.

Since the innovation in returns can be attributed to changes in expectation regarding future cash flows and to changes in expectation of future returns, it is important to identify which of these news the fund manager has private information about. In order to answer this, we follow the same procedure as we do to estimate skill except for the final step. Instead of using the total news term in equation (7), we use the cash-flow news estimated from VAR and compute $skill\ cash_{j,t}$ as $corr(\epsilon_{i,j,t},\ N_{CF,t+1})$, where $\epsilon_{i,j,t}$ is the unexplained changes in holdings. This measure captures the extent of skill that the manager has in predicting the future cash-flow news of the firm(s). In a manner similar to that shown above, we compute $skill\ discount_{j,t}$ as $corr(\epsilon_{i,j,t},\ N_{DR,t+1})$ to assess the manager's ability to predict discount-rate news. If the manager is skilled in predicting the changes in future cash flows, then one should expect the stocks that she buys (sells) to be positively (negatively) correlated with future cash-flow news. When a stock experiences a positive expected return shock, the price of that stock drops. Therefore, a manager who is skilled in predicting future discount-rate news should have his trades negatively correlated with discount-rate news. Panel B of Table III reports the mean of the empirical distribution for each of the two skill measures at the fund level. The positive and statistically significant coefficients in the top row of the panel suggest that the managers have the ability to predict future cash-flow news. Similarly, the negative coefficients in the second row of Panel B of Table III show that the managers also have the ability to predict the changes to the firm's future expected returns. Although these results suggest that fund managers have the ability to predict both kinds of news, one needs to be careful when interpreting this result. Cash-flow news and discount-rate news are not orthogonal to each other. The correlation between them could also lead us to the above conclusion.[14] We explore this idea a little further using a multivariate regression below.

[14] Table II presents the correlation between the two shocks. Also see Vuolteenaho (2002) for an extensive discussion on the correlation between cash-flow and discount-rate news.

Kosowski et al. (2006) documents that the skill of active fund managers has diminished in the last decade. One potential explanation could be the explosive growth in the mutual fund industry in last decade or so, leading to intense competition, and hence limiting the chances of a manager having private information. One other possibility for such a finding is the structural changes in the disclosure requirements in the last decade. Regulation Fair Disclosure is an example of such change. Alternatively, on account of improved technology and the advent of faster information systems, it could also be possible that a fund manager is able to gather more information from variety of sources and trade faster and therefore is able to mitigate the effects of increased competition. In Panel C of Table III, we test for differences in mean skill in the two sub-periods of our sample. The average skill in the initial half of the sample (between Jan 1994 - Dec 2002) is 0.022 compared to that of 0.003 in the latter half of the sample. A first look at the mean skill in the two sub-periods does suggest that the level of skill has dropped in recent times. Statistical tests of differences in the mean confirm that the difference of 0.018 is statistically significant.

In Panel D of Table III, we present the correlations between skill and the other fund characteristics. A few interesting relations emerge. First, a negative relationship between the size and turnover of the fund seems to support the view that larger funds do find it harder to trade. Because of their size, it is often the case that their holdings are fairly big and their trades are very transparent. Since the price impact of their trades is very high, they refrain from trading too frequently. Second, Chen et al. (2004) document that fund returns decline in the lagged fund size. We augment their result and show that this is the case because their trades are less informed. Skill is negatively related to the size of the fund. Third, Pástor, Stambaugh and Taylor (2017) show that a fund's turnover predicts the fund's subsequent performance positively. The positive correlation between skill and the turnover of the fund complements the key idea of Pástor, Stambaugh and Taylor (2017) that if the fund has the ability to identify and exploit profitable opportunities, the fund should trade more heavily and therefore have a high turnover. Finally, consistent with the arguments in

Berk and Green (2004), we find that more skilled funds charge more fees. To the extent that investing skill is a scarce resource, one would expect higher-skilled managers to extract more rent. Therefore, the positive relationship between skill and expenses is not surprising.

B. Distributional Tests of Skill

The previous analysis clearly displays that managers, on average, have a positive and statistically significant skill. However, it is not immediately clear if the null hypothesis of zero skill is the correct benchmark. As a next step, we conduct an alternative analysis to test the statistical significance of our skill measure against the proverbial null of "monkey throwing darts". Much of this analysis is in the spirit of the distributional tests presented in Kosowski et al. (2006) and Fama and French (2010). For each cross-section, we start with the actual funds trades. To this data, for each stock traded, we randomly assign a quarterly news. The news terms are randomly drawn from the actual time-series of the relevant stock's news distribution. In each iteration, we execute this process for all the stocks and for all the cross-sections and then use the aforementioned methodology to compute the hypothetical skill exhibited by the fund. We perform this iteration 1000 times.

Table IV presents the results from comparing the actual empirical distribution of skill to the bootstrapped null of managers having no skill and purely trading on noise. At selected percentiles, columns (2) and (3) show the actual skill estimates whereas columns (4) and (5) show the average values of the 1000 simulation runs. The simulated median manager with no information about future innovations in stock returns displays a skill of 0.004 (or 0.008 for two-period skill). In contrast, manager at the the 50^{th} percentile displays a skill of 0.009 (or 0.019 for two-period skill), which is over twice the size of the simulated skill coefficient. We also provide the confidence interval to test the statistical significance of our point estimates. For each selected percentile, the variation in the point estimates, from the 1000 iterations, of the bootstrapped skill distribution is presented. The point estimate at the median is way above the 95% percentile, providing robust support in favor of its statistical significance. The left tail of the actual distribution is significantly lower than that of the simulated distribution, which clearly indicates that some managers do destroy value. However, the empirical distribution of our skill measure outperforms the simulated distribution above the 50th percentile. Overall, there is considerable stock picking skill exhibited by the portfolio managers.

As an additional benchmark, we compute the skill exhibited by index funds. These funds mimic a passive index and produce a return that can be earned by investing in all the index constituents. Given their investment strategy, they are generally considered as unskilled, and provide a useful benchmark to compare our results. We identify index funds using the CRSP flag and the fund names and estimate the skill measure analogously. The distribution of skill for index funds is presented in the final two columns of Table IV. The results are in stark contrast to those presented in Crane and Crotty (2018) who apply the bootstrap methodology of Fama and French (2010) to index funds and show that even index funds outperform the bootstrapped sample over a large part of the distribution. However, Crane and Crotty (2018) use fund returns to argue that some index funds are skilled. We reconcile the differences by positing that a substantial portion of index fund return is earned through security lending business and not by taking active long or short positions in stocks.[15] Regardless, when compared, the active funds show significantly more skill than the index funds at the median and at the right tail of the distribution. The combination of these results bolster our earlier claim.

C. Skill and Performance

As mentioned above, the key aspect of the measure proposed here is that it does not rely on the performance of the fund to infer the skill of the manager. However, it is economically relevant to ask if skill gets translated to fund performance. According to Berk and Green (2004), higher-skilled managers should earn a higher gross abnormal return. Considering the

[15] For example, see Johnson and Weitzner (2019).

extent of unobserved activity in mutual funds (Kacperczyk, Sialm and Zheng (2008)) and also that only a small fraction of the assets held in the portfolio are traded each quarter, it is not obvious, in our set up, that higher skill should lead to a higher performance. Based on this discussion, we state the null and alternative hypothesis as follows:

H_N: Managerial skill represented as the precision of private information is not related to subsequent portfolio performance.

H_A: Managerial skill is related to subsequent portfolio performance.

To test this hypothesis, we estimate the following model:

$$\alpha_{j,t} = \beta_0 + \beta 1 \ skill_{j,t-1} + \gamma \ Controls_{j,t-1} + \epsilon_{j,t}, \tag{8}$$

where j represents the fund. The $\alpha_{j,t}$ is the performance of the fund measured as the abnormal returns using CAPM, three-factor and four-factor models for risk adjustments. To estimate the alpha, we follow the methodology used in Carhart (1997). For each fund, we first estimate a time-series regression of the excess fund returns on the returns of excess market return ($RMRF_t$), size (SMB_t), value (HML_t), and momentum (MOM_t) portfolios. Similarly, for the three-factor and CAPM-based alpha, we use the relevant zero-investment portfolio(s). From these regressions, we collect the factor loadings for each fund. We use return data from the previous 36 months or 12 quarters to estimate these loadings. The alpha of the fund for a particular quarter is then given by

$$\alpha_{j,t} = R_{j,t} - R_{F,t} - \hat{b}_{j,t-1} RMRF_t - \hat{s}_{j,t-1} SMB_t - \hat{h}_{j,t-1} HML_t - \hat{m}_{j,t-1} MOM_t. \tag{9}$$

Since the literature has identified a variety of fund characteristics that affect fund performance, we control for these in our specification. We control for the log age of the fund, the log size of the fund represented by the amount of assets managed, the expense ratio at the end of the previous year, and the turnover ratio at the end of previous year. To alleviate the concern of return momentum associated with the flow-induced trades (i.e., Lou (2012)), we also control for the amount of flows to the fund in the previous quarter. Results from the multivariate regression are reported in Table V. All the specifications in Table V include time and fund fixed effects, which control for time-invariant unobserved heterogeneity that could cause the coefficients to be biased. The standard errors for the estimates have been clustered in two dimensions: time and fund. The clustering accounts for correlation in errors within the fund and over time. It also accounts for heteroskedasticity in the residuals.

In Table V, columns (1), (2), and (3) have the CAPM, three-factor alpha, and four-factor alpha, respectively, as the dependent variable. In all three cases, we find that the proposed skill measure has a positive and significant relationship with the future fund performance. A one standard deviation increase in skill results in an approximately 0.48% increase in the quarterly three-factor alpha or 1.9% increase in the annual terms. For the four-factor alpha, the quarterly increase is approximately 0.35% and the annual increase is approximately 1.4%. The mean four-factor net alpha in our sample is approximately -0.22%. In light of this net alpha, the above relationship is economically very significant. Other variables like the fund's size and expenses also have explanatory power in a manner consistent with prior literature. Furthermore, including RPI which guages the extent of pubic information used by the manager (i.e., Kacperczyk and Seru (2007)) does not change the explanatory power of *skill*.

Given the manner in which the skill measure is constructed, our skill measure might be mechanically related to future alpha. However, note that the value of stocks traded is less than 22% of the overall portfolio's value (see Table I). This leaves returns of over 78% of the fund's assets unaccounted for. Stocks that are not traded but merely held in the portfolio could perform very poorly. Moreover, Elton et al. (2010) document that using quarterly holding data misses close to 18.5% of the trades that can be observed by using monthly holdings data.[16] There is a substantial variation in the benefits and costs of these interim trades, and this can severely affect investor return (see Kacperczyk, Sialm and Zheng (2008)). Therefore, the relationship between skill and a fund's future abnormal performance is far from trivial.

In the current multivariate setting, we explore the nature of skill required to generate a positive alpha. As before, we split the current skill measure into two sub-measures $skill\ cash_{j,t-1}$, the manager's ability to predict future cash-flow news, and $skill\ discount_{j,t-1}$, the manager's ability to predict a firm's future discount-rate news. Columns (5), (6), and (7) in Table V report the role of these sub-measures in predicting abnormal returns. Most of the variation in the abnormal returns (alpha) is attributed to the manager's skill in predicting the future cash-flow shocks to the company. This finding is consistent with Baker et al. (2010), who find a relationship between a fund's trades and returns around the earning announcement dates. Although the economic magnitude of the skill to predict future discount-rate news ($skill\ discount_{j,t-1}$) is relatively small, the sign of coefficient estimates is correct. Kacperczyk, Sialm and Zheng (2008) estimate the impact of unobserved actions on fund performance using the return gap. The return gap is defined as the difference between the reported fund return and the return on a portfolio that invests in the previously disclosed fund holdings. We test whether the effect of our skill measure is subsumed when we control for the return gap in the regression model. In Table V, we observe that the results are qualitatively similar even after we include another holdings-based skill measure. This result suggests that our measure captures a distinct aspect of the skill.

We also test the relationship between our skill measure and other holdings-based performance measures. We use the characteristic selectivity (CS) and characteristic timing (CT) measures of Daniel et al. (1997) and present the relevant results in Table VI. These results are consistent with the idea that our skill measure is associated with stock selection but not much with a timing story. Overall, based on the above evidence, we conclude that managers

[16] The monthly holdings data provided by Morningstar is not used for this study because it covers only a subset of the entire mutual fund universe.

having higher skill do earn higher risk-adjusted return.

D. *Skill and Persistence*

In the theoretical framework of Berk and Green (2004), a fund manager's skill is implicitly assumed to be constant and the investors learn about this over time. This implies that there should be some persistence in skill, at least in the short run. Over longer horizons, as investors update their beliefs about the manager's skill and direct their flows to the fund, it might be harder to identify skill empirically because there might be fewer trades on the part of bigger funds as they are worried about the price impact of their trades. Persistence of skill has also been a subject of active debate. The evidence on persistence has been mixed. Hendricks, Patel and Zeckhauser (1993) are the first to report that mutual funds have "hot hands," i.e., winning funds continue to win in the future period and the losing funds continue to lose. Subsequently, Carhart (1997) concludes that most of the persistence in fund performance can be explained by the common factors in stock returns. It is important to note that the above studies focus on the persistence of a fund's excess returns or performance. More recently, Berk and Van Binsbergen (2015) argue that the managerial skill is better measured by considering the fund's gross return and assets under management jointly. By using the value that a mutual fund extracts from capital markets as the measure of skill, Berk and Van Binsbergen (2015) document large cross-sectional differences in skill that persist for as long as ten years.

Here, we examine whether skill is indeed persistent. For each period, we sort funds into decile portfolios based on their level of skill. We then look at the subsequent levels of skill for each of these portfolios. This procedure is repeated for every cross-section, and the time series average of these cross-sections is reported in Table VII. Contrary to the finding of Chen, Jegadeesh and Wermers (2000) and consistent with the finding of Berk and Van Binsbergen (2015), we find evidence of persistence. The level of future skill decreases gradually over the two-quarter horizon. However, Table VII suggests that the group of the most skilled managers in the current quarter continues to be so in the following time period, i.e., the portfolio that shows the most skill in a given quarter t is also the portfolio that will continue to display the highest skill in the subsequent quarters $(t+1)$ and $(t+2)$. The same is true of the portfolio of managers that have the least skill. We test for differences in the mean of the top and the bottom decile portfolios. The results from using a t-test and a non-parametric bootstrapped test are reported at the bottom of Table VII. These tests confirm that there is persistence in skill. It is important to note that this persistence is not on account of momentum in the stocks of the portfolio. This persistence is based on the trades made by the fund manager. The persistence of future return innovation predicted by a mutual fund's trades strengthens the argument that this is on account of ability and not due to luck.

E. Skill and Flows

Understanding how money flows to funds is central to mutual fund literature. Flow is also one of the key drivers for the equilibrium derived in Berk and Green (2004). In the model of Berk and Green (2004), individual investors learn about the manager's skill, based on available public information, and direct their money to the fund according to their updated beliefs. Information about the manager's past performance is public and can be easily accessed by the investors. The media also plays its part in disseminating this information.[17] Previous studies have documented that investor capital follows past fund performance (see Sirri and Tufano (1998)). However, for the most part, managerial skill is latent and unobservable, especially when compared with a fund's performance. Therefore, an important question is whether, conditional on past performance, past skill predicts future flows. Based on the this discussion, we test the following hypothesis:

H_N: Investors do not identify skill and hence skill is unrelated to future flows.

[17] For example, Kaniel and Parham (2017) examine the impact of media attention on consumer investment decisions.

H_A: Managerial skill is related to subsequent flows to the funds.

In testing the above hypothesis, it is important to consider the convexity in the flow-performance relationship. Sirri and Tufano (1998) show that there is bias in the way flows respond to performance. Poorly performing funds do not have nearly as much outflows as the amount of inflows into well-performing funds. Using an ordinary least square (OLS) model in this case would lead to biased and incorrect results. Instead, we perform a quantile regression analysis that estimates the conditional distribution of quarterly flows given the skill and other variables. To test the above hypothesis, we estimate the following specification:

$$Q_q(Netflows_{j,t+1}|\{I_{t-1}, I_t\}) = \beta_0 + \beta_1 \ skill_{j,t-1} + \gamma \ Controls_{j,t} + \epsilon_{j,t+1}, \tag{10}$$

where $Q_q(.|.)$ is the conditional quantile function, $Netflows_{j,t}$ is given by equation (5), and I_{t-1} and I_t are the information sets available at $(t-1)$ and t, respectively. Note that $skill_{j,t-1}$ uses the trades made between quarter $(t-2)$ and $(t-1)$ and correlates this to the news in quarter $(t-1)$ to t. This skill measure cannot be observed earlier than time t. Therefore, the above specification tests whether investors respond with flow between time t and $(t+1)$, conditional on observing the trades at $(t-1)$ and the related news at t. In the specification, we control for the previous period's (i.e., between $(t-1)$ to t) performance by including the net returns as well as the four-factor alpha. Other controls in the regression include the cross-sectionally demeaned age, the log of the size of the fund given by the amount of money managed, the previous year's turnover, and the previous year's expenses. The results from the multivariate analysis are reported in Table VIII. Columns (1), (2), (3), and (4) of Table VIII report the estimates for the 25^{th}, 50^{th} (median), 75^{th}, and the 90^{th} quantiles, respectively. Each of these regressions include time-fixed effects. The bootstrapped standard errors associated with the point estimates are also reported.

All the specifications in Table VIII show a positive relationship between managerial skill and mutual fund flows. For example, in the 90^{th} percentile of flows distribution, a unit change in the level of skill will increase the level of inflows by approximately 1%.[18] This effect occurs after controlling for a fund's past return and past alpha, which have been shown to increase future fund inflows. Panel A of Figure 2 plots the marginal effect of skill at different points of the flows distribution and suggests a convex relation between them. Consistent with flow-performance literature, we find a positive relationship between future flows and past performance. In most cases, funds that charge higher expense ratios receive lower inflows. The parameters associated with turnover ratio show an interesting pattern. The direction of the marginal effects changes based on the quantile of the flows variable. In the lower quantiles of the net flows distribution, increasing the turnover ratio reduces the amount of future inflows. However, in the higher quantile, there is a positive relationship between turnover and net flows. One possible explanation is that fund managers with lower inflows are really managers with lower skill and do not trade on information and hence are penalized for having a high turnover. Overall, the evidence suggests that investors do learn about the skill of the fund manager and adjust their flows accordingly. Managerial skill is positively related to future fund flows. In a related context, Berk and Van Binsbergen (2016) and Barber, Huang and Odean (2016) examine which performance metrics (or equivalently risk models) investors attend to by analyzing capital flows into and out of funds. Our results establish a relationship between the skill of managers and fund flows even after controlling for the documented performance metrics that investors care about.[19] Moreover, this relationship confirms the key premise of Berk and Green (2004): investors can identify skilled managers and compensate them by allocating capital accordingly.

Berk and Green (2004, eqn (6)) also argue that the age of the fund has important implications for the relationship between skill and flows. They claim that flows to younger firms

[18] Our one period skill has a standard deviation of 0.239 and average actively managed fund size in Table I is \$1,540 million. Thus, a one standard deviation increase in skill, holding alpha and other explanatory variables constant, implies an increase in annual flow of \$14.66 million ($0.239 * 0.996\% * 4 * \$1{,}540$ million).

[19] Berk and Van Binsbergen (2016) and Barber, Huang and Odean (2016) show that investors attend most to market risk. In an unreported result, we include CAPM alpha instead of four-factor alpha. The result is qualitatively similar.

respond much more dramatically to skill than flows to more mature funds. The role of the age of the fund is motivated by the idea of learning. Intuitively, the younger funds are less known, compared to older funds, since they have a shorter track record and hence there are frictions in forming prior beliefs about them. Therefore, the degree to which investors have to update their prior beliefs about the skill of the fund manager, when younger funds show skill, is much more significant. This causes investors to respond more dramatically when when younger funds show stock-picking skill. Following this discussion, we test the following hypothesis:

H_N: The age of the fund is not related to the relationship between skill and future flows.

H_A: The age of the fund significantly affects the relationship between skill and future flows.

Columns (5), (6), (7), and (8) of Table VIII present the relevant results based on a quantile regression. The results are again reported for the 25^{th}, 50^{th} (median), 75^{th}, and 90^{th} quantiles, respectively. In addition to the variables used earlier, the specifications have an additional interaction term based on the age of the fund and the level of skill. Each of these regressions also include time-fixed effects. The standard errors reported are bootstrapped standard errors. The relationship between the skill of the fund and future flows continues to be positive and significant. The coefficient on skill refers to the effect on flows of an average-aged fund, since the crossectionally demeaned age is used in Table VIII. The age of a fund in itself reduces the extent of flows to the fund. Interestingly, the coefficients on the interaction term are negative for all quantiles. The negative coefficient implies that the effect of skill on future flows decreases as the age of the fund increases. Furthermore, it is not a surprise that we observe the monotonic results across the quantiles. Age should matter the most at the highest quantile as investors learn more from a young fund showing positive skill. The negative relationship for different quantiles of the flows distribution is displayed in Panel B of Figure 2. We find these results consistent with the prediction of Berk and Green (2004) and therefore reject the null hypothesis.

V. Robustness

In this section, we test the robustness of the main findings of the paper. Specifically, we start by varying the manner in the which the correlation is computed. Later, we present results computed using more robust VAR specifications.

A. *Value-weighted measure of skill*

An important concern regarding the measure of skill is that the measure does not consider the value or the size of the trade. It could be that the fund managers have private information for only a subset of stocks in their portfolio. Equal-weighting all the trades could then distort the skill measure and wrongly identify a manager as being skilled. To overcome this problem, we compute a weighted-correlation where the weight is defined as follows:

$$weight_{i,j,t} = |\frac{(ShareAmount_{i,j,t} - ShareAmount_{i,j,t-1}) * SharePrice_{i,t}}{TNA_{j,t}}|.$$

$ShareAmount_{i,j,t}$ is the number of shares of security i in fund j at time t. Essentially, the weight is the absolute value of the change in the amount of money invested in a particular stock as a percentage of the fund's asset at the end of the quarter. Panel A of Table IX presents the distribution of the adjusted skill measure, and the results are similar to the earlier findings. The average and the median fund manager continue to show a positive and statistically significant skill. This result holds irrespective of the time horizon used to compute the news.

B. *Skill computed using all the assets*

In the earlier section, we use the model presented in Kacperczyk and Seru (2007) to motivate the use of a fund's trades to capture the extent and quality of private information that a manager generates. In all the analyses thus far, in order for a stock to be included in the skill computation, the split-adjusted holding of a particular stock in the portfolio should have changed. Using data on the trades made by the manager, the measure correctly attributes skill to the manager if her private information is precise and penalizes her in the event that the trades are negatively correlated with future news. However, one can also make an argument that the manager should be penalized for not being able to generate information about a stock. In other words, if there is an upcoming negative news about a particular stock and the manager did not preemptively reduce the holdings of this stocks, then she should be categorized as less skilled.[20] In order to address this point, we include all the stocks in the portfolio for the computation of skill, *i.e.,* both stocks that are traded and stocks that are not.[21] A summary of the distribution of the skill measure using all the stocks in the portfolio is reported in Panel B of Table IX. Just like the earlier analysis, we continue to find evidence to support the hypothesis that the average fund manager is skilled in picking stocks.

C. *Tax and window dressing*

The literature has identified tax and window dressing as other motives for funds to trade.[22] Ever since the 1986 Tax Reform Act, all mutual funds have the end of October as their mandated tax year-end. Therefore, their tax-motivated sales should occur around that point in time. Further, the literature on tournaments in mutual funds suggests that funds

[20] In order to differentiate skill from luck, we ignore the statically held stocks and their associated news in our main results and do so only as robustness here.

[21] The stocks that were not traded have 0% change in holdings.

[22] In order to minimize the taxable distributions, funds tend to trade a lot more as they get closer to the tax year-end (see Gibson, Safieddine and Titman (2000)). Further, in order to attract more flows, funds tend to engage in what is regarded as window dressing as they get closer to the fiscal year-end (see O'Neal (2001)).

have the highest incentive to window-dress from October to December. In order to mitigate the effects of these two motives for trading on the measure of skill, as they are not driven by private information, we exclude the trades made in the fourth quarter of the calendar year. The distribution of the skill measure computed using just the trades between January and September is presented in Panel C of Table IX. Overall, the result continues to be similar to the main findings of the paper. The average fund manager continues to show stock-picking ability.

D. Alternate two-period news

The return "news" or the innovation in return is essentially the deviation of the realized return from the conditional expectation. In computing the skill (for trades made between $(t-1)$ and t) using the two-period news between t and $(t+2)$, only the publicly available information at time t is used to form the expectation. The total news, $N_{TN,t\to t+2}$, for the period t to $(t+2)$, is expressed as the following:

$$N_{TN,t\to t+2} = E_{t+2}(r_{t,t+2}) - E_t(r_{t,t+2}),$$

where $r_{t,t+2}$ is the two-period return. An important prerequisite for a trade to be included in the skill computation is that the fund manager does not trade in the opposite side in the period after. However, the fund manager uses the information available at time $(t+1)$ and makes a decision about whether to trade in the opposite direction of the previous period's trades. Therefore, it could be argued that the two-period news used to compute the skill should incorporate this decision. In order to mitigate this concern, we compute the news for the two-period horizon in the following way:

$$N_{TN,t\to t+2} = (r_{t+1,t+2} - E_{t+1}(r_{t+1,t+2})) + (r_{t,t+1} - E_t(r_{t,t+1})).$$

In the above equation, the two-period news is treated as the sum of two separate shocks at $(t+1)$ and $(t+2)$ to the return process. We use the above-mentioned alternate two-period news term and compute the cross-sectional distribution of the stock-picking skill. The results reported in Panel D of Table IX are consistent with the earlier result of the average fund manager being skilled.

E. Skill and predictability

The positive correlation between the fund's trades and future innovation in returns can also be attributed to microstructural effects. The idea is that "copycat" investors follow the fund's trading strategies after the quarterly disclosure of holdings. This action puts pressure on the price of the stock in the precise direction of trade and hence leads to *predictability*. This argument is not tenable in an equilibrium where agents dynamically update their beliefs about the fund manager's ability. Investors will continue to copy the previous quarter's trades only if they perceive informational content in them. Further, mutual funds have 60 days after their quarter ends to file their holdings with the SEC. Very few mutual funds file their disclosures early. Assuming that copycat investors mimic the fund's trades no more than a month after the disclosure, a reasonable assumption, then the trades made in the previous quarter should not be correlated with news of *only* two quarters later under the null of no skill. In order to test this, we compute the skill of the fund manager as the correlation between the unexplained changes in holdings and the news of the stocks two periods later. The two-quarter later total news, $N_{TN,t+1\to t+2}$, is computed as follows:

$$N_{TN,t+1\to t+2} = r_{t+1,t+2} - E_t(r_{t+1,t+2})$$

where $r_{t+1,t+2}$ is the return of the stock between one and two quarters after the end of the trading quarter t. The report of the correlation using this measure is presented in Panel E of Table IX. Although it is impossible to completely rule out microstructural effects, the positive mean presented in Panel E of Table IX suggests that fund managers do generate private information about stocks.

F. Expected return and institutional holdings

Gompers and Metrick (2001) find that the level of institutional ownership in a stock can help forecast its future return. In order to incorporate this effect in forming the expectation about future returns, we update the parsimonious VAR specification used earlier and introduce the fraction of shares outstanding held by institutions as one of the state variables. The data about the quarterly institutional holdings are obtained from Thompson Reuters' institutional ownership database, which is collected from the 13f filings. The four-variable VAR specification includes the quarterly log excess returns of the individual stocks, the cross-sectionally demeaned log book-to-market ratio of the firm, the cross-sectionally demeaned average of quarterly profits of the previous 20 quarters, and the cross-sectionally demeaned fraction of total outstanding shares held by institutional investors. The first three variables are included to capture the empirical return-predictability results mentioned above. The reduced-form VAR is estimated by using a pooled weighted least square method. Each cross-section is weighted by the inverse of the number of firms in the cross-section. The parameter estimates are reported in Panel A of Table X. In order to account for any cross-sectional correlation in errors, the standard errors are clustered by cross-section. Resampling-based robust standard errors are also reported. As predicted, the level of institutional ownership has a positive effect on the firm's future returns. The magnitude of the remaining coefficients is very similar to those found in Table II. Using these parameter estimates, we compute the innovation in returns of the firm and also compute the skill of the manager. The estimates of the mean level of skill along with other attributes of the distribution are reported in Panel B of Table X. Skill using both one- and two-period news is still positive and statistically significant.

G. Long VAR

In order to further test the robustness of the results presented thus far, we estimate a richer VAR specification. The predictive variables used here include four lags of past (quarterly) stock return, the book-to-market ratio of the firm, two lags of quarterly profitability, two lags of leverage, and one lag of the size of the firm. This VAR specification is borrowed from the *"Long VAR"* in Vuolteenaho (2002). Leverage is computed as book equity over the sum of book equity and book debt. Book debt is the sum of debt in current liabilities, total long-term debt, and preferred stock. Size is the market capitalization of equity. Size and leverage are included in the specification because historically small firms have earned higher average stock returns than large firms and highly leveraged firms have outperformed firms with low leverage. Additional lags of returns are included to capture possible longer-horizon return auto-correlation. The distributional properties of skill estimated using the specification described above are reported in Panel C of Table X. The evidence still suggests that the average fund manager has positive stock-picking skill. Overall, we conclude that the qualitative results of the paper are not sensitive to the alternate VAR specifications.

VI. Conclusion

Extensive literature is devoted to understanding the mutual fund industry and, more specifically, its economic relevance. The central question of interest is whether fund managers have superior information. It is often the case that, in an attempt to answer this, this question is translated into whether the mutual fund can outperform the market or a benchmark. Berk and Green (2004) provide convincing arguments about why these two questions are not equivalent. So, it is still a matter of debate whether fund managers possess any skill.

In this paper, we propose a way to address this issue. Since the economic value of private information is captured by the knowledge of future innovation in returns, we estimate the skill of U.S. equity fund managers as the correlation between the current changes in mutual fund holdings and the future news in the stocks that they traded. This is a conditional measure of skill that distinguishes skill from luck. Using this measure, we find evidence to show that the *average* mutual fund manager is skilled in stock picking. This skill is more common among smaller funds. Managers who have skill turn over their portfolio more often and charge higher expenses (possibly due to higher management fees as a compensation for skill). The skill is fairly persistent, and this persistence in skill is not explained by the momentum effect. Importantly, we find a positive and significant relationship between managerial skill and future fund performance. This suggests that the managers, through their skill, do add economic value. Finally, we substantiate the view that investors learn about managers' skill. After controlling for past performance, new money does follow the skilled manager. Overall, our findings corroborate the substance and the implications of the theoretical model proposed by Berk and Green (2004) and argue that fund managers are important agents in keeping the market efficient.

References

Alexander, G. J., Cici, G. and Gibson, S.: 2007, Does Motivation Matter When Assessing Trade Performance? An Analysis of Mutual Funds, *Review of Financial Studies* **20**(1), 125–150.

Baker, M., Litov, L., Wachter, J. A. and Wurgler, J.: 2010, Can mutual fund managers pick stocks? evidence from their trades prior to earnings announcements, *Journal of Financial and Quantitative Analysis* **45**, 1111–1131.

Baker, M. and Wurgler, J.: 2006, Investor sentiment and the cross-section of stock returns, *The journal of Finance* **61**(4), 1645–1680.

Barber, B. M., Huang, X. and Odean, T.: 2016, Which factors matter to investors? evidence from mutual fund flows, *The Review of Financial Studies* **29**(10), 2600–2642.

Berk, J. B. and Van Binsbergen, J. H.: 2015, Measuring skill in the mutual fund industry, *Journal of Financial Economics* **118**(1), 1–20.

Berk, J. B. and Van Binsbergen, J. H.: 2016, Assessing asset pricing models using revealed preference, *Journal of Financial Economics* **119**(1), 1–23.

Berk, J. and Green, R.: 2004, Mutual fund flows and performance in rational markets, *Journal of Political Economy* **112**(6), 1269–1295.

Brown, N., Wei, K. and Wermers, R.: 2009, Analyst recommendations, mutual fund herding, and overreaction in stock prices, *Available at SSRN: http://ssrn.com/abstract=1092744* .

Campbell, J.: 1991, A variance decomposition for stock returns, *The Economic Journal* **101**(405), 157–179.

Campbell, J. Y.: 1996, Understanding risk and return, *Journal of Political Economy* **104**(2), pp. 298–345.

Campbell, J. Y., Polk, C. and Vuolteenaho, T.: 2009, Growth or Glamour? Fundamentals and Systematic Risk in Stock Returns, *Review of Financial Studies* **23**(1), 305–344.

Campbell, J. Y. and Vuolteenaho, T.: 2004, Bad beta, good beta, *American Economic Review* **94**(5), 1249–1275.

Carhart, M.: 1997, On persistence in mutual fund performance, *Journal of finance* **52**(1), 57–82.

Chen, H., Jegadeesh, N. and Wermers, R.: 2000, The value of active mutual fund management: An examination of the stockholdings and trades of fund managers, *Journal of Financial and quantitative Analysis* **35**(03), 343–368.

Chen, J., Hong, H., Huang, M. and Kubik, J. D.: 2004, Does fund size erode mutual fund performance? the role of liquidity and organization, *The American Economic Review* **94**(5), 1276–1302.

Christoffersen, S. E., Evans, R. and Musto, D. K.: 2013, What do consumers' fund flows maximize? evidence from their brokers' incentives, *The Journal of Finance* **68**(1), 201–235.

Crane, A. D. and Crotty, K.: 2018, Passive versus active fund performance: Do index funds have skill?, *Journal of Financial and Quantitative Analysis* **53**(1), 33–64.

Cremers, K. J. M. and Petajisto, A.: 2009, How Active Is Your Fund Manager? A New Measure That Predicts Performance, *Review of Financial Studies* **22**(9), 3329–3365.

Daniel, K., Grinblatt, M., Titman, S. and Wermers, R.: 1997, Measuring mutual fund performance with characteristic-based benchmarks, *Journal of Finance* **52**(3), 1035–1058.

Dow, J. and Gorton, G.: 1997, Noise trading, delegated portfolio management, and economic welfare, *Journal of Political Economy* **105**(5), pp. 1024–1050.

Edelen, R.: 1999, Investor flows and the assessed performance of open-end mutual funds, *Journal of Financial Economics* **53**, 439–466.

Elton, E. J., Gruber, M. J., Blake, C. R., Krasny, Y. and Ozelge, S. O.: 2010, The effect of holdings data frequency on conclusions about mutual fund behavior, *Journal of Banking & Finance* **34**(5), 912–922.

Evans, R.: 2010, Mutual fund incubation, *The Journal of Finance* **65**(4), 1581–1611.

Fama, E. and French, K.: 2010, Luck versus Skill in the Cross-Section of Mutual Fund Returns, *The Journal of Finance* **65**(5), 1915–1947.

Ferson, W. and Schadt, R.: 1996, Measuring fund strategy and performance in changing economic conditions, *The Journal of Finance* **51**(2), 425–461.

Frazzini, A. and Lamont, O. A.: 2008, Dumb money: Mutual fund flows and the cross-section of stock returns, *Journal of financial economics* **88**(2), 299–322.

Gibson, S., Safieddine, A. and Titman, S.: 2000, Tax-motivated trading and price pressure: An analysis of mutual fund holdings, *Journal of Financial and Quantitative Analysis* **35**(3), 369–386.

Gompers, P. A. and Metrick, A.: 2001, Institutional investors and equity prices, *The quarterly journal of Economics* **116**(1), 229–259.

Grinblatt, M. and Titman, S.: 1993, Performance measurement without benchmarks: An examination of mutual fund returns, *Journal of Business* **66**(1), 47–68.

Grossman, S. and Stiglitz, J.: 1980, On the impossibility of informationally efficient markets, *The American Economic Review* **70**(3), 393–408.

Hendricks, D., Patel, J. and Zeckhauser, R.: 1993, Hot hands in mutual funds: Short-Run persistence of relative performance, 1974-1988, *The Journal of Finance* **48**(1), 93–130.

Jensen, M.: 1968, The performance of mutual funds in the period 1945-1964, *Journal of finance* **23**(2), 389–416.

Johnson, T. L. and Weitzner, G.: 2019, Distortions caused by lending fee retention, *Available at SSRN 3081123* .

Kacperczyk, M., Nieuwerburgh, S. V. and Veldkamp, L.: 2014, Time-varying fund manager skill, *The Journal of Finance* **69**(4), 1455–1484.

Kacperczyk, M. and Seru, A.: 2007, Fund manager use of public information: New evidence on managerial skills, *The Journal of Finance* **62**(2), 485–528.

Kacperczyk, M., Sialm, C. and Zheng, L.: 2005, On the industry concentration of actively managed equity mutual funds, *The Journal of Finance* **60**(4), 1983–2011.

Kacperczyk, M., Sialm, C. and Zheng, L.: 2008, Unobserved actions of mutual funds, *The Review of Financial Studies* **21**(6), 2379–2416.

Kaniel, R. and Parham, R.: 2017, Wsj category kings–the impact of media attention on consumer and mutual fund investment decisions, *Journal of Financial Economics* **123**(2), 337–356.

Keswani, A. and Stolin, D.: 2008, Which money is smart? mutual fund buys and sells of individual and institutional investors, *The Journal of Finance* **63**(1), 85–118.

Kosowski, R., Timmermann, A., Wermers, R. and White, H.: 2006, Can mutual fund stars really pick stocks? New evidence from a bootstrap analysis, *The Journal of finance* **61**(6), 2551–2595.

Kothari, S. and Warner, J. B.: 2001, Evaluating mutual fund performance, *The Journal of Finance* **56**(5), 1985–2010.

Lou, D.: 2012, A flow-based explanation for return predictability, *The Review of Financial Studies* **25**(12), 3457–3489.

O'Neal, E.: 2001, Window dressing and equity mutual funds, *Babcock Graduate School of Management working paper* .

Pástor, L., Stambaugh, R. F. and Taylor, L. A.: 2017, Do funds make more when they trade more?, *The Journal of Finance* **72**(4), 1483–1528.

Pástor, u. and Stambaugh, R. F.: 2002, Investing in equity mutual funds, *Journal of Financial Economics* **63**(3), 351–380.

Sensoy, B. A.: 2009, Performance evaluation and self-designated benchmark indexes in the mutual fund industry, *Journal of Financial Economics* **92**(1), 25–39.

Shao, J. and Rao, J.: 1993, Jackknife inference for heteroscedastic linear regression models, *Canadian Journal of Statistics* **21**(4), 377–395.

Shumway, T.: 1997, The delisting bias in CRSP data, *Journal of Finance* **52**(1), 327–340.

Sirri, E. and Tufano, P.: 1998, Costly search and mutual fund flows, *The Journal of Finance* **53**(5), 1589–1622.

Vuolteenaho, T.: 2002, What drives firm-level stock returns?, *The Journal of Finance* **57**(1), 233–264.

Zheng, L.: 1999, Is money smart? a study of mutual fund investors' fund selection ability, *the Journal of Finance* **54**(3), 901–933.

Table I: Summary statistics

This table reports the summary statistics regarding the different variables in Thompson Reuters mutual fund holdings data as well as in the CRSP Survivorship bias free data. TNA is the dollar value of the total net assets managed by the fund. Number of stocks represents the stocks in the manager's portfolio. Expenses are the annual expense ratio of the fund. Similarly, turnover is the reported annual turnover of the fund. Age of the fund is the time in quarter-years from the date the fund became public. Carhart α is the quarterly abnormal return earned by the fund in excess of the four Carhart factors. Factor loadings were estimated from a time series regression using 36 previous monthly return.

	Mean	Median	Standard Deviation
Number of funds	3,858		
Number of fund-quarter observation	110,567		
Number of funds per quarter	1,164	1,270	
Number of stock held	123	82	160
Value of trades relative to TNA_{t-1} (in %)	22.13	11.89	377.52
TNA(in millions)	1,540.02	250.80	6,361.19
Expense ratio (in %)	1.21	1.18	0.47
Turnover ratio (in %)	83.41	60.00	109.61
Age (in quarter years)	60.60	45.00	56.56
Carhartα - net (in %)	-0.22	-0.23	9.27

Table II: Firm level VAR parameter estimates

Estimates from the firm level vector autoregression (VAR) are reported here. The VAR has three state variables. $r_{i,t+1}$ is the quarterly log excess returns of the individual stocks. $BM_{i,t+1}$ is the cross-sectionally demeaned log book-to-market of the firm at quarterly intervals. $\overline{ROE}_{i,t+1}$ is the cross-sectionally demeaned average of log quarterly profits of the previous 20 quarters. They are computed using the accounting clean surplus identity. The VAR is a pooled analysis involving all the firms and all time periods. All the firms share the same transition matrix. A weighted least square procedure was used to estimate the parameters, where each cross-section is weighted by the inverse of the number of firms in the cross-section. The sample involves observations from 1994-2017. Estimates of the VAR are reported in bold. The second number (in parentheses) is the robust standard errors clustered along each cross-section. The third number (in brackets) is a robust jackknife standard error computed using the method outlined in Shao and Rao (1993). The table also shows the variance-covariance matrix of the cash-flow news (N_{CF}) and the discount rate news (N_{DR}) terms and the relevant robust jackknife standard errors. Discount rate news is computed as $e1'\lambda u_i$ and cash-flow news as $(e1' + e1'\lambda)u_i$. In this function $e1$ is a vector with first element equal to one and the remaining elements equal to zero, u_i is the vector of residuals from the VAR, and $\lambda \equiv \rho\Gamma(I - \rho\Gamma)^{-1}$. Γ is point estimate of the VAR transition matrix and ρ is the linearization parameter set equal to 0.95.

	$r_{i,t}$	$BM_{i,t}$	$\overline{ROE_{i,t}}$	R^2
$r_{i,t+1}$	**0.0394**	**0.0212**	**0.0987**	0.6%
(Log stock returns)	(0.0026)	(0.0007)	(0.0081)	
	[0.0025]	[0.0007]	[0.0078]	
$BM_{i,t+1}$	**0.0645**	**0.9494**	**0.1332**	86.2%
(log book-to-market)	(0.0031)	(0.0014)	(0.0120)	
	[0.0030]	[0.0014]	[0.0115]	
$\overline{ROE}_{i,t+1}$	**0.0136**	**-0.0022**	**0.6999**	69%
(five-year profitability)	(0.0004)	(0.0001)	(0.0123)	
	[0.0004]	[0.0001]	[0.0118]	

Variance-covariance matrix

	-N_{DR}	N_{CF}
-N_{DR}	0.0031	-0.0020
	[0.0001]	[0.0001]
N_{CF}		0.0529
		[0.0002]

Table III: Skill and relationship with fund characteristics

This table reports the summary of the skill measure and also presents its relationship with other fund characteristics. Skill is computed as the correlation between the unexplained changes in manager's portfolio holdings and news about the firm in subsequent quarter. Skill_2 is computed as the correlation between the unexplained changes in manager's portfolio holdings and news about the firm in subsequent two quarters. Change in portfolio holdings of an asset i is computed as the % change in the split-adjusted holdings of the asset between the two quarters. In Panel A, we present the summary of the distribution of skill across all fund managers. Significance of mean is tested under standard t-test as well as using a non-parametric bootstrapped test. The correlation between changes in portfolio holdings and subsequent cash-flow news and the correlation between changes in portfolio holdings and subsequent discount rate news are reported in Panel B. They are reported for news of one and two quarter respectively. In Panel C, we present the variation in skill across two sub-periods. Results of testing differences in mean are reported. Panel D reports the contemporaneous correlation between skill and other relevant fund characteristics. The significance levels are denoted by *, **, and *** and indicate whether the results are statistically different from zero at the 10%, 5%, and 1% significance levels, respectively.

Panel A: Distribution Summary

	Mean	p-value of one-sided test		25 pct	Median	75pct	Std dev
		bootstrapped	t-test				
Skill	0.0080***	(<0.001)	(<0.001)	-0.1279	0.0092	0.1469	0.2390
Skill_2	0.0166***	(<0.001)	(<0.001)	-0.1363	0.0189	0.1748	0.2607

Panel B: Type of Skill

	1 quarter horizon	2 Quarter horizon
Skill (Cash flow news)	0.0083***	0.0173***
Skill (Discount rate news)	-0.0053***	-0.0066***

Panel C: Variation in Skill

Period	Total News	Discount News	Cash Flow News
Jan 1994 - Dec 2002	0.0215***	-0.0178***	0.0207***
Jan 2003-Dec 2016	0.0032	-0.0010	0.0039
Difference	0.0183***	-0.0168	0.0168***

Panel D: Correlation Structure

Variables	Skill	Tna	Expenses (%)	Turnover (%)	Age
Skill	1				
log(TNA)	-0.0087***	1			
Expenses (%)	0.0196***	-0.1663***	1		
Turnover (%)	0.0271***	-0.0726***	0.2209***	1	
Age	-0.0061**	0.3053***	-0.1877***	-0.0928***	1

Table IV: Skill against bootstrapped random distribution

This table reports the summary of the skill measure against a simulated distribution of skill where stock news were randomized. For each cross-section, we start with the observations of the fund's actual trades. For each stock traded, we assign a randomly chosen quarterly news. The news terms are randomly drawn from the actual time-series of the relevant stock's news distribution. Skill of the fund is then computed as the correlation between the unexplained changes in manager's portfolio holdings and the randomly drawn news. We perform 1000 iterations of this randomization exercise. Pct describes the percentile of the relevant distribution. Actual distribution and the mean from the 1000 iterations at respective percentiles are presented in columns (2)-(5). We also present the percentage of the times the simulated distribution is greater than the actual distribution (% > Act) and the simulated skill at the 5^{th} and 95^{th} percentiles (columns (8) to (11)) to consrtuct a bootsrapped confidence interval. As an additional benchmark, in the final two columns, we also show the skill of index funds.

Pct	Actual		Sim		% > Act		5^{th} pct		95^{th} pct		Index funds	
	Skill	Skill_2	Skill	Skill_2	Skill	Skill_2	Skill	Skill_2	Skill	Skill_2	Skill	Skill_2
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
5	-0.390	-0.424	-0.362	-0.393	1000	1000	-0.366	-0.397	-0.358	-0.389	-0.229	-0.245
10	-0.281	-0.304	-0.257	-0.280	1000	1000	-0.260	-0.283	-0.254	-0.277	-0.148	-0.158
15	-0.216	-0.233	-0.195	-0.213	1000	1000	-0.198	-0.215	-0.193	-0.210	-0.107	-0.114
20	-0.167	-0.179	-0.151	-0.164	1000	1000	-0.153	-0.166	-0.149	-0.162	-0.081	-0.086
25	-0.128	-0.136	-0.116	-0.126	1000	1000	-0.118	-0.128	-0.114	-0.123	-0.062	-0.065
30	-0.095	-0.099	-0.087	-0.093	1000	1000	-0.089	-0.095	-0.085	-0.091	-0.046	-0.048
35	-0.066	-0.066	-0.061	-0.065	1000	856	-0.063	-0.067	-0.060	-0.063	-0.033	-0.034
40	-0.039	-0.036	-0.038	-0.039	908	11	-0.040	-0.041	-0.036	-0.037	-0.021	-0.022
45	-0.015	-0.008	-0.016	-0.015	29	0	-0.018	-0.017	-0.015	-0.013	-0.010	-0.011
50	0.009	0.019	0.004	0.008	0	0	0.003	0.006	0.006	0.010	0.000	0.001
55	0.033	0.047	0.025	0.031	0	0	0.023	0.029	0.027	0.033	0.011	0.012
60	0.058	0.075	0.047	0.055	0	0	0.045	0.053	0.048	0.057	0.022	0.024
65	0.084	0.105	0.070	0.081	0	0	0.068	0.079	0.071	0.083	0.034	0.036
70	0.114	0.138	0.095	0.109	0	0	0.094	0.107	0.097	0.111	0.047	0.051
75	0.147	0.175	0.125	0.141	0	0	0.123	0.139	0.126	0.144	0.063	0.068
80	0.185	0.217	0.159	0.179	0	0	0.157	0.177	0.161	0.182	0.083	0.090
85	0.233	0.267	0.203	0.227	0	0	0.200	0.224	0.205	0.230	0.110	0.119
90	0.296	0.334	0.263	0.292	0	0	0.260	0.289	0.266	0.295	0.151	0.164
95	0.398	0.442	0.366	0.402	0	0	0.363	0.398	0.370	0.406	0.231	0.251
Mean	0.008	0.017	0.004	0.007	0	0	0.002	0.005	0.005	0.009	0.001	0.002

Table V: Relationship between managerial skill and performance

This table reports the results from regressions relating performance to managerial skill. $skill_{t-1}$ is computed as the correlation between the unexplained changes in manager's portfolio holdings and subsequent news about the firm. Change in portfolio holdings of an asset i is computed as % change in the split-adjusted holdings of the asset between the two quarters. $skill\ cash_{t-1}$ is correlation between changes in portfolio holdings and subsequent cash-flow news. Similarly, $skill\ discount_{t-1}$ is correlation between changes in portfolio holdings and subsequent discount rate news. The dependent variable is the quarterly factor-based α computed using CAPM, three factor, and the four factor model, respectively. Factor loadings are estimated from a time series regression using returns of previous 36 months. RPI is the reliance on public information measure calculated as described in Kacperczyk and Seru (2007). $Log(TNA)$ is the natural logarithm of total net assets lagged one quarter. Expenses represent the fund's expense ratio lagged one year. Log(age) is the age of the fund lagged one quarter. Turnover is the turnover of the fund which is lagged one year. NMG represents the flows to the funds lagged one quarter. All specifications account for time fixed and fund fixed effects. In order to correct for any cross-sectional correlation or time-series correlation in errors, the standard errors are clustered in the both dimensions, fund and time. This should also account for hetroskedasticity. Standard errors are reported below the estimates in parentheses. The significance levels are denoted by *, **, and *** and indicate whether the results are statistically different from zero at the 10%, 5%, and 1% significance levels, respectively.

	CAPM α(%) (1)	3-factor α(%) (2)	4-factor α(%) (3)	4-factor α(%) (4)	CAPM α(%) (5)	3-factor α(%) (6)	4-factor α(%) (7)	4-factor α(%) (8)	4-factor α(%) (9)
$skill_{t-1}$	2.098***	2.004***	1.465***	1.467***				1.474***	
	(0.102)	(0.107)	(0.126)	(0.126)				(0.133)	
$skill\ cash_{t-1}$					2.068***	1.828***	1.411***		1.438***
					(0.114)	(0.120)	(0.141)		(0.149)
$skill\ discount_{t-1}$					−0.059	−0.323***	−0.108		−0.073
					(0.115)	(0.120)	(0.141)		(0.150)
RPI_{t-1}				0.252					
				(0.262)					
$ReturnGap_{t-1}$								0.265***	0.267***
								(0.047)	(0.047)
$Log(TNA)_{t-1}$	−0.012	0.031*	−0.033*	−0.032	−0.012	0.031*	−0.033*	−0.030	−0.030
	(0.016)	(0.017)	(0.020)	(0.020)	(0.016)	(0.017)	(0.020)	(0.021)	(0.021)
NMG_{t-1} (%)	0.0005	−0.0001	−0.001	−0.001	0.0005	−0.0001	−0.001	−0.001	−0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$Log(age)_{t-1}$	−0.051	−0.065*	0.018	0.017	−0.051	−0.066*	0.017	0.046	0.046
	(0.034)	(0.035)	(0.042)	(0.042)	(0.034)	(0.035)	(0.042)	(0.046)	(0.046)
$expenses_{t-1}$ (%)	−0.207***	−0.032	−0.097	−0.102	−0.207***	−0.032	−0.097	−0.081	−0.081
	(0.059)	(0.061)	(0.072)	(0.072)	(0.059)	(0.061)	(0.072)	(0.077)	(0.077)
$Turnover_{t-1}$ (%)	−0.0003	0.0004	−0.001**	−0.001**	−0.0003	0.0004	−0.001**	−0.001**	−0.001**
	(0.0002)	(0.0002)	(0.0003)	(0.0003)	(0.0002)	(0.0002)	(0.0003)	(0.0003)	(0.0003)
Observations	80,321	80,321	80,321	80,267	80,321	80,321	80,321	75,362	75,362
R^2 (%)	0.5	0.4	0.2	0.2	0.5	0.4	0.2	0.2	0.2

Table VI: Relationship between skill and holding based performance measures

This table reports the results from regressions relating holding based performance measures to managerial skill. $skill_{t-1}$ is computed as the correlation between the unexplained changes in manager's portfolio holdings and subsequent news about the firm. Change in portfolio holdings of an asset i is computed as % change in the split-adjusted holdings of the asset between the two quarters. $skill\ cash_{t-1}$ is correlation between changes in portfolio holdings and subsequent cash-flow news. Similarly, $skill\ discount_{t-1}$ is correlation between changes in portfolio holdings and subsequent discount rate news. CS is the characteristic selectivity measure from Daniel, Grinblatt, Titman and Wermers (1997). It is defined as $CS = \sum w_{i,t-1}[R_{i,t} - R_t^{b,t-1}]$ where $R_t^{b,t-1}$ is the return for time t of the benchmark portfolio to which i was allocated at time *(t-1)*. CT is the characteristic timing measure which measures the timing ability of the manager. It is computed as $CT = \sum[w_{i,t-1}R_t^{b,t-1} - w_{i,t-13}R_t^{b,t-13}]$ where $w_{i,t-13}$ is weight of the portfolio 13 months ago and $\mathrm{R}_t^{b,t-13}$ is the return of the benchark portfolio to which the stock was allocated 13 months ago. RPI is the reliance on public information measure calculated as described in Kacperczyk and Seru (2007). $Log(TNA)$ is the natural logarithm of total net assets lagged one quarter. Expenses represent the fund's expense ratio lagged one year. Log(age) is the age of the fund lagged one quarter. Turnover is the turnover of the fund which is lagged one year. NMG represents the flows to the funds lagged one quarter. All specifications account for time fixed and fund fixed effects. In order to correct for any cross-sectional correlation or time-series correlation in errors, the standard errors are clustered in the both dimensions, fund and time. Standard errors are reported below the estimates in parentheses. The significance levels are denoted by *, **, and *** and indicate whether the results are statistically different from zero at the 10%, 5%, and 1% significance levels, respectively.

	CS (%)	CT (%)	CS (%)	CT (%)
$skill_{t-1}$	1.140***	0.006		
	(0.047)	(0.047)		
$skill\ cash_{t-1}$			1.171***	0.023
			(0.053)	(0.052)
$skill\ discount_{t-1}$			0.052	0.057
			(0.053)	(0.052)
RPI_{t-1}	0.307***	−0.336***	0.306***	−0.336***
	(0.098)	(0.097)	(0.098)	(0.097)
$Log(TNA)_{t-1}$	−0.011	−0.078***	−0.011	−0.078***
	(0.007)	(0.007)	(0.007)	(0.007)
NMG_{t-1}	0.001***	−0.0001	0.001***	−0.0002
(%)	(0.0004)	(0.0003)	(0.0004)	(0.0003)
$Log(age)_{t-1}$	0.022	−0.026*	0.022	−0.026*
	(0.015)	(0.015)	(0.015)	(0.015)
$expenses_{t-1}$	0.004	0.010	0.004	0.010
(%)	(0.027)	(0.026)	(0.027)	(0.026)
$Turnover_{t-1}$	−0.0002*	0.001***	−0.0002*	0.001***
(%)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Observations	80,807	80,807	80,807	80,807
R^2(%)	0.8	0.4	0.8	0.4

Table VII: Persistence of skill

This table reports the persistence of the mutual fund manager's stock picking skill. Skill is the correlation between the unexplained changes in manager's portfolio holdings and subsequent news about the firm. Change in portfolio holdings of an asset is computed as the % change in split-adjusted holdings of the asset between the two quarters. Each quarter funds are sorted into decile portfolios based on their level of skill. Mean level of the skill, for each of these portfolios, for future quarters is reported. $Skill_t$, $Skill_{t+1}$, and $Skill_{t+2}$ are the mean for the three consecutive quarters. Standard errors are reported below the estimates in parentheses. The third number (in brackets) is standard error from a non-parametric bootstrap test. Results of testing differences in mean are also reported. The significance levels are denoted by *, **, and *** and indicate whether the results are statistically different from zero at the 10%, 5%, and 1% significance levels, respectively.

	Total News			CF News		
Decile	$Skill_t$	$Skill_{t+1}$	$Skill_{t+2}$	$Skill_t$	$Skill_{t+1}$	$Skill_{t+2}$
1	-0.4170	-0.0059	-0.0067	-0.4149	-0.0044	-0.0035
	(1.000)	(0.989)	(0.999)	(1.000)	(0.975)	(0.991)
	[1.000]	[0.9735]	[0.9874]	[1.0000]	[0.9272]	[0.8792]
2	-0.2167	-0.0034	0.0009	-0.2160	0.0013	0.0018
	(1.000)	(0.986)	(0.855)	(1.000)	(0.724)	(0.781)
	[1.0000]	[0.9096]	[0.3551]	[1.000]	[0.3045]	[0.2383]
3	-0.1279	0.0003	0.0072*	-0.1269	0.0011	0.0072*
	(1.000)	(0.872)	(0.082)	(1.000)	(0.789)	(0.084)
	[1.000]	[0.4517]	[0.0013]	[1.000]	[0.329]	[0.0013]
4	-0.0655	0.0021	0.0045	-0.0649	0.0043	0.0057
	(1.000)	(0.701)	(0.365)	(0.999)	(0.355)	(0.223)
	[1.0000]	[0.1884]	[0.0203]	[1.0000]	[0.0321]	[0.0056]
5	-0.0142***	0.0063	0.0025	-0.0140***	0.0053	0.0070*
	(0.008)	(0.1270)	(0.725)	(0.006)	(0.218)	(0.076)
	[1.0000]	[0.0026]	[0.1263]	[1.0000]	[0.0101]	[0.0006]
6	0.0340***	0.0095***	0.0092***	0.0337***	0.0089**	0.0106***
	(<0.001)	(0.010)	(0.008)	(<0.001)	(0.0220)	(<0.001)
	[<0.001]	[<0.001]	[<0.001]	[<0.001]	[<0.001]	[<0.001]
7	0.0856***	0.0159***	0.0143***	0.0854***	0.0151***	0.0091**
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(0.011)
	[<0.001]	[<0.001]	[<0.001]	[<0.001]	[<0.001]	[<0.001]
8	0.1475***	0.0141***	0.0130***	0.1467***	0.0129***	0.0129***
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
	[<0.001]	[<0.001]	[<0.001]	[<0.001]	[<0.001]	[<0.001]
9	0.2328***	0.0187***	0.0169***	0.2325***	0.0166***	0.0175***
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
	[<0.001]	[<0.001]	[<0.001]	[<0.001]	[<0.001]	[<0.001]
10	0.4237***	0.0209***	0.0170***	0.4241***	0.0188***	0.0144***
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
	[<0.001]	[<0.001]	[<0.001]	[<0.001]	[<0.001]	[<0.001]
10-1	0.8407***	0.0268***	0.0237***	0.8390***	0.0232***	0.0179***
	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)
	[<0.01]	[<0.01]	[<0.01]	[<0.01]	[<0.01]	[<0.01]

Table VIII: Relationship between managerial skill and flows

This table reports the results from a quantile regression relating skill to flows. $skill_{t-1}$ is computed as the correlation between the unexplained changes in manager's portfolio holdings and subsequent news about the firm. Change in portfolio holdings of an asset i is computed as % change in the split-adjusted holdings of the asset between the two quarters. The dependent variable is the amount of flows to the mutual fund computed as $Netflow_{j,t}=(TNA_{j,t+1}-TNA_{j,t}(1+R_{j,t+1}))/TNA_{j,t}$. R_t is one period lagged quarterly returns of the fund. α_t is quarterly abnormal returns computed using the four factor model. Factor loadings are estimated from a time series regression using the returns of the previous 36 months. $Log(TNA)$ is the natural logarithm of total net assets lagged one period. Expenses represent the fund's expense ratio lagged one quarter. age_t is the cross-sectionally demeaned age of the fund lagged by one quarter. Turnover is the turnover of the fund which is lagged one quarter. The table reports the results of a quantile regression, where the column show the 25th, 50th, 75th, and the 90th percentile respectively. The regression include fixed time effects. Bootstrapped standard errors are reported below the estimates in parentheses. The significance levels are denoted by *, **, and *** and indicate whether the results are statistically different from zero at the 10%, 5%, and 1% significance levels, respectively.

	$NetFlows_{t+1}(\%)$							
	25th Pct (1)	50th Pct (2)	75th Pct (3)	90th Pct (4)	25th Pct (5)	50th Pct (6)	75th Pct (7)	90th Pct (8)
$skill_{t-1}$	0.525***	0.279***	0.568***	0.996***	0.648***	0.390***	0.789***	1.525***
	(0.079)	(0.075)	(0.132)	(0.383)	(0.120)	(0.096)	(0.161)	(0.458)
$skill_{t-1}$*age_t					-0.003 ***	−0.003 ***	−0.005 ***	−0.010 ***
					(0.001)	(0.001)	(0.001)	(0.004)
α_t	0.004**	0.004***	0.021**	0.035**	0.004*	0.004***	0.020*	0.034**
	(0.002)	(0.001)	(0.009)	(0.017)	(0.002)	(0.0001)	(0.011)	(0.016)
R_t (%)	0.223***	0.254***	0.381***	0.647***	0.222***	0.254***	0.380***	0.645***
	(0.006)	(0.005)	(0.009)	(0.023)	(0.006)	(0.004)	(0.009)	(0.024)
$expenses_t$	−0.646***	−0.634***	−0.201**	−0.173	−0.645***	−0.642***	−0.189**	−0.187
(%)	(0.061)	(0.049)	(0.090)	(0.265)	(0.060)	(0.049)	(0.092)	(0.245)
age_t	0.002***	−0.006***	−0.015***	−0.024***	0.002***	−0.006***	−0.015***	−0.024***
	(0.0002)	(0.0002)	(0.0003)	(0.001)	(0.0002)	(0.0001)	(0.0003)	(0.001)
$log(tna_t)$	0.149***	0.028***	−0.093***	−0.796***	0.148***	0.025***	−0.091***	−0.806***
	(0.013)	(0.011)	(0.019)	(0.055)	(0.013)	(0.010)	(0.019)	(0.052)
$turnover_t$	−0.008***	−0.005***	−0.001	0.015***	−0.008***	−0.005***	−0.001	0.015***
(%)	(0.0005)	(0.0003)	(0.001)	(0.003)	(0.0005)	(0.0003)	(0.001)	(0.003)
Observations	68,193	68,193	68,193	68,193	68,193	68,193	68,193	68,193

Table IX: Robustness of skill measure

This table reports the summary of the skill of fund managers under different specifications. *Skill* is computed as the correlation between the unexplained changes in manager's portfolio holdings and news about the firm in subsequent quarter. *Skill_2* is computed as the correlation between the unexplained changes in manager's portfolio holdings and news about the firm in subsequent two quarters. In Panel A, the skill is computed by weighting each trade differently. In computing the correlation, the following weight was used: $weight_{i,j,t} = |\frac{(ShareAmount_{i,j,t} - ShareAmount_{i,j,t-1}) * SharePrice_{i,j,t}}{TNA_{j,t}}|$. Panel B also reports summary of the skill distribution. Here, the skill is computed by including all stocks in the portfolio, irrespective of whether they were traded. In Panel C, the skill is computed by ignoring the trades made in the fourth quarter. In Panel D, *Skill_2* is computed using an alternate two period news estimation. Here the two period news is computed as the sum of two conditional expectations, $[r_{t+1} - E_t(r_{t+1})] + [r_{t+2} - E_{t+1}(r_{t+2})]$. In Panel E, *Skill* is computed as the correlation between unexplained changes in holdings and news from only two periods later. The news from only two periods later is computed as $[r_{t+1,t+2} - E_t(r_{t+1,t+2})]$. For all panels, significance of mean is tested under standard t-test as well as using the Wilcox rank test, a non-parametric test. The significance levels are denoted by *, **, and *** and indicate whether the results are statistically different from zero at the 10%, 5%, and 1% significance levels, respectively.

Panel A: Skill Value

	Mean	25 pct	Median	75pct	Std dev
Skill	0.0030***	-0.2008	0.0041	0.2035	0.3311
Skill_2	0.0087***	-0.1970	0.0179	0.2202	0.3405

Panel B: Skill - All Stocks

	Mean	25 pct	Median	75pct	Std dev
Skill	0.0065***	-0.1073	0.0068	0.1215	0.2002
Skill_2	0.0139***	-0.1153	0.0136	0.1446	0.2218

Panel C: Skill - No 4^{th} quarter

	Mean	25 pct	Median	75pct	Std dev
Skill	0.0074***	-0.1290	0.0093	0.1474	0.2399
Skill_2	0.0187***	-0.1342	0.0209	0.1772	0.2617

Panel D: Alternate Two Period News

	Mean	25 pct	Median	75pct	Std dev
Skill_2	0.0164***	-0.1363	0.0187	0.1747	0.2608

Panel E: Skill and predictability

	Mean	25 pct	Median	75pct	Std dev
Skill	0.0058***	-0.1438	0.0090	0.1594	0.2574

Table X: Alternate VAR specifications

Estimates from the firm level vector autoregression (VAR) and the resulting skill measure are reported here. Panel A presents the parameter estimates of the VAR with the four state variables. $r_{i,t+1}$ is the quarterly log excess returns of the individual stocks. $BM_{i,t+1}$ is the cross-sectionally demeaned log book-to-market of the firm at quarterly intervals. $\overline{ROE}_{i,t+1}$ is the cross-sectionally demeaned average of quarterly log profits of the previous 20 quarters. They are computed using the accounting clean surplus identity. $IST_{i,t+1}$ is cross-sectionally demeaned fraction of total outstanding shares held by institutional investors. The VAR is a pooled analysis involving all the firms and all time periods. All the firms share the same transition matrix. A weighted least square procedure is used to estimate the parameters, where each cross-section is weighted by the inverse of the number of firms in the cross-section. The sample involves observations from 1994-2017. Estimates of the VAR are reported in bold. The standard errors are clustered along each cross-section and are reported in the parentheses below the estimates. The resulting R^2 is also presented. Panel B presents the summary of the distribution of skill across all fund managers. *Skill* is computed as the correlation between the unexplained changes in manager's portfolio holdings and news about the firm in subsequent quarter. *Skill*_2 is computed as the correlation between the unexplained changes in manager's portfolio holdings and news about the firm in subsequent two quarters. The news is computed using the VAR set up in Panel A. Significance of mean is tested under standard t-test as well as using a non-parametric bootstrapped test. Panel C reports the skill computed using an alternate VAR specification (Long VAR). The long VAR includes four lags of quarterly log excess returns, the cross-sectionally demeaned log book-to-market ratio, two lags of the cross-sectionally demeaned log quarterly profits, two lags of cross-sectionally demeaned leverage, and the size of the firm. The significance levels are denoted by *, **, and *** and indicate whether the results are statistically different from zero at the 10%, 5%, and 1% significance levels, respectively.

Panel A: VAR parameter estimates

	$r_{i,t}$	$BM_{i,t}$	$\overline{ROE}_{i,t}$	$IST_{i,t}$	R^2
$r_{i,t+1}$	**0.0385**	**0.0210**	**0.0812**	**0.0002**	0.5%
(Log stock returns)	(0.0026)	(0.0007)	(0.0079)	(0.0000)	
$BM_{i,t+1}$	**0.0642**	**0.9488**	**0.1322**	**0.0002**	86.4%
(log book-to-market)	(0.0031)	(0.0015)	(0.0121)	(0.0001)	
$\overline{ROE}_{i,t+1}$	**0.0127**	**-0.0024**	**0.6989**	**0.0003**	68.9%
(five-year profitability)	(0.0004)	(0.0001)	(0.0130)	(0.0003)	
$IST_{i,t+1}$	**-0.0033**	**-0.0558**	**0.7128**	**0.0311**	0.2%
	(0.0124)	(0.0034)	(0.0307)	(0.0298)	

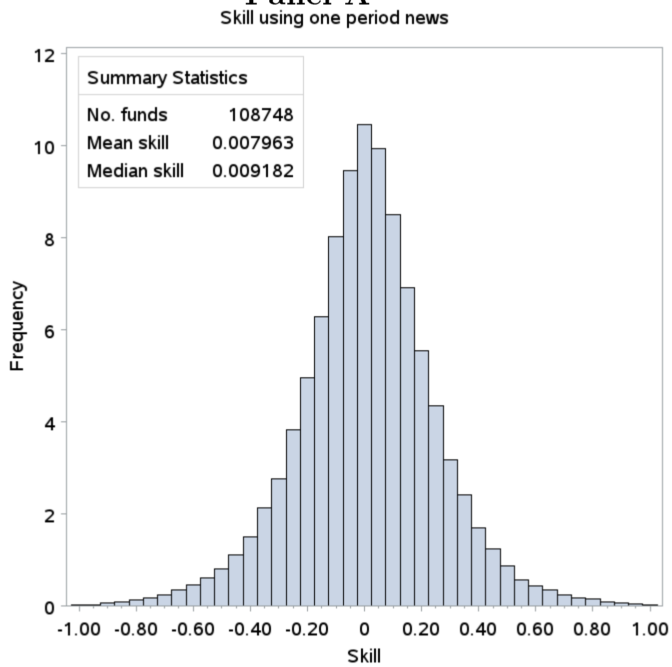
Panel B: Skill - Alternate VAR specification

	Mean	p-value of one-sided test		25 pct	Median	75pct	Std dev
		bootstrapped	t-test				
Skill	0.0082***	<0.01	<0.01	-0.1278	0.0095	0.1471	0.2391
Skill_2	0.0166***	<0.001	<0.001	-0.1362	0.0189	0.1747	0.2608

Panel C: Skill - Long VAR specification

	Mean	25 pct	Median	75pct	Std dev
Skill	0.0050***	-0.0330	0.0039	0.0448	0.0952
Skill_2	0.0177***	-0.0361	0.0138	0.0788	0.1223

Panel A



Panel B

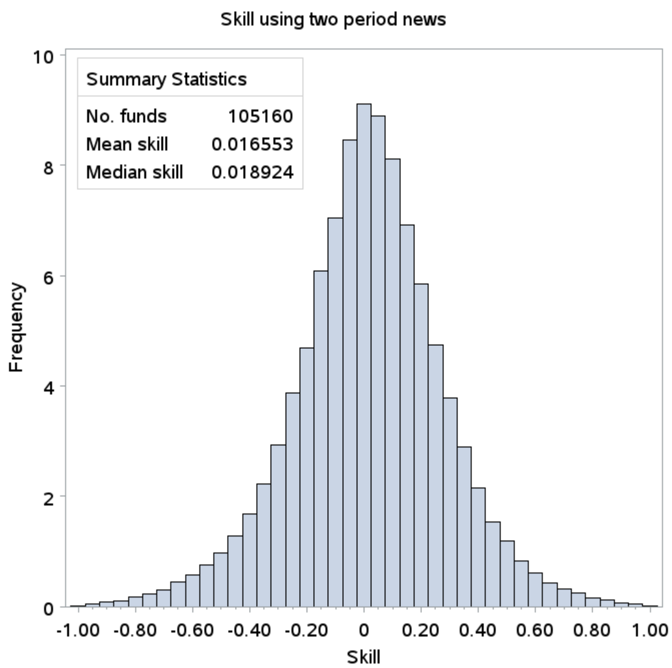


Figure 1. : Distribution of Skill

This figure plots the histogram of the skill measure. Summary of the distribution is provided in inset. Skill is computed as the correlation between the unexplained changes in manager's portfolio holdings and subsequent news about the firm. Panel A reports the skill using news from one period in the future. Panel B uses the news from two future periods.

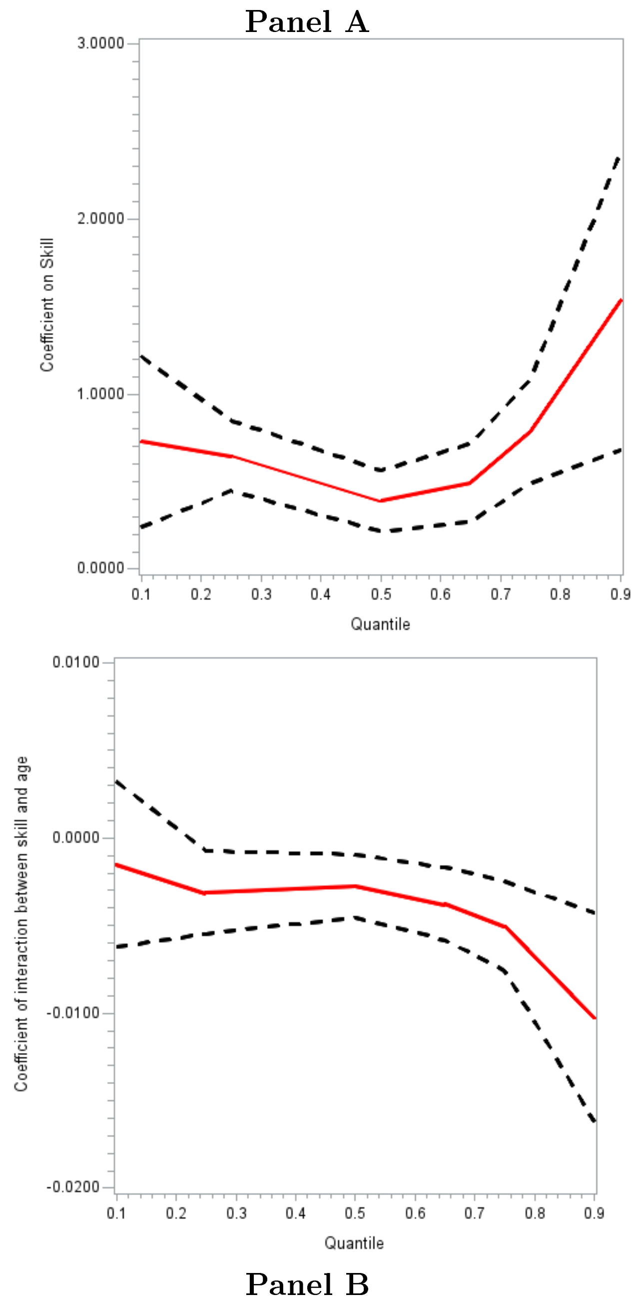


Figure 2. : Quantile Regression of Flows

This figure plots the paratmeter estimates and the related 95% confidence interval from the quantile regression for each of the different quantiles. The solid line is the parameter estimate and the dashed lines are the lower and upper confidence intervals. Panel A presents the marginal effects of the skill variable on flows at the different quantiles. Similarly, Panel B presents the marginal effects of the interaction between age and skill on the flows of the fund. Skill is computed as the correlation between the unexplained changes in manager's portfolio holdings and subsequent news about the firm.