Measuring the skill of the fund manager*

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Abstract

I introduce a conditional measure of skill, the correlation between fund's trades and future "news" of the stocks traded. Using this measure, I show that the average fund manager in the cross-section of U.S. equity mutual funds has stock picking skill. This skill is mainly driven by manager's ability to predict firm's cash-flow news. Importantly, this skill has short term persistence, which is not explained by momentum effect, and is positively related to the traditional measures of performance. Consistent with theory, fund flows are increasing in managerial skill.

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I Introduction

Do mutual funds managers add economic value? With approximately \$13 trillion[1] invested through mutual funds in 2012, this issue remains as salient as ever. Numerous researchers, starting from Jensen (1968), have looked to examine the skill of a fund manager and have used a variety of empirical methodology. Typically, tests exploit the cross sectional distribution of mutual fund returns to verify fund manager's skill. Overall, the results have been mixed.[2] Berk and Green (2004) argue that in an economy with rational profit maximizing investors who compete for investment opportunities, the expected risk-adjusted returns of all fund managers should be zero. The argument is rooted to the presence of diseconomies of scale in fund performance. Money will flow to the most skilled manager until the assets managed by her is such that, given her skill, she won't be able to deliver superior performance any further. At this point, money flows to the next most skilled manager in the ordering. This process will follow until the investors are indifferent between investing in an active mutual fund and indexing. Even though the expected abnormal return is zero, an aggregate management fees of approximately \$20 billion was paid in 2012. Berk and Green (2004) assert that this is because managers have stock picking skill which generates gross returns to the fund. Managers capture rents from their skill and this results in a zero net return to the investors. Therefore, the fact that the average manager fails to beat her benchmark is simply an evidence that the capital markets are competitive and provides no insight on the manager's ability.

The primary objective of this paper is to ascertain whether fund managers have any stock picking skill. Serious concerns of lack of power (see Kothari and Warner (2001)), inability to distinguish skill from luck, appropriateness of a benchmark, and model misspecification (see Pástor and Stambaugh (2002) and Kosowski et al. (2006)) are reasons why applying the traditional tests and studying gross excess return (α) of the fund is not fruitful.[3]

I introduce a new measure of managerial skill. I argue that the manager's skill is determined by the correlation between changes in portfolio holdings and the innovation in returns of those firms, controlling for changes in portfolio holdings due to reasons other than private information. A higher correlation implies that the manager is more skilled. Using correlation mitigates the criticisms of using the gross abnormal return as a measure of managerial ability. First, the power of this approach to identify skill is substantially better than the traditional regression based methodology. Kothari and Warner (2001) present simulation based results on the power of different performance measures. They show that the power of the test can be significantly improved by using event-study procedures that analyzes stock trades, as in this paper, than when traditional performance measures, like alpha, are used. Second, it is possible that the manager is just lucky and trades on a stock which is then positively correlated with the future changes in expectation. In order to mitigate this con-

[1] The 2013 Investment Company Fact Book is available at http://www.icifactbook.org/fb_ch2.html#investor.

[2] Jensen (1968), Carhart (1997), and more recently Lewellen (2011) find no evidence to support the existence of skilled or informed managers. However, Daniel, Grinblatt, Titman and Wermers (1997), Chen, Jegadeesh and Wermers (2000), and Kosowski, Timmermann, Wermers and White (2006) show evidence to support that there exist fund managers who make value enhancing decisions.

[3] Data availability also impedes the use of gross excess return of the fund (returns before managerial fees) to comment on managerial skill. This data is incomplete and does not go back in time. Also, the large variation in mutual fund alpha, compared to the mean, is another challenge to reliable inference.

cern, I require that the manager does not change her position on a stock in the period(s) following the trade. Given the level of fund's turnover and changes in fund's liquidity over time, this condition improves the identification of those trades that are driven by fund manager's private information. A test of persistence in the correlation measure is also performed to further alleviate concerns regarding luck. Third, the vector autoregression (VAR) used here to estimate the innovation in returns, often also called "news", is well specified as shown by Vuolteenaho (2002) and Campbell et al. (2009). Finally, most importantly, 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 $t+1$. Using this approach ensures that only innovation in returns is attributed to manager's skill and not ex-post returns. This differentiates my paper from existing literature including the paper by Chen et al. (2000) and Alexander, Cici and Gibson (2007).

I use a large panel of 3,955 actively managed U.S. equity funds over the period 1994 to 2011 and evaluate the skill at the fund-quarter level. In computing the skill, I control for flows to the funds (see Edelen (1999)) and for mutual fund herding (see Brown et al. (2009)) since these could be potential reasons why funds change their holdings. 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, I find evidence to reject the null hypothesis. The average fund manager in the cross-section has a positive and statistically significant stock picking ability. Next, I test for persistence in this skill and find evidence to support it. Although funds do not show nearly the same level of skills in the consecutive periods, portfolio managers maintain their ordering, i.e., fund managers who are the most skilled in current period continue to be the most skilled in the periods following and vice versa. Importantly, this persistence in skill cannot be attributed to momentum effect as the conditional measure of skill already accounts for the auto-correlation in returns in forming the expectations about future returns. Furthermore, I find a positive and significant relationship between skill and fund performance. This result is robust to different specifications. One standard deviation increase in skill increases the quarterly risk/style adjusted excess return by 0.11% (or 0.44% annually). This finding clarifies that the traditional measures of performance actually captures some aspect of managerial skill. A closer look at the manger's predictive ability suggests that the skill is primarily in predicting the cash flow news, as opposed to the discount rate news, of the firm. Finally, Berk and Green (2004), among others, asserts that new money follows skill. Therefore the prediction is that, controlling for other factors, skill should be positively related to future flows. I find empirical evidence to support this claim.

In order to motivate the measure of skill introduced here, I rely on the theoretical model presented in Kacperczyk and Seru (2007).[4] Using a model of rational expectations, Kacper-

[4] The model in Kacperczyk and Seru (2007) is adapted from the Rational Expectations Equilibrium model of Grossman and Stiglitz (1980). In this model, the economy has two assets: risk-free and a risky asset. The model has two periods such that the agent chooses his portfolio at time one and the payoffs from these assets are realized in the future at time two. The agents are risk averse, have a CARA utility function, and it is assumed that the future value of the risky asset is normally distributed. The model further assumes that some investors receive signals about the future value of the asset. Signals are of two kinds, private signal and public signal. Only a certain fraction of the agents receive private information. Public information on the other hand is observed by everybody. Within the framework of this model, Kacperczyk and Seru (2007) solve for the demand

czyk and Seru (2007, Appendix A) solve for the demand function (for risky assets) of an informed investor. They show that on arrival of good (bad) private signal the informed investor increases (decreases) her holdings in the risky asset, relative to the uninformed investor. Typically, manager's skill is defined by the precision of the private information she generates (see Cohen, Coval and Pástor (2005)). The above model describes the manager's actions in the event that she receives private information. Since we can observe the changes made to the portfolio, this affords us an opportunity to ex-post assess the quality of her information. Having private information implies that there is disparity, among the investors, in the amount of information about the future value of the asset. The economic usefulness of private information is realized only when subsequently it becomes public knowledge and the uninformed agents change their expectations about the future value of the asset.[5] Based on this discussion I argue that the precision of the manager's information can be judged by studying how the changes in her portfolio covaries with future changes in expectations about the value of the individual assets.

Campbell (1991) provides an excellent framework to precisely measure the changes in expectations about the future value of the asset. He further decomposes the return innovation into two components; discounted value of changes in expectation regarding the future cash flows (cash-flow news) and the discounted value of changes in expectation regarding the future expected return (discount rate news). These are the discounted effects of current shocks out to the infinite future. The identification of cash-flow news and the discount rate news provides further opportunity to assess the nature of private information the manager possess. Following Vuolteenaho (2002), who applies this technology to firm level data, I fit a VAR with log returns, log book to market, and log profitability as the three state variables and estimate return innovation. Based on the above discussion, if the manager is skilled and changes her holdings based on her private information then these changes should predict the future news about the firms.

In summary, through this paper, I contribute to the existing literature in three ways. First, I address the standard problem of using returns or performance based measures in evaluating the skill of the manager. I propose a new, theoretically well motivated, measure that relates changes in portfolio holdings to innovation in stock returns. Using the proposed measure of skill I test a hypothesis that is central to fund literature and demonstrate that the *average* fund manager has stock picking ability. Predictability of return innovation by mutual fund trades asserts that fund managers are important agents in making markets efficient and also challenges the notion that a majority of their trades are noise trades (see Dow and Gorton (1997)).[6] Second, I establish a relationship between managerial skill and performance of the fund and between skill and flows. Finally, the measure suggested here can help in understanding managerial actions. The portfolios held by active mutual fund managers

function (for risky assets) of the informed as well as the uninformed investor who maximize their expected utility subject to their budget constraint. The key result of the model is the sensitivity of the demand function to changes in private information.

[5]This mechanism does not preclude the markets from being efficient ex-ante. It merely means that the markets are semi-strong efficient where are all the publicly available information is incorporated in the price and private information is slowly revealed in a manner consistent with Kyle (1985) and Glosten and Milgrom (1985).

[6]Keeping in mind the nature of contracts that are designed for portfolio managers, Dow and Gorton (1997) argue that fund managers have an incentive to trade even when, despite their best efforts, they fail to discover profitable trading opportunities. Since the principal cannot distinguish "actively doing nothing" from "simply doing nothing", mangers trade in order to show that they have exerted effort. Dow and Gorton (1997) further contend that such noise trades are significant part of the trading activity in the market place.

substantially deviate from the market portfolio (see Kacperczyk, Sialm and Zheng (2005), Cremers and Petajisto (2009), and Pool, Stoffman and Yonker (2012)). Researchers are often interested in understanding why mutual funds would concentrate their holdings as opposed to holding a well diversified portfolio which minimizes the portfolio's idiosyncratic risk. There could be two potential reasons. The manager has informational advantage about certain stocks and she seeks to exploit it. Alternatively, the convex flow-performance relationship could be another reason why mutual fund holdings differ from the market portfolio .[7] Using the information-based measure of skill introduced in this paper, researchers can disentangle the two motivations.

The remaining part of the paper is arranged as follows. In section II I briefly discuss the related literature and how this paper differs from some of the earlier work. Section III provides a detailed description of the data used in this study. In section IV I discuss the procedure followed for computing the measure. Section V and Section VI present the empirical analysis and the robustness of the results respectively. Finally, I conclude in section VII.

II Related Literature

The literature pertaining to performance evaluation[8] is vast and dates back to Jensen (1968). After controlling for risk, Jensen (1968) finds that mutual fund managers, on an average, were not able to outperform the market and hence concluded that they were not skillful. Carhart (1997) also measures the performance of mutual fund managers and specifically focuses on the persistence of their performance. After controlling for common factors of returns, the three factor model in Fama and French (1993) and the momentum factor discussed in Jegadeesh and Titman (1993), Carhart (1997) finds no persistence in the returns of mutual funds. Carhart (1997) points out that funds classified as winners based on past performance continue to perform better, an earlier finding by Hendricks, Patel and Zeckhauser (1993), only because of the momentum effect in the stocks that are held. Brown and Goetzmann (1995) also study mutual fund persistence and conclude that after controlling for survivorship bias there is some persistence in mutual fund performance. Kosowski, Timmermann, Wermers and White (2006) present another view of the problem. They point to the non-normality of the individual fund's return distribution and, hence, that of the cross-sectional distribution of mutual fund alpha. This rules out using traditional tests to verify existence of skilled managers. Kosowski et al. (2006) introduce a new bootstrapping methodology to correct the empirical distribution in order to test if there are any skilled managers in the entire cross-section. Fama and French (2010) also uses a similar methodology. They incorporate the cross-sectional covariance of fund returns in their bootstrap. The methodology used in these two papers is designed only to test if *any* manager in the cross-section is skilled. It cannot distinguish those that are skilled from those that are unskilled. More importantly, all the above mentioned articles use return based measure of performance and often label fund's performance as manager's skill.

[7] On account of convex flow-performance relationship, managers with lower skill have the incentive to take on more risk and concentrate their portfolio. See Sirri and Tufano (1998), Brown, Harlow and Starks (1996), and Busse (2001) for empirical evidence.

[8] Also see Wermers (2011) for a more detailed review of this literature.

Holdings based measures of performance like in Grinblatt and Titman (1993) and Daniel et al. (1997) are other measure that are widely used. Cohen et al. (2005) also propose a holding based measure for managerial performance. Their measure involves comparing the holdings of a fund manager with the holdings of those who have performed well in the past. In their relative benchmarking approach, Cohen et al. (2005) look at the similarity to and distinctiveness from well performing and poorly performing funds respectively. These measures are often criticized because fund's decision to hold assets are passive decisions and could be driven by reasons like taxes and transaction cost which have nothing to do with the skill of the manager. Trading, as opposed to holding, is costlier because of the transaction cost involved and the potential for realizing capital gains. Hence, trading is a better identification of managerial intent.

The paper by Chen, Jegadeesh and Wermers (2000) is closely related to the current paper since they look at the buys and sells of mutual funds. They find that in the aggregate, firms which have high mutual fund ownership don't outperform those with lower mutual fund holdings. However, when they look at trades they find evidence to support that firms that mutual funds increased their holdings in, overall, have higher returns than those that were sold. The focus of their paper is at the overall mutual fund industry level and it does not address whether the average mutual fund manager is skilled. Moreover, they do not use a conditional measure of skill.

Perhaps, the paper by Kacperczyk and Seru (2007) is closest to this current paper. Kacperczyk and Seru (2007) introduce a measure of managerial skill called Reliance on Public Information (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, they are unskilled and those who use the least amount of public information are skilled. Although an extremely creative idea, it suffers from the following criticisms. Passively managed funds don't change their holdings very often, irrespective of changes in public information. Therefore based on RPI they would wrongly be classified as skilled funds. In addition, their measure does not consider how the manager responds to the changes in analyst's consensus (their proxy of public information) i.e., whether the manager trades in the same or the opposite direction of the prediction. Also in measuring RPI, Kacperczyk and Seru (2007) do not account for other factors which could influence changes in holding, for e.g., new flows to the funds. In the measure I introduce in this paper, I address all these concerns. Although index funds have been excluded from my sample, it is important to note that the correlation between changes in their portfolio holdings and the future news would be correctly identified as zero, since passive funds do not change their holdings. Similarly, if the direction of the portfolio change does not match that of the future news, the manager's skill is penalized. Finally, by relating manager's private information to future cash-flow and discount rate news I provide more granularity and identify the nature of information that the manager has.

III Data and Summary Statistics

I 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 like return, total net assets, expenses, turnover etc. In the empirical analysis I focus exclusively on domestic equity mutual funds since the data on the holdings of these funds are most complete. Therefore, I eliminate balanced, bond, money market, sector, and international funds from my sample. I do so based on the type of securities held by the fund and using the policy variable in the CRSP mutual fund database. I follow Kacperczyk, Sialm and Zheng (2008) and select funds based on their objective codes. At first, I select funds with ICDI objectives: AG, GI, LG, IN. If a fund does not have any of the above objectives, then I look for funds with strategic insight objectives: AGG, GMC, GRI, GRO, ING, or SCG. If neither of the above objectives exist, I then look at the Wiesenberger Fund Type code and include funds with the following objectives G, G-I, AGG, GCI, GRI, GRO, LTG, MCG, and SCG. Also, in order 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 CRSP mutual fund data set and are excluded from the sample. I then merge the holdings information to this file.

Although CRSP has data on holdings of mutual funds, this information is not reliable and moreover it does not go back in time. I use Thompson Reuters CDA/Spectrum holdings database which collects data from reports filed with SEC and from voluntary reports by the funds. Wermers (2000) provides information about the holdings database in greater detail. I impose similar filters for the holdings data and exclude balanced, bond, money market, sector, and international funds. Furthermore, I also drop funds which hold fewer than 10 stocks in the portfolio and those that do not report their holdings on a calendar quarter basis. Evans (2010) points out that mutual fund families engage in the practice of incubating the funds. In order to create a positive return history or a track record, several private funds are incubated. Only data on the surviving funds are made public. No data is available for funds that cease to exist. Since this creates a bias towards positive returns, Evans (2010) suggests that smaller funds should be removed from the sample, since typically incubated funds tend to be really small. Therefore, consistent with prior literature, I exclude funds that have less than $5 million under their management. I also exclude observations that pertain to a period prior to the fund's starting date. Quarterly holdings are not available for all the funds through out the sample period. After 2004, SEC mandates all funds to 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, I assume that the funds follow a buy-and-hold strategy and so I fill the holdings with previous quarter's information.

Data regarding the price and returns of the individual firms in the portfolio are obtained from CRSP. I restrict my focus to ordinary common shares of firms incorporated in US (share codes 10 and 11). Mutual funds also tend to have multiple share classes and the CRSP mutual fund database reports data at these share class level. Different share classes have the same holdings. However, for obtaining fund characteristics such as expenses and turnover which are particular to the share class, I consolidate the data at the fund level. In order to consolidate the variables, I take the value weighted average of individual classes where the weight is determined by the proportionate share of TNA. I use the quarterly COMPUSTAT file for all the firm level characteristics. In computing the skill of the fund manager, I use data regarding the analyst's past recommendations. For this purpose I 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". I discuss the construction of consensus recommendation in greater detail below. The IBES database begins only from 1993 and so majority of the analysis presented here pertains to the period between January 1994 and December 2011.

Table 1 reports summary statistics about the fund characteristics in the sample. The sample has 3955 unique active mutual funds and 108,840 fund-quarter observations. The sample of funds in the database is steadily increasing from 714 in 1994 to 1826 in 2011. There is also substantial growth the average TNA over time (see Wahal and Wang (2011)). Statistics on expense ratio, turnover ratio, and age are also reported. Since there are no index funds in the sample the expense ratio might be a little higher than found in previous literature. Average fund in the sample trades close to 96% of their portfolio each year. Finally, consistent with what researchers have found before, the average mutual fund alpha in the sample is negative.

IV Skill Measure

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

IV.A Estimating news

IV.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 and Shiller (1988) begin with a simple definition of returns and provide a linear approximation of the present value relationship. They approximate the linear relationship using a first order Taylor expansion of the log returns function ($r_{t+1} = log(P_{t+1} + D_{t+1}) - log(P_t)$) around the mean log dividend-price ratio $\overline{(d_t - p_t)}$. Above, P denotes the price, D denotes dividends and all lowercase variables are the log transformed version of the variables. Using this methodology, return can be expressed in the following linear form

$$r_{t+1} \approx k + \rho p_{t+1} + (1-\rho)d_{t+1} - p_t,$$

where ρ and k are parameters of linearization. Taking the expectation after iterating this relationship forward we have

$$p_t - d_t = \frac{k}{1-\rho} + E_t \sum_{j=0}^{\infty} \rho^j [\Delta d_{t+1+j} - r_{t+1+j}], \tag{1}$$

where Δd represents the log dividend growth. An assumption that there are no infinite bubbles ($\lim_{j\to\infty} \rho^j (d_{t+j} - p_{t+j}) = 0$) or that dividend-price ratio is nonexplosive also needs to be made. The interpretation of this relationship is straightforward. It says that if the log price-dividend ratio is high then one of two things should be true; future dividends is expected to grow rapidly or stock returns are expected to be low in the future. It could also be that both of these might be true. This identity makes intuitive sense. If today's stock prices are the expected discounted value of future cash-flows then in order to have a high price today it has to be that either expected future cash flows are high or that the future discount rates are low.

Later, Campbell (1996) extends the above present value relationship to a decomposition of returns. Using equation (1) it can be shown that

$$\begin{aligned} r_{t+1} - E_t r_{t+1} &= (E_{t+1} - E_t) \sum_{j=0}^{\infty} \rho^j \Delta d_{t+1+j} - (E_{t+1} - E_t) \sum_{j=1}^{\infty} \rho^j r_{t+1+j} \\ &= N_{CF,t+1} - N_{DR,t+1}, \end{aligned} \tag{2}$$

where N_{CF} is the cash-flow news or changes in expectation about the future cash flows of the firm and N_{DR} represents the news about the future discount rates or expected returns. The interpretation of this is much like equation (1). It highlights that any unexpected return has only two sources; either 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 current shock out to the infinite future. Although this shock is latent, the economic effects of it 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)).

IV.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). Subsequently, a variety of studies have used this approach (for e.g. see Campbell and Mei (1993), Bansal, Dittmar and Lundblad (2005), and Campbell, Polk and Vuolteenaho (2009)). I follow the same methodology. Return innovation can be further decomposed into cash-flow news and discount rate news. It is common practice to first estimate the discount 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 (2) to back out the cash-flow news as the residual. I assume that the data are generated by a first order VAR model

$$z_{t+1} = \Gamma z_t + u_{t+1}, \tag{3}$$

where z_{t+1} is an $m\,x\,1$ vector of state variables with r_{t+1} as its first element, Γ is an $m\,x\,m$ 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:

$$\begin{aligned} N_{DR,t+1} &= e1'\lambda u_{t+1}, \\ N_{CF,t+1} &= (e1' + e1'\lambda) u_{t+1}. \end{aligned} \tag{4}$$

In the above formulation e1 is an $m\,x\,1$ vector which has one as the first element and the remaining elements are all zero. λ is a $m\,x\,m$ matrix which maps the VAR shocks to the news.

It is given by $\lambda \equiv \rho\Gamma(I-\rho\Gamma)^{-1}$ where I is an $m\,x\,m$ identity matrix. In equation (4) $e1'\lambda$ captures the long run significance of the individual VAR shock to expected discount-rate. This formulation also suggests that greater the value of the variable's coefficient in the return prediction equation of VAR system, the greater the weight it receives in the discount rate formula.[9] Campbell (1991) also points out that persistent variables receives more weight, this is captured by the term $(I-\rho\Gamma)^{-1}$.

IV.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 also followed in Campbell, Polk and Vuolteenaho (2009). I follow the specification prescribed in Vuolteenaho (2002) and estimate a vector autoregression (VAR). Since the holdings data is in quarterly terms, the VAR is also estimated using quarterly data. I now present the state variables used in the VAR and also 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 I substitute a value of zero. Whenever there is delisiting I substitute the delisting returns, where available. Following Shumway (1997), I substitute a value of -30% as the delisting returns when they are missing.[10] Vuolteenaho (2002) points that log transformation of firm's return may turn extreme values into influential observations and suggests that we can avoid this problem by unlevering the stocks by 10%. I 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.

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. In order to compute the book value of equity (BE) I follow the method described in Cohen, Polk and Vuolteenaho (2003). The market value (ME) is the product of number of shares outstanding and the price. Again, in order to avoid the influential observation created by log transformations the log book-to-market ratio is computed as $BM \equiv log[(0.9BE + 0.1ME)/ME]$. The book-to-market is included to capture the value effect in cross-section of stock returns (see Fama and French (1992)).

The final state variable is the long-run profitability of the firm, ($\overline{ROE}$). Haugen and Baker (1996) point that firms with higher profitability have earned higher returns, even after controlling for book-to-market ratio. Inclusion of firm profitability is also consistent with production based models of asset pricing (see Chen and Zhang (2010)). This data is generated using the accounting clean-surplus relationship. The clean-surplus earnings (X_t)

[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 also 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] Shumway (1997) points out that there is delisting bias in the returns data maintained by CRSP and discusses its implications. Beaver et al. (2007) also suggest methods to address the problem of delisting returns. None of the results of this paper are sensitive to using this alternative method.

is computed after adjusting for equity offerings in the following manner

$$X_t = [\frac{(1+R_t)ME_{t-1} - D_t}{ME_t}] \, . \, BE_t - BE_{t-1} + D_t, \tag{5}$$

where R_t is the firm rate of return and D_t is the dividend computed as the difference between returns including dividend (CRSP variable *ret*) and returns without dividends (CRSP variable *ret*x). The above relationship is straight forward. It defines any change in the book value of the firm after adjusting for new stock issues and dividends as profitability. I 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, I subtract the log value-weight CRSP index returns from $r_{i,t}$. I also remove cross-sectional means from $BM_{i,t}$ and $\overline{ROE}_{i,t}$. Further, Vuolteenaho (2002) points out that relatively few firms are going to be in sample for the entire time period and that conditioning on survival is going to 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, I fit a panel VAR using a quarterly firm level sample. The coefficients are estimated using weighted least squares method. Since there are differences in the number of firms in each cross-section, I 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 (4). The above VAR specification and the news term computed are fairly robust.[11] Additional test to confirm the robustness is performed below.

IV.B Estimating Skill

I now discuss in detail the steps involved in computing the skill of the manager. Above, I proposed that the manager's skill should be the correlation between the changes she makes to her portfolio and the 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 divided by the number of stocks held at the beginning of the quarter. The percentage change in the holdings are 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. With the exception of Alexander et al. (2007), majority of the recent literature on performance evaluation has ignored this point.

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, I control for changes in consensus recommendation. Details about the consensus recommendations are provided in the IBES database. Multiple analysts report their recommendations on stocks. Analyst's recommendations are standardized to a five

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

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 et al. (2009) show that a significant part of the herding behavior is exhibited in the quarter after the recommendation change. Therefore, before the beginning of the current quarter, for each stock, I collect the previous two consensus recommendation ($\overline{rec}_{i,t-1}$ *and* $\overline{rec}_{i,t-2}$). I then term the difference between the last two consensus recommendation as *"herding",* which represents the change in the consensus about a stock. It should also be noted that this variable is measured before the beginning of the quarter of trade. This avoids any endogeneity that might arise from the analyst changing his recommendations based on the mutual fund manager changing her holdings.

Another reason why funds might change their holdings is because of flows to the funds. New money is an important aspect of mutual fund industry and is in fact the core area of competition. Even those 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. Edelen (1999) highlights the level of liquidity motivated trades and the implications of it for fund performance. I compute the net flows to the fund, j, for each quarter, t, as

$$Netflow_{j,t} = \frac{TNA_{j,t} - TNA_{j,t-1}(1 + R_{j,t})}{TNA_{j,t-1}}, \tag{6}$$

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

Following this discussion, I estimate the skill in two steps. I first fit the following regression

$$\%change\ in\ holdings_{i,j,t} = \beta_{0,j} + \beta_1 * herding_{i,t-1} + \beta_2 * Netflow_{j,t} + \epsilon_{i,j,t} \tag{7}$$

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

I collect residuals, $\epsilon_{i,j,t}$, from (7). These $\epsilon_{i,j,t}$ represents the unexplained changes in holdings. In the second step I compute the skill of the manager$j$ at time t as

$$skill_{j,t} = corr(\epsilon_{i,j,t},\ news_{i,t+1}). \tag{8}$$

Correlation is the sample estimate computed using all the *traded* assets in the portfolio.[12] $news_{i,t+1}$ is the innovation in returns estimated earlier. In another specification, I also compute the correlation between unexplained changes in holdings and the news for two periods after the end of quarter of trade.

[12] Note, skill estimated using equations (7) and (8) is in spirit a partial correlation coefficient. This procedure is netting out the effect of herding and net-flows to the fund. As long as changes in consensus recommendation between quarter $(t-2)$ and $(t-1)$ and flows to the funds between $(t-1)$ and t does not affect the news in a stock for the period t to $(t+1)$, a reasonable assumption, skill is well identified (see Frisch–Waugh–Lovell theorem).

The issue of distinguishing 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. In order to address this concern, I further require that after the trade is made in a particular quarter, there are no trades in the opposite direction in the future periods. For example, if the manager purchases a stock between $t-1$ and t, I include this particular stock in computing skill only if the holdings of this stock does not decrease in the time t to $t+1$ ($t+2$, in case two period news is used). Similarly, if the manager sold the asset in current quarter then she should not increase her holdings in the future quarter(s). This filter helps in improving the identification of information driven trades and reduces the probability of the results being driven by pure chance. 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 risk and return of the overall portfolio. It might be that some managers might have information but they do not change their holdings because it might increase the overall portfolio risk. In this paper I focus on the precision of a manager's private information. Since one cannot observe the private information the manager receives, one has to rely on her actions from having private information. Therefore, I rely on observing portfolio changes. However, this inaction (despite having information) will only impart a downward bias on the measure of skill.

V Empirical Analysis

V.A Firm-level VAR Estimation

I start the estimation of skill by fitting a firm level VAR. Log returns of the firm, log book-to-market, and log profitability are the three state variables in the model. A detailed description regarding the construction of these variables is presented in section IV.A.3. The coefficients are estimated using the weighted least squares approach. The results from the firm level VAR are presented in Table 2. Two sets of relevant standard errors are reported below the estimated coefficients. First, in order 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. I 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 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 the future firm profitability. The high persistence in these measures are the main reason why 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 found in the earlier studies. It is also clear from looking at the variance-covariance matrix of the cash-flow and discount rate news that most of the firm-level stock returns are driven by cash-flow news.

V.B Skill and Persistence

I collect the residuals from the above estimation, which are the innovation in returns. The parameters estimated in Table 2, along with equation (4), are used to estimate the cash-flow news and the discount rate news. I then follow equations (7) and (8) above to estimate the skill for each fund-quarter to 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 fund is unskilled. Figure 1 provides the distribution of skill. Based on the definition it should be clear that the values of skill are 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 3 presents the numerical results. Panel A reports the distributional properties of the skill measure after aggregating it at the fund level across time. *skill_1* and *skill_2* are the skill measures computed using news from one and two quarters after the trade respectively. I find evidence to reject the null hypothesis and report that there is considerable stock picking ability among the fund managers. I use a standard t-test to test the significance of the mean and also a non-parametric wilcoxon signed-rank test. Both these tests suggests that the fund managers have 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 cannot beat her passive benchmark does not imply that the average manager lacks skill. Although the average alpha is my sample is negative, consistent with the above argument, I find that the fund managers have skill and make informed trades. These results are also in line with the recent findings of Chen et al. (2000), Alexander et al. (2007), and Baker et al. (2010) who also find evidence of stock picking skill.

Since the innovation in returns can be attributed to changes in expectations regarding future cash flows and to changes in future expectation of returns, it is important to identify which of these news does the fund manager have private information about. In order to answer this, I follow the same procedure as I did to estimate skill except the final step. Instead of using the total news term in equation (8), I use the cash-flow news estimated from VAR and compute $skill\ cash_{j,t}$ as $corr(\epsilon_{i,j,t},\ cashflow\ news_{i,t+1})$, where $\epsilon_{i,j,t}$ is the unexplained changes in holdings. This measure captures the extent of skill the manager has in predicting the future cash-flow news of the firm(s). In a manner similar to above, I compute $skill\ discount_{j,t}$ as $corr(\epsilon_{i,j,t},\ discount\ news_{i,t+1})$, 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 that the stocks that she buys to be positively and that she sells to be 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 3 reports the mean of the empirical distribution for each of the two skills measures at the fund level. The positive and statistically significant coefficients at 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 3 show that the managers also have the ability to predict the changes to 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.[13] I explore this idea a little further using a multivariate regression below.

Kosowski et al. (2006) and more recently Barras, Scaillet and Wermers (2010) document that the skill of the active fund managers has diminished in the last decade. There is no clear reason why the skill level would diminish over time. However, one potential explanation could be the explosive growth in the mutual fund industry in last decade or so[14], leading to intense competition, and hence limiting the chances of manager having private information. Alternatively, on account of improved technology and 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 be able to mitigate the effects of increased competition. In Panel C of Table 3, I test for differences in mean skill in the two periods of my sample. The average skill in the initial half of the sample (between Jan 1994 - Dec 2002) is 0.035 compared to that of 0.008 in the latter half of the sample. Interestingly, there is evidence of skill in both sub-periods. This ensures that the above results are not driven by one part 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 the recent times. Statistical tests of differences in mean confirm that the difference of 0.027 is statistically significant. One other possible reason for such a finding could be due to the structural changes in the disclosure requirements in the last decade. Regulation fair disclosure would be one such change.

In Panel D of Table 3, I present the correlations between skill and the other fund characteristics. A few interesting relationships 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 their holdings are fairly big and their trades are very transparent. Since the price impact of their trade is very high they refrain from trading too frequently. Second, Chen, Hong, Huang and Kubik (2004) document that fund returns decline in the lagged fund size. I 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. Finally, consistent with the arguments in Berk and Green (2004), I find that more skilled funds charge more in 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.

In the theoretical framework of Berk and Green (2004), 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 investor's update their beliefs about the manager's skill and direct their flows to the fund, it might be harder to identify skill in the data because there might be fewer trades on 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 et al. (1993) were 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.

[13] Table 2 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.

[14] Wahal and Wang (2011) document that between 1980 and 2008 domestic equity mutual funds have grown at a compounded rate of 16% per year.

Subsequently, Brown and Goetzmann (1995) and Carhart (1997) look into this issue and make diverging conclusions. The former finds evidence in support of persistence while the latter concludes that most of the persistence in fund performance can be explained by the common factors in stock returns. It is important to notice that the above studies focus on persistence of fund's excess returns or performance.

Here, I examine whether skill is indeed persistent. For each period I sort funds into decile portfolios based on their level of skill. I 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 4. Contrary to the findings of Chen et al. (2000), I find evidence of persistence. The level of future skill of the portfolio(s) is not the same as when it was formed. However, Table 4 suggests that the group of most skilled managers in the current quarter continue to be so in the following time period i.e. the portfolio of managers that showed the most skill at a given time t, is also the portfolio which has the highest skill in the subsequent quarters $t+1$, and $t+2$. The same is true of the portfolio of managers which had the least skill. I test for differences in the mean of the top and the bottom decile portfolios. I also perform a similar test for differences in mean of the top half and bottom half. The results from using a t-test and a wilcoxon signed-rank are reported at the bottom of Table 4. These test 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 in predictability of future return innovation by mutual fund's trades strengthens the argument that this on account of ability and not due to luck.

V.C Skill and Performance

As mentioned above, the key aspect of the measure proposed here is that it does not rely on performance of fund to infer information about 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. Based on this, I 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, I estimate the following model:

$$\alpha_{j,t} = \beta_0 + \beta 1\ skill_{j,t-1} + \gamma\ Controls_{j,t-1} + \epsilon_{j,t}, \tag{9}$$

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 model for risk adjustments. To estimate the alpha, I follow the methodology used in Carhart (1997). For each fund, I first estimate a time series regression of the excess fund returns on the four factor portfolios, namely excess market return, size, value, and momentum. Similarly, for the three factor and CAPM based alpha, I use the relevant zero-investment portfolio. From these regressions I collect the factor loadings for each fund. I use return data from the previous 36 months or 12 quarters to estimate these loadings. Alpha of the fund for a particular quarter is then given by

$$\alpha_{j,t} = R_{j,t} - R_{F,t} - \hat{b}_{j,t-1}RMRF_t - \hat{s}_{j,t-1}SMB_t - \hat{h}_{j,t-1}HML_t - \hat{m}_{j,t-1}MOM_t, \quad (10)$$

which is nothing but the sum of the intercept and residue of the model. Since the literature has identified a variety of fund characteristics that effect the performance of the fund, I control for these in my specification. I control for log age of the fund, log size of the fund represented by the amount of assets managed, expense ratio at the end of previous year, turnover ratio at the end of previous year and the amount of flows to the fund in the previous quarter. I follow Kacperczyk and Seru (2007) and compute the reliance on public information measure *(RPI)*. It is also one of the controls in the regression. Results from the multivariate regression are reported in Table 5. All the specifications in Table 5 include time fixed-effects 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 (see Thompson (2011)). The clustering accounts for correlation in errors within the fund and over time. It is also accounts for heteroskedasticity in the residuals.

In Table 5, columns 2, 3, and 4 have the CAPM, 3-factor alpha and the 4-factor alpha respectively as the dependent variable. In all three cases I 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 approximately 0.11% (0.09%) increase in the quarterly three (four) factor alpha or 0.44% (0.36%) increase in the annual terms. The median four-factor net alpha in my sample is approximately -0.23 %; in light of this the above relationship is economically significant. Other variables like the fund's size and fund's expenses also have explanatory power and is in a manner consistent with prior literature. Since RPI measures the extent of pubic information used by the manager, skilled managers should have lower RPI. Therefore Kacperczyk and Seru (2007) predict a negative relationship between RPI and performance. The inclusion of this measure to the regression does not change the explanatory power of *skill*.

Given the manner in which the skill measure is constructed, it might seem that it should mechanically be related to future alpha. However, note that the value of stocks traded is less than 20% of the overall portfolio's value (see Table 1). This leaves returns of over 80% of the fund's assets unaccounted for. Stocks that were not traded, but merely held in the portfolio, could perform very poorly. Moreover, using data on monthly holdings for select funds, Elton et al. (2010) document that close to 18.5% of the trades are not observable using a quarterly holdings data.[15] There is substantial variation in the benefits and costs of these interim trades and it can severely affect investor's return (see Kacperczyk, Sialm and Zheng (2008)) and hence the relationship between skill and fund's future abnormal performance is far from trivial.

In the current multivariate setting, I explore the nature of skill required to generate a positive alpha. As before, I split the current skill measure into two sub-measures $skill\ cash_{j,t-1}$,

[15] The monthly holdings data provided by morningstar is not used for this study because it has a very low coverage of mutual funds and does not contain historical holdings data.

manager's ability to predict future cash flow news, and *skill discount*$_{j,t-1}$, manager's ability to predict firm's future discount rate news. Column 4, 5, and 6 in Table 5 report the role of these sub measures in predicting the abnormal returns. The advantage of this setting is that the estimates presented are partial regression coefficients *i.e.* the effects are after controlling for any correlation between the cash flow news and the discount rate news of the firm. 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 fund's trades and returns around earning announcement dates. Although the sign of coefficient estimates on *skill discount*$_{j,t-1}$ are correct, the variation in the skill to predict future discount rate news is large and hence lacks statistical significance.

I also test the relationship between skill and performance using holdings based performance measures. I use the characteristic selectivity (CS) and characteristic timing (CT) measures of Daniel et al. (1997). Columns 1 and 2 of Table 6 present the results of regression. A positive and statistically significant relationship between skill and holding based performance can be observed. Further, consistent with Table 5, columns 3 and 4 of Table 6 confirm that most of the performance can be attributed to the manager's ability to predict future cash flow shocks. Overall, I conclude that managers having higher skill do earn a higher risk-adjusted return in the following period.

V.D Skill and Flows

Understanding how money flows to funds is central to mutual fund literature. Flows is also one of the key drivers for the equilibrium derived in Berk and Green (2004). In the above model, individual investors learn about the manager's skill, based on available public information, and direct their money to the funds according to their updated beliefs. Information about the manager's past performance is public information and can be easily accessed by the investors. Media also plays its part in disseminating this information. Previous studies, have documented that outside money follows past fund performance (see Chevalier and Ellison (1997)). However, skill is very abstract. For the most part, managerial skill is latent and unobservable, especially when compared to fund's performance. Therefore conditional on past performance, does past skill predict future flows? Based on the this discussion, I test the following hypothesis:

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

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 flow-performance relationship. Sirri and Tufano (1998) show that there is bias in the way flows respond to performance. Poorly performing funds do not nearly have as much outflows as the amount of inflows in to well performing funds. Using an ordinary least square (OLS) model in this case would lead to biased and incorrect results. Instead, I perform a quantile regression analysis which estimates the conditional distribution of quarterly flows given the skill and other variables.[16] To test the above hypothesis I estimate the following specification.

$$Q_q(Netflows_{j,t+1}|\{I_{t-1}, I_t\}) = \beta_0 + \beta_1 \; skill_{j,t-1} + \gamma \; Controls_{j,t} + \epsilon_{j,t+1}, \tag{11}$$

where $Q_q(.|.)$ is the conditional quantile function, $Netflows_{j,t}$ is given by equation (6) and I_{t-1} and I_t are the information sets available at $(t-1)$ and t respectively. Note, $skill_{j,t-1}$ uses the trades made between $(t-2)$ 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 knowing the level of skill at t. In the specification, I control for previous period's performance by including the net returns as well as the 4-factor alpha. Other controls in the regression include log of age, log of the size of the fund given by the amount of money managed, previous year's turnover, and previous year's expenses. The results from the multivariate analysis are reported in Table 7. Columns 2-5 of Table 7 report the estimates for 25^{th}, 50^{th} (median), 75^{th}, and the 90^{th} quantile respectively. Each of these regression include time-fixed effects. I follow the two-step method described in Canay (2011) for dealing with fixed effects in a quantile regression in a panel data setting. The bootstrapped standard errors associated with the estimates are also reported. The bootstrapping process takes into account the correlation in fund's innovations over time i.e. they are clustered by fund.

All the specifications (col 2 - col 5) in Table 7 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 is going to increase the level of inflows by 2.41%. This effect is after controlling for fund's past return and past alpha, which have been shown to increase funds future inflows. Consistent with that literature, I find a positive relationship between future flows and past performance. Funds that charge higher expense ratios receive lower inflows, across all quantiles. The parameters associated with turnover ratio show an interesting pattern. They direction of the marginal effects change based on the quantile of the net flows variable. In the lower quantiles of the net flows distribution, increasing the turnover ratio reduces the amount of future inflows. However, at higher quantiles there is a positive relationship between turnover and net flows. One possible explanation, of course, could be that the net flows variable and skill are extremely correlated. In such a case, fund managers with lower inflows are really managers with lower skill and who 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. Managerial skill is positively related to fund's future flows.

[16] The linear conditional quantile model was popularized by Koenker and Bassett (1978). It can be shown that when the loss function is an absolute error loss function (symmetric or asymmetric) a conditional quantile function is the optimal predictor (Cameron and Trivedi (2005)). The model assumes that the data is generated such that the q^{th} conditional quantile function is given by $Q_q(y|x) = x'\beta_q$. Note, the conditional quantile function is linear in the independent variables. The q^{th}quantile regression estimator $(\hat{\beta}_q)$ is minimizing the following function

$$Q_N(\beta_q) = \sum_{i:y_i \geq x_i'\beta}^{N} q|y_i - x_i'\beta| + \sum_{i:y_i < x_i'\beta}^{N} (1-q)|y_i - x_i'\beta|.$$

The coefficients from the above estimation are the marginal effects. To see this note that $\frac{\partial Q_q(y|x)}{\partial x_j} = \beta_{qj}$. The parameter estimate $\hat{\beta}_{qj}$ is the change in the quantile q of the dependent variable produced by an infinitesimal change in the independent variable.

Berk and Green (2004, eqn (6)) also argue that the age of the fund has important considerations for the relationship between skill and flows. They claim that flows to younger firms respond much more dramatically to skill than the flows to more mature funds. The role of 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 priors 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 I test the following hypothesis:

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

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

Columns 6-9 of Table 7 present the relevant results based on a quantile regression. The results are again reported for 25^{th}, 50^{th} (median), 75^{th}, and the 90^{th} quantile respectively. In addition to the variables used earlier, the specification used in Columns 6-9 have an additional interaction term based on the age of the fund and the level of skill. Each of these regression also include time-fixed effects. The standard errors reported are bootstrapped standard errors. They are clustered at the fund level. The relationship between the skill of the fund and future flows continue to be positive and significant. Interestingly, the marginal effects of skill is increasing in the quantiles. Using the parameter estimate of 8.956 and related standard error of 1.981 at the 90^{th} percentile, we can estimate the 95% confidence limits of the estimator to be 5.277 and 12.634. Similarly the confidence intervals of the slope coefficient at the 25^{th} and 50^{th} are (-1.209, 2.052) and (0.111, 2.969) respectively. Based on these confidence intervals, it is clear that the slope coefficients at the 25^{th} and 50^{th} quantile are statistically different from that at the 90^{th} percentile. This justifies the use of quantile regression in this particular case. The results of Table 7 also supports the widely accepted convex relationship between skill and flows. Panel A of Figure 2 graphically represents this convexity and shows the marginal effect of skill at different points of the flows distribution.The age of fund, in itself, reduces the extent of flows to the fund. In addition, the coefficients on the interaction term are negative for all the quantiles but for the 25^{th}. The negative coefficient implies that the effect of skill on future flows decreases as the age of the fund increases. This negative relationship for different quantiles of the flows distribution is displayed in Panel B of Figure 2. I find these results consistent with the prediction of Berk and Green (2004) and therefore reject the null hypothesis.

VI Robustness

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

VI.A Value weighted measure of skill

An important concern regarding the measure of skill is that it does not pay attention to the value or the size of the trade. It could be that the fund managers have private information only about stocks which form a small part of their portfolio. Equally weighting all the trades could then distort the skill measure and wrongly identify a manager to be skilled. In order to overcome this problem, I compute a weighted correlation where the weight is given by

$$weight_{i,j,t} = |\frac{value_{i,j,t} - value_{i,j,t-1}}{TNA_{j,t-1}}|.$$

$value_{i,j,t}$ is the dollar value of security i in manager $j's$ portfolio 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 net assets at the beginning of the quarter. $value_{i,j,t-1}$ is not used in the denominator because it could be zero. Panel A of Table 8 presents the summary of the distribution of the new skill measure computed using the above weights. The results are consistent with earlier findings. The average and the median fund manager continue to show and positive and statistically significant skill. This is true irrespective of the horizon of time that is used to compute the news.

VI.B Skill computed using all the assets

Above, I use the model presented in Kacperczyk and Seru (2007) to motivate the use of fund's trades to capture the extent and quality of private information a manger generates. In all of the analysis 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 generating information about a stock. In order to address this point, I include all the stocks in the portfolio for the computation of skill *i.e.* both stocks that are traded as well as those that were not. A summary of distribution of skill measure using all the stocks in the portfolio is reported in Panel B of Table 8. Like before, I continue to find empirical evidence to support the hypothesis that the average fund manager skilled in picking stocks.

VI.C Tax and Window Dressing

Literature has identified tax and window dressing as other motives for funds to trade.[17] Ever since the 1986 Tax Reform Act all mutual funds have Oct 31 as the mandated tax year-end. Therefore, their tax motivated sales should be around that point in time. Further, from the literature on tournaments in mutual funds it is also clear that Oct-Dec is when the funds have the highest incentive to window dress.[18] In order to mitigate the effects on these two motives of trade on the measure of skill, as they are not driven by private information, I

[17]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), Morey and O'Neal (2006)).

[18]see Brown et al. (1996) and Busse (2001).

exclude the trades made in the fourth quarter of the calendar year *i.e.* between Oct - Dec. The distribution of the skill measure computed using just the trades between Jan-Sep is presented in Panel C of Table 8. Overall, these results continue to be consistent with the main findings of the paper. The average fund manager continues to show stock picking ability.

VI.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 *i.e.* 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 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, I compute the news for the two period horizon 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. I use the above mentioned alternate two period news term and compute the cross-sectional distribution of stock picking skill. The results reported in Panel D of Table 8 is consistent with the earlier result of the average fund manager being skilled.

VI.E Skill and predictability

The positive correlation between the fund's trades and future innovation in returns can also be attributed to micro-structural 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 it. Further, funds report their holdings at most 60 days from the end of the previous quarter. Assuming that copycat investors mimic the fund's trades no more than a month after the disclosure, a reasonable assumption, then under the null of no skill the trades made in the previous quarter should not be correlated with news of *only* two quarters later. In order to test this, I compute the skill of the fund manager as the correlation between the unexplained changes in holdings and news of the stocks two periods later. The two quarter later total news, $N_{TN,t+1\to t+2}$, is computed as

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

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 8. Although it is impossible to completely rule out micro-structural effects, a positive mean presented in Panel E of Table 8 suggests that fund managers do generate private information about stocks.

VI.F Expected return and institutional holdings

Gompers and Metrick (2001) find that the level of institutional ownership in a stock can help to forecast its future return. Wermers (1999) also find weak evidence to support the above claim. In order to incorporate these effects in forming the expectation about future returns, I update the parsimonious VAR specification used before and introduce the fraction of shares outstanding held by institutions as one of the state variables.[19] The data about the quarterly institutional holdings is obtained from Thompson Reuters institutional ownership database which are collected from the 13f filings. The four-variable VAR specification has the quarterly log excess returns of the individual stocks, the cross-sectionally demeaned log book-to-market 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 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 9. In order to account for any cross-sectional correlation in errors, the standard errors are clustered by the 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 are very similar to those found in Table 2. Using these parameter estimates I compute the innovation in returns of firm and also compute 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 9. Skill using both one and two period news is still positive and statistically significant.

VI.G Long VAR

In order to further test the robustness of the results presented thus far, I estimate a richer VAR specification. The predictive variables used here include four lags of past (quarterly) stock return, the book-to-market 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

[19] Badrinath, Kale and Noe (1995) present a model of cross-autocorrelations in equity returns. On account of the fiduciary responsibility of portfolio managers, some stocks are institutionally favored and hence will have information quickly impounded into the price. Although some of this information will be firm specific, a portion is of general nature. Uninformed investors learn about this information and subsequently update the prices for the institutionally unfavored firms. Since we are interested in the stocks that are held by mutual funds and not in the stocks that are institutionally unfavored, results from the alternate VAR specification are not materially affected by cross-autocorrelations.

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 a higher average stock returns than large firms and high-leverage firms have outperformed low-leverage firms. Additional lags of returns are included to capture possible longer horizon return auto-correlation. Distributional properties of the skill estimated using the above specification in reported in Panel C of Table 9. Evidence still suggests that the average fund manager has positive stock picking skill. Overall, I conclude that the qualitative results of the paper are not sensitive to the alternate VAR specifications.

VII 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, the above question is translated to 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 posses any skill.

In this paper I propose a way to address this issue. Since the economic value of private information is captured by innovation in returns, I 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 and it distinguishes skill from luck. Using this measure, I 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 turnover their portfolio more often and charge higher expenses (possibly due to higher management fees as a compensation for skill). The above skill is fairly persistent. and this persistence in skill is not explained by the momentum effect. Importantly, I find a positive and significant, both statistically and economically, relationship between managerial skill and gross future fund performance. This suggests that the managers, through their skill, do add economic value. Finally, I substantiate the view that investors learn about manager's skill. After controlling for past performance, new money does follow the skilled manager. Overall, my findings corroborate the substance and the implications of the theoretical model proposed by Berk and Green (2004) and argues that fund managers are important agents in keeping the market efficient.

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Table 1: 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	3955		
Number of fund-quarter observation	108840		
Number of funds per quarter	1506	1665	
Number of stock held	115	58	225
Value of trades relative to TNA_{t-1} (in %)	19.58	6.3	81.52
TNA(in millions)	1309.94	217.40	5585.74
Expense ratio (in %)	1.25	1.22	0.51
Turnover ration(in %)	95.82	63.3	164.6
Age (in quarter years)	54.07	37	54.32
Carhartα - net (in %)	-0.18	-0.23	6.5

Table 2: 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 1994-2011. 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 third number 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
$r_{i,t+1}$	**0.0227**	**0.0267**	**0.0646**	0.6%
(Log stock returns)	(0.0154)	(0.0043)	(0.0165)	
	[0.0001]	[< 0.0001]	[0.0001]	
$BM_{i,t+1}$	**0.0600**	**0.9401**	**0.0444**	86.32%
(log book-to-market)	(0.0123)	(0.0040)	(0.0133)	
	[0.0001]	[< 0.0001]	[0.0001]	
$\overline{ROE}_{i,t+1}$	**0.0155**	**-0.0024**	**0.6237**	53.66%
(five-year profitability)	(0.0013)	(0.0003)	(0.0153)	
	[< 0.0001]	[< 0.0001]	[0.0001]	

Variance-covariance matrix

	-N_{DR}	N_{CF}
-N_{DR}	**0.0033**	**0.0048**
	[< 0.0001]	[< 0.0001]
N_{CF}	**0.0048**	**0.0460**
	[< 0.0001]	[< 0.0001]

Table 3: 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_1 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, I 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 the Wilcox rank test, a non-parametric 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, I present the variation in skill across two sub-periods. The mean of skill and the standard errors (in paranthesis) are reported. Result of testing differences in mean is also reported. Panel D reports the contemporaneous correlation between skill and other relevant fund characteristics.

Panel A: Distribution Summary

	Mean	25 pct	Median	75pct	Std dev
Skill_1	0.0074***	-0.0308	0.0053	0.04702	0.0928
Skill_2	0.0201***	-0.0342	0.0159	0.0806	0.1228

Panel B: Type of Skill

	1 quarter horizon	2 Quarter horizon
Skill (Cash flow news)	0.0072***	0.0206***
Skill (Discount rate news)	-0.0054***	-0.0128***

Panel C: Variation in Skill

Period	Avg Skill
Jan 1994 - Dec 2002	0.037*** (0.002)
Jan 2003-Dec 2011	0.010*** (0.001)
Difference	0.027*** (0.002)

Panel D: Correlation Structure

Variables	Skill	Tna	Expenses (%)	Turnover (%)	Age
Skill	1				
Tna	-0.0083**	1			
Expenses (%)	0.0286***	-0.1763***	1		
Turnover (%)	0.0339***	-0.0651***	0.1921***	1	
Age	-0.0034	0.2370***	-0.1480***	-0.1078***	1

***1% significance, **5% significance, *10% significance

Table 4: 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 period 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. Results of testing differences in mean are also reported.

Decile	$skill_t$	$skill_{t+1}$	$skill_{t+2}$
1	-0.479***	-0.038***	-0.009*
(Lowest)	(0.002)	(0.005)	(0.005)
2	-0.246***	-0.022***	-0.001
	(0.001)	(0.004)	(0.005)
3	-0.140***	-0.001	0.005
	(0.001)	(0.004)	(0.004)
4	-0.065***	-0.006**	0.007**
	(0.001)	(0.004)	(0.004)
5	-0.004***	0.013***	0.014***
	(0.001)	(0.004)	(0.004)
6	0.054***	0.019***	0.013***
	(0.001)	(0.004)	(0.004)
7	0.117***	0.029***	0.026***
	(0.001)	(0.004)	(0.004)
8	0.191***	0.044***	0.036***
	(0.001)	(0.004)	(0.004)
9	0.289***	0.063***	0.040***
	(0.001)	(0.004)	(0.004)
10	0.494***	0.073***	0.062***
(highest)	(0.002)	(0.005)	(0.005)
10 - 1		0.111***	0.071***
		(0.006)	(0.007)
2nd half - 1st		0.054***	0.032***
		(0.002)	(0.003)

***1% significance, **5% significance, *10% significance

Table 5: 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 $\alpha_{m,t}$ computed using CAPM, three factor, and the four factor model respectively. Factor loadings were 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 period. 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.

	CAPM α (%)	3-factor α (%)	4-factor α (%)	CAPM α (%)	3-factor α (%)	4-factor α (%)
$skill_{t-1}$	1.152***	1.109***	0.857***			
	(0.253)	(0.227)	(0.184)			
$skill\ cash_{t-1}$				1.146***	1.012***	0.778***
				(0.252)	(0.208)	(0.186)
$skill\ discount_{t-1}$				-0.035	-0.168	-0.134
				(0.129)	(0.12)	(0.111)
RPI_{t-1}	0.052	0.094	-0.340	0.054	0.094	-0.341
	(0.424)	(0.468)	(0.471)	(0.424)	(0.468)	(0.471)
$Log(TNA)_{t-1}$	-0.822***	-0.445***	-0.522***	-0.823***	-0.445***	-0.523***
	(0.173)	(0.138)	(0.127)	(0.173)	(0.138)	(0.127)
NMG_{t-1}	0.015***	0.013***	0.007***	0.015***	0.013***	0.007***
(%)	(0.004)	(0.003)	(0.002)	(0.004)	(0.003)	(0.002)
$Log(age)_{t-1}$	-0.067	-0.147	0.116	-0.066	-0.146	0.117
	(0.157)	(0.204)	(0.235)	(0.157)	(0.204)	(0.235)
$expenses_{t-1}$	-0.728**	-0.214	-0.056	-0.727**	-0.214	-0.056
(%)	(0.279)	(0.238)	(0.215)	(0.280)	(0.239)	(0.215)
$Turnover_{t-1}$	0.001	0.001	0.001	0.001	0.001	0.001
(%)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)

***1% significance, **5% significance, *10% significance

Table 6: Relationship between managerial 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 $R_t^{b,t-13}$ 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 period. 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.

	CT (%)	CS (%)	CT (%)	CS (%)
$skill_{t-1}$	0.107**	0.753***		
	(0.050)	(0.092)		
$skill\ cash_{t-1}$			0.135**	0.701***
			(0.053)	(0.092)
$skill\ discount_{t-1}$			0.037	-0.089*
			(0.037)	(0.050)
RPI_{t-1}	-0.013	0.315	-0.012	0.315
	(0.130)	(0.226)	(0.13)	(0.226)
$Log(TNA)_{t-1}$	-0.087***	-0.312***	-0.087***	-0.312***
	(0.029)	(0.057)	(0.029)	(0.057)
NMG_{t-1}	-0.001***	-0.002	-0.001***	-0.002
(%)	(0.001)	(0.002)	(0.001)	(0.002)
$Log(age)_{t-1}$	0.047	0.067	0.047	0.068
	(0.036)	(0.055)	(0.036)	(0.055)
$expenses_{t-1}$	-0.081	-0.059	-0.081	-0.059
(%)	(0.057)	(0.094)	(0.057)	(0.094)
$Turnover_{t-1}$	-0.001*	-0.0002	-0.001*	-0.001
(%)	(0.001)	(0.001)	(0.001)	(0.001)

***1% significance, **5% significance, *10% significance

Table 7: 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 $Netflow_{m,t}=(TNA_{m,t+1}-TNA_{m,t}(1+R_{m,t+1}))/TNA_{m,t}$. 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 were 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 year. $Log(age_t)$ is the age of the fund lagged one quarter. Turnover is the turnover of the fund which is lagged one year. 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. Also, in order to correct for any correlation in errors of the fund over time, the standard errors are clustered by the fund. Bootstrapped standard errors are reported below the estimates in parentheses.

	$NetFlows_{t+1}(\%)$							
	25th Pct	50th Pct	75th Pct	90th Pct	25th Pct	50th Pct	75th Pct	90th Pct
$skill_{t-1}$	1.251***	0.969***	1.082***	2.410***	0.422	1.540**	2.865***	8.956***
	(0.190)	(0.148)	(0.210)	(0.432)	(0.767)	(0.723)	(0.907)	(1.981)
$skill_{t-1}$*age					0.217	-0.133	-0.440**	-1.538***
					(0.195)	(0.193)	(0.208)	(0.403)
α_t	7.352***	7.921***	11.891***	20.468***	7.406***	8.039***	11.643***	20.337***
	(0.869)	(0.805)	(1.383)	(2.309)	(0.941)	(0.865)	(1.293)	(2.542)
R_t (%)	0.056***	0.065***	0.097***	0.170***	0.057***	0.065***	0.098***	0.165***
	(0.004)	(0.003)	(0.004)	(0.008)	(0.004)	(0.003)	(0.004)	(0.007)
$expenses_t$	-1.492***	-1.711***	-1.849***	-2.709***	-1.472***	-1.713***	-1.880***	-2.724***
(%)	(0.111)	(0.085)	(0.114)	(0.244)	(0.120)	(0.089)	(0.126)	(0.235)
$log(age_t)$	-1.603***	-2.296***	-3.329***	-5.158***	-1.661***	-2.319***	-3.303***	-5.158***
	(0.056)	(0.050)	(0.054)	(0.105)	(0.053)	(0.052)	(0.053)	(0.104)
$log(tna_t)$	0.276***	0.140***	-0.027	-0.628***	0.281***	0.140***	-0.031	-0.638***
	(0.032)	(0.022)	(0.031)	(0.052)	(0.028)	(0.020)	(0.030)	(0.056)
$turnover_t$	-0.013***	-0.005***	0.004***	0.030***	-0.014***	-0.005***	0.004***	0.030***
(%)	(0.001)	(0.001)	(0.001)	(0.003)	(0.001)	(0.001)	(0.001)	(0.003)

***1% significance, **5% significance, *10% significance

Table 8: Robustness of skill measure

This table reports the summary of the skill of fund managers under different specifications. *Skill_1* 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, $weight_{i,j} = |\frac{value_{i,j,t} - value_{i,j,t-1}}{TNA_{j,t-1}}|$. 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.

Panel A: Skill Value					
	Mean	25 pct	Median	75pct	Std dev
Skill_1	0.0035**	-0.0487	0.0043	0.0615	0.1233
Skill_2	0.0150***	-0.0491	0.0158	0.0948	0.1500

Panel B: Skill - All Stocks					
	Mean	25 pct	Median	75pct	Std dev
Skill_1	0.0046***	-0.0242	0.0039	0.0369	0.0770
Skill_2	0.019 ***	-0.0266	0.0126	0.0635	0.1021

Panel C: Skill - No 4^{th} quarter					
	Mean	25 pct	Median	75pct	Std dev
Skill_1	0.0066***	-0.0368	0.0061	0.0537	0.1047
Skill_2	0.0205 ***	-0.0379	0.0175	0.0867	0.1366

Panel D: Alternate Two Period News					
	Mean	25 pct	Median	75pct	Std dev
Skill_2	0.0207 ***	-0.0332	0.0161	0.0805	0.1224

Panel E: Skill and predictability					
	Mean	25 pct	Median	75pct	Std dev
Skill	0.009***	-0.0353	0.0079	0.0571	0.112

***1% significance, **5% significance, *10% significance

Table 9: 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 1994-2011. 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 third number is a robust jackknife standard error computed using the method outlined in Shao and Rao (1993). The resulting R^2 is also presented. Panel B presents the summary of the distribution of skill across all fund managers. *Skill_1* 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 the Wilcox rank test, a non-parametric 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.

Panel A: VAR parameter estimates

	$r_{i,t}$	$BM_{i,t}$	$\overline{ROE_{i,t}}$	$IST_{i,t}$	R^2
$r_{i,t+1}$	**0.0248**	**0.0248**	**0.0614**	**0.0008**	0.6%
(Log stock returns)	(0.0164)	(0.0045)	(0.0175)	(0.0006)	
	[0.0002]	[< 0.0001]	[0.0002]	[0.0002]	
$BM_{i,t+1}$	**0.0598**	**0.9414**	**0.0491**	**0.0001**	86.61%
(log book-to-market)	(0.0132)	(0.0041)	(0.0143)	(0.0001)	
	[0.0001]	[< 0.0001]	[0.0001]	[< 0.0001]	
$\overline{ROE}_{i,t+1}$	**0.0148**	**-0.0026**	**0.6265**	**0.0003**	53.66%
(five-year profitability)	(0.0013)	(0.0003)	(0.0170)	(0.0003)	
	[0.0001]	[< 0.0001]	[0.0002]	[< 0.0001]	
$IST_{i,t+1}$	**0.0316**	**-0.0501**	**0.3934**	**0.0267**	0.15%
	(0.0143)	(0.0056)	(0.0234)	(0.0252)	
	[0.0002]	[0.0004]	[0.0033]	[0.0084]	

Panel B: Skill - Alternate VAR specification

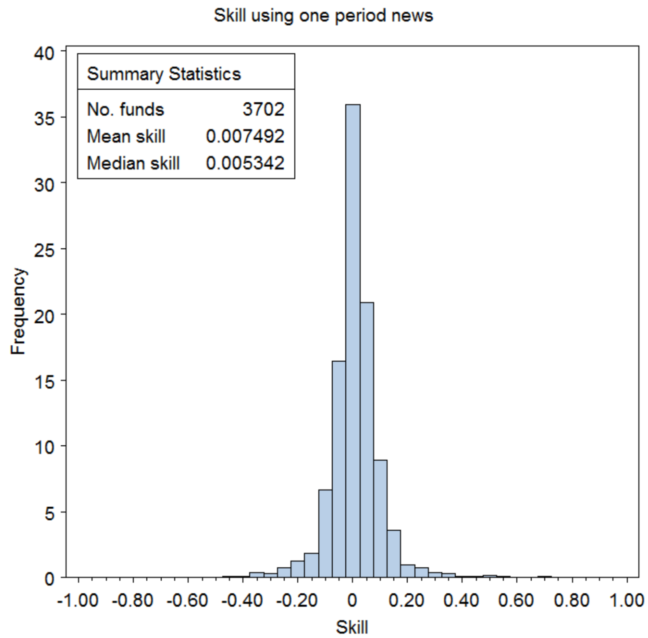
	Mean	25 pct	Median	75pct	Std dev
Skill_1	0.0073***	-0.0309	0.0051	0.0467	0.0929
Skill_2	0.0197***	-0.0346	0.0156	0.0802	0.1227

Panel C: Skill - Long VAR specification

	Mean	25 pct	Median	75pct	Std dev
Skill_1	0.0050***	-0.0330	0.0039	0.0448	0.0952
Skill_2	0.0177***	-0.0361	0.0138	0.0788	0.1223

***1% significance, **5% significance, *10% significance

Panel A



Panel B

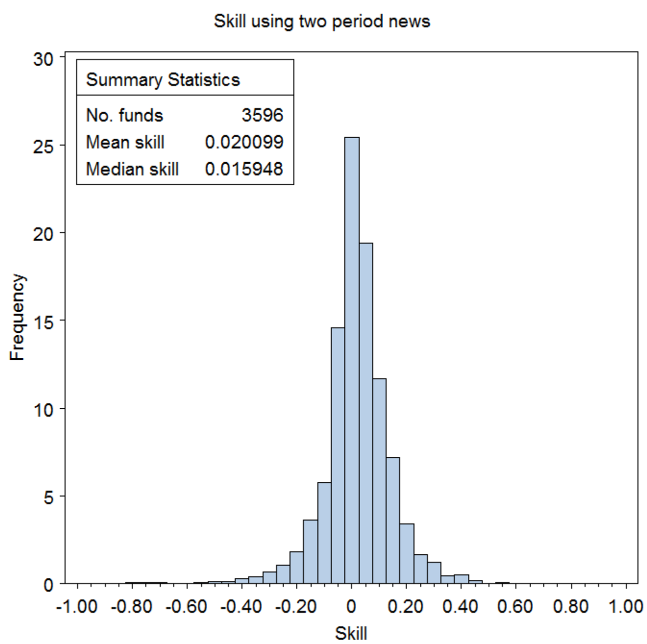
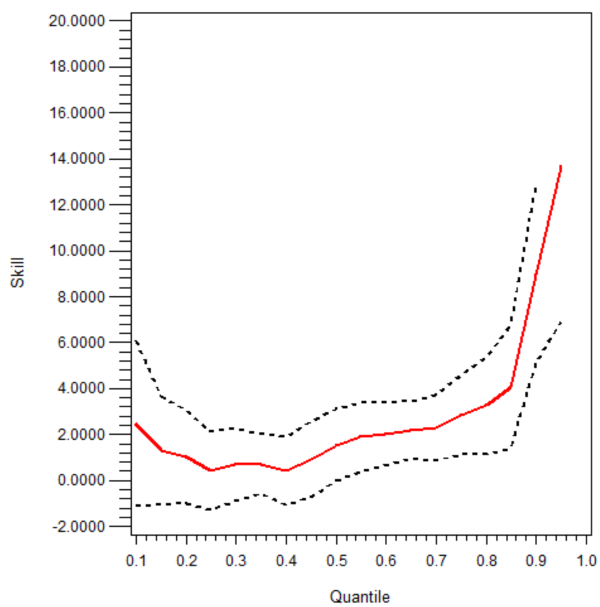


Figure 1: **Distribution of Skill**

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.

Panel A



Panel B

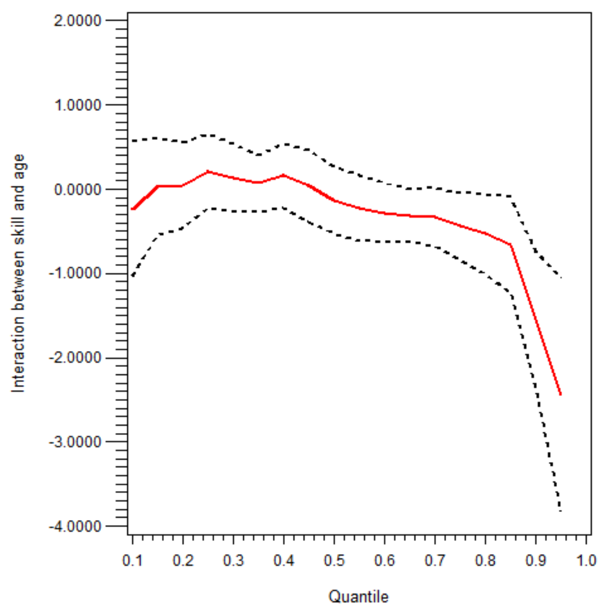


Figure 2: Quantile Regression of Flows

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.