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By

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Abstract

I propose that various measures of mutual funds' performance are more consistent with their investment capability when mutual funds present low idiosyncratic risks. This paper finds conditional predictor for funds' returns: alpha predicts returns positively for low idiosyncratic risk funds. It suggests that mutual funds which showed high alpha and low idiosyncratic risk in the past may be capable in investment. Their performance is consistently higher than funds with low idiosyncratic risk and low alpha. On the other hand, the performance of high idiosyncratic risk funds is more likely to reverse in the future: expected returns are low for high alpha funds, and low alpha funds' expected returns are high. I split the sample into 3 categories: funds with high idiosyncratic risk, low idiosyncratic risk and low alpha, low idiosyncratic risk and high alpha. Following Barras, Scaillet and Wermer(2010)'s method, I find out that the proportion of zero-alpha fund is highest within high idiosyncratic risk funds, and low alpha low idiosyncratic risk funds include the most unskilled funds. This paper also studies the predictive power of a variety of fund characters: alpha, idiosyncratic risk exposure, information ratio, and so on. However, none of them shows clear predictive pattern for expected returns. My observation reveals that information ratio does not predict returns in the full sample, but it indeed has strong predictive power for funds which keep long term growth, or growth and income investment objective.

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1. Introduction

Institutional investors are now a dominant force in financial markets, representing a large fraction of equity ownership and an even larger proportion of trading volume. Equity mutual funds hold more than 70% shares on stock market in United States. Presently, both academicians and practitioners face a problem on how to select the funds with persistent outperformance. Recent studies, like Kosowski et al. (2006), Pastor and Stambaugh (2002) and Avramov and Wermers (2006), indicate that some fund managers may possess the investment capability. They document the outperformance by some funds, and argue that actively management does add value to mutual fund investment[1]. On the other hand, Carhart (1997) and several papers find zero returns or negative performance, net of trading cost and management expenses. Barras, Scaillet and Wermer (2010) further document that nearly 75% of the population exhibit zero-alpha all through their life time. Less than 1% is skilled fund managers who possess the "hot hand" to invest.

There is a large body of researches on unconditional predictor for funds' expected returns. Amihud and Goyenko (2009) indicate that the R square computed from the 4-factor regression negatively predicts future returns across the whole sample. Their result is consistent with Cremer and Petajisto's (2009) findings on effect of selectivity, which also document positive relation between active investment strategy and expected performance. Brand, Brown and Gallagher (2005) find similar pattern that their divergence index predicts fund performance positively[2]. Their story is straightforward: low R square and high divergence index proxy active management. And actively managed mutual funds create

[1] Amihud and Goyenko (2009) use R-square to measure the active management, and their result is also supportive for the idea that active management adds to the value.
[2] The divergence index is defined as the sum of squared deviations of the fund portfolio's stock weights from the market portfolio.

significant profit to investors. The behavior interpretation is that, for one thing, active management may proxy the ambition and capability of the fund managers. Managers will expand their risk exposure when they are certain about the investment opportunity; for another, past loser may manually increase their portfolio volatility, under the pressure of cash outflow or tournament effect.

Although the active management predicts the expected returns positively, it may not be a reliable proxy for investment ability. Investors may care more about their risk bearing under some market condition[3]. Trusts and pension funds have more rigorous restriction on risk controlling over profit earning. Actually, for a long time investors use Sharpe Ratio (abnormal return over return volatility) to access the performance of institutional investors. Information ratio (abnormal return over idiosyncratic volatility) also proxies fund managers' profiting capability while manage the risk in controllable level[4]. Treynor and Black (1973) show that an optimally constructed risky portfolio P, composed of a passive index portfolio M and an active investment portfolio A, has the following Sharpe ratio:

$$SR_p^2 = SR_M^2 + \left[\frac{alpha_A}{RMSE_A}\right]^2$$

where $alpha_A$ and $RMSE_A$ are measured with respect to the passive index M. Thus, the contribution of mutual fund A to the Sharpe ratio of the investor's portfolio is increasing in the fund's Information Ratio. This means that a higher Information Ratio makes the fund more attractive to investors. Information Ratio has been used as performance measure by Brands, Brown and Gallagher (2005) and by Kacperczyk, Sialm and Zheng (2005).

[3] Quite a number of behaviour researches document that investors are more sensitive to volatility when market goes down.
[4] Bodie, Kane and Markus (2009) show that the larger is the information ratio, the greater is the demand for the fund.

This paper studies the predictive power for both Sharpe Ratio and Information Ratio. Abnormal return is the alpha from Carhart's (1997) 4-factor based model. And idiosyncratic risk is calculated as the standard deviation of the residuals from the regression above (root mean square error). We conduct the tests on both whole sample and sub-samples based on different investment objectives[5]. The result is consistent with investors' intuitive: Sharpe Ratio and Information Ratio have significant positive predictive power for funds with Growth or Growth and Income objectives, which put more weight on return stability. Meanwhile, the power of prediction is very weak for funds with Aggressive Growth object. Since Aggressive Growth funds are more likely to expand their return volatility (or idiosyncratic volatility) for a higher profit.

This paper also contributes to the body of literature by introducing reliable predictor for expected returns conditional on fund idiosyncratic risk. Although fund alpha or idiosyncratic risk alone shows little predictive power for future returns in the whole sample, we do document that alpha positively predicts returns for low idiosyncratic risk funds. And predictive power is quite significant. My argument is that alpha proxies mutual fund managers' investment capability. For low idiosyncratic risk funds, high alpha may represent outstanding capability for investment, and low alpha indicates unskilled in investing. Funds with low idiosyncratic risk and high alpha successfully keep their excellent performance for a long period. In addition, funds with low idiosyncratic risk and low alpha keep underperforming their peers with high idiosyncratic risk. On the other hand, high idiosyncratic risk funds' performance is more likely to reverse: expected returns are low for high alpha funds, and low alpha funds' expected returns are high. Instead of cautious stock selection, they expand the idiosyncratic risk exposure to seize profit opportunity. I further prove that most of their performance is due to luck.

[5] The whole sample is divided into 3 styles: Aggressive Growth, Growth and Growth and Income, based on their investment objective.

2. Related Researches and Literature

A lot of previous researches have searched predictors for expected fund returns. Amihud and Goyenko (2009) argue that R square measures the selectivity of mutual funds, thus predict expected returns negatively. Brands, Brown and Gallagher (2005) studies the Australian stock market; they also find that expected returns are positively correlated with their divergence index. Cremers and Petajisto (2009) create a proxy called “Active Share”, which counts the share of the portfolio holding that differ from the benchmark index holding. They further document that their “Active Share” predict fund performance positively. Wermers (2003) documents that the standard deviation of S&P 500-adjusted fund returns are positively related to the contemporaneous fund performance, measured by 4-factor alpha.

The argument behind these predictors is that active management of the mutual funds is valuable. Fund selectivity is shown to enhance performance. Daniel, Grinblatt, Titman and Wermers(1997) analyze selectivity at the equity level, and they find that securities that are picked by funds averagely outperform a characteristic-based benchmark, although the gain from stock picking approximately equals their management fee in average. Chen, Jegadeesh and Wermers (2000) study the stock holding and turnover of mutual funds. Their finding is that stocks widely held by mutual fund do not outperform others. However, stocks purchased by funds have significant better performance then they sell. Wermers (2000) finds that the average U.S. domestic equity fund underperforms its overall market, size, book-to-market, and momentum benchmarks by 1.2% per year over the 1975-1994 periods. More optimistic evidence in support of active management skills is shown in recent studies: Moskowitz (2000) provides evidence on the value of active management during different phases of the business cycle. He demonstrates that active strategy generates additional 6% per year during economic recessions versus expansions. Kacperczyk, Sialm and Zheng (2005) suggest that funds exhibit superior performance if they present greater industry concentration for their holdings compared to the diversified portfolio. One step further, Kacperczyk and Seru (2007) document that funds whose stocks holdings are highly related to company specific information from analysts' expectations have better performance.

These studies believe that investors could examine the quality of fund managers by studying their actions. Active management is sound proxy for investment capability and ambition. Chevalier and Ellison (1999) support this idea by studying the relationship between fund performance and fund managers' characters. They argue that most of the performance can be attribute to the behavior of managers instead of their static characters. However, their previous paper in 1997 also argues that the risk taking behavior of fund managers may simply the response for incentives.

Some other researches insist that mutual funds' high risk exposure is a natural response for their managerial incentives. Chevalier and Ellison (1997) apply a semi-parametric model to study this potential agency conflict issue. Their argument is that the investors and mutual fund companies bear different investment objectives: investors care both return and risk exposure, while company does not charge on risk controlling but only on the profit they earned. In this case, it is a natural response that mutual fund managers may manually expand their idiosyncratic risk. Brown, Harlow and Starks (1996) find supporting evidence for this: they argue that the competition among the fund managers determines their fundamental payment; therefore the bad performers have incentive to expand risk exposure in the second half of fiscal year to catch up with peers on the market. Berk and Green (2004) develop a rational equivalent model on mutual fund performance. They suggest that mutual fund would expand their return volatility after experiencing fund outflows. Alexander, Cici and Gibson (2007) further unveil mutual fund managers' investment motivations: a fund manager who buys stocks when there are heavy investor outflows is likely to be motivated by the belief that the stocks are significantly undervalued. In contrast, when there are heavy inflows, the managers are likely to be motivated to work off excess liquidity by buying stocks. Their argument supports the tournament effect hypothesis by proving that fund manager is better in investment under pressure.

The studies on hedge fund find similar evidence in support of active management. Titman and Tiu (2008) suggest that hedge funds have better performance when they hedge less against common stock benchmarks on the market. And they conclude that choosing smaller instead of larger exposure to pricing factor risk may reflect fund managers' confidence in their investment capability. Wang and Zheng (2008) define $\hat{\varepsilon}^2 / \sigma^2$ as the "hedge fund distinctiveness index," they argue that the index they develop may proxy the investment capability of hedge fund managers.

Although a lot of empirical evidence has been documented to support the existence of investment ability of mutual fund managers, a huge body of researches finds little evidence on this. Some papers even document negative alpha after controlling the transaction cost and management expenses. Jensen (1968) and Elton et al. (1993) document that averagely mutual fund alpha is significantly negative. Carhart (1997) argues that the superior performance for some mutual fund measured by Fama-French 3-factor alpha[6] could be explained by his momentum factor. He revisit the sample in previous researches with his new momentum benchmark model, and find little evidence in support of significant risk adjusted returns. He also concludes that fund alpha computed by 4-factor model is powerless in predicting expected returns.

[6] The 3 factors included are *RM-Rf* (the market portfolio excess return), *SMB* (small minus big size stocks), *HML* (high minus low book-to-market ratio stocks)

Some empirical researches also support this idea by studying the fund managers' trading behavior. Lakonishok, Shleifer and Vishny (1992) find that institutional investors are frequently alleged to herd and to follow potentially destabilizing investment strategies. Sias (2004) documents the herding pattern among institutional investors. Badrinath and Wahal (2001) study the quarterly share holding by institutions, and find that institutions act as a momentum trader when entering the market, as a contrarian when they quit.

Latest researches have set up the criteria and studied the investment capability directly by capturing their performance distribution. Barras, Scaillet and Wermer (2010) develop a new method to control "false discoveries" issues or mutual fund that exhibit significant alphas by luck alone. With their technique, most of the funds earn zero alpha all though the sample period. The proportion of skilled fund manager is not significant from zero. The returns for more than 23% funds in the sample cannot cover their trading cost and management expenses, thus exhibit significant negative alphas. They further suggest that Aggressive Growth funds in average perform better due to their active investment strategy.

All the papers above apply the same assumption on fund managers' capability that predictors they found work for all the institutional investors, thus cannot explain the confliction on the existence of skilled fund managers.

3. Data and Sample Selection

Data about mutual fund returns is downloaded from CRSP Survivorship Bias free Mutual Fund database for 1965 to 2007 periods. It is on monthly basis, and reports the net monthly return for all classes of each mutual fund[7]. The CRSP database identifies each share class separately, whereas this paper only studies the performance for underlying funds. The Mutual Fund Links tables assign each share class to the underlying fund. We calculate mutual fund returns by taking the value weighted average over Total Net Asset across all the classes in that fund for each month. If Total Net Asset (TNA hereafter) is not available for some classes, fund return equals to the class returns with largest Total Net Asset. We take the simple average of the class returns when the TNA is missing for all the classes of that fund. The return file has been merged to MFLINK (which is available from CRSP) to include the fund characters, like investment objectives, fund age, expenses ratio and turnover. Investment objectives are jointly determined by S&P investment objective code, ICDI investment objective code and CRSP investment code. Most of the funds in our sample report these characters on quarterly basis. Expenses ratio, investment objectives and 12b1 fees are annually reported before 1999. And quarterly data is available since 1999 onward[8]. However we apply the annual data by simply taking the last observation in each fiscal year[9]. The alpha for Carhart's momentum based model is used to estimate the benchmark adjusted performance. The monthly 4 factors are collected from Ken French's website.

Actively managed equity funds are analyzed in this paper. Included are funds with investment objective codes from CRSP to be Small Company Growth, Other Aggressive Growth,

[7]The net return we use is after fees, expenses,and brokerage commissions but before any front-end or back-end loads.

[8] See Cici (2008) for more detailed explanations.

[9] Usually we take the fourth quarter data for each fiscal year. If the fourth quarter is missing, we will take the third quarter instead, and so on.

Growth, Income, Growth and Income, Maximum Capital Gains[10]. If no code is available for a fund-year and a fund has a past year with the style identified, that fund-year is assigned the style of the previously identified style-year. If no fund style is identified, it is not included in our sample. As mentioned in Section 2, roughly we classify the funds into three categories: Aggressive Growth, Growth, Growth and Income based on their investment strategies. The similar classification is also shown in Barras, Scaillet and Wermers (2010). Elton, Gruber and Blake (1996) and Amihud and Goyenko (2009) eliminate funds with total net assets of less than 15 million U.S.D. at the end of the year preceding the test year. They believe that the inclusion of such funds can cause survivorship bias in estimation due to reporting conventions[11]. Still a lot of papers have introduced winsorizing method to include this consideration. This paper sheds light on both of these two treatments: the result is calculated in both settings, and we find the return difference is not fundamental for our findings. In this paper we only report the result after winsorizing top and bottom 0.5% TNAs. Besides that we require funds to have at least cumulative 36 monthly returns data to be eligible in our sample, since we have to use them to estimate lagged values of alpha and idiosyncratic risk. We also require funds to have data in the first year about expenses, turnover, total net assets, age and managerial tenure[12].

[10] See Pastor and Stambaugh (2002) for more details.
[11] Their argument is that the extremely small fund is probably to be out of market in the next year after the observation.
[12] Age counts the years since the funds is public tradable. And managerial tenure equals to the number of years since the incumbent manager take control of the fund.

4. Research Method

This paper studies the predictive power of Sharpe Ratio and Information Ratio, and fund alpha conditional on idiosyncratic risk level. For the funds that satisfy the requirement in section 3, we estimate fund alpha and idiosyncratic risk by regressing the past 36 months' excess returns[13] on Carhart's four factors[14] for all the funds separately.

$$\mathrm{r}_{\mathrm{i,t}} - \mathrm{rf}_{\mathrm{t}} = \alpha_{\mathrm{i}} + \beta_{1,\mathrm{i}} * \mathrm{Mktrf}_{\mathrm{t}} + \beta_{2,\mathrm{i}} * \mathrm{HML}_{\mathrm{t}} + \beta_{3,\mathrm{i}} * \mathrm{SMB}_{\mathrm{t}} + \varepsilon_{\mathrm{i,t}}$$

$$\text{Idiosyncratic risk} = \sqrt{\sum_{\mathrm{i}=1}^{\mathrm{N}} \varepsilon_{\mathrm{i}}^{2}}$$

Fund alpha is the intercept of this regression, and idiosyncratic risk is calculated as the standard error of the residuals. The sigma measures the return volatility for the past 36 months.

We have two conventional methods to study the predictive power of these ratios and characters. Firstly we use investment based method to form portfolios in each month based on funds' past characters, and hold the portfolio for one month or one year.

[13] Fund return over risk free rate.
[14] It includes RM-RF (market portfolio excess returns), SMB (small minus big size stocks), HML (high minus low book-to-market ratio stocks) and UMD (winner minus loser stocks).

$$\mathrm{Ret}_i = \sum_{t=1}^{T} \sum_{j=1}^{N_t} r_{j,t}$$

The portfolio analysis technique is widely employed to study the spread of expected returns between different groups. Investors could buy one share of top portfolio and short one share of the bottom portfolio to earn the profit of this spread. The significant returns of this portfolio help to identify the predictive powers for the fund characters. In the second place we could also reveal the predictive pattern by employing Fama-MacBeth's setting[15], which is a two-step process: we first regress the expected returns on fund characters in the first 36 months. Then we split the sample based on their factor loadings, and study the average of the loadings. In each month, Fama-MacBeth regression specifies cross-sectional regression that future one month return is regressed on current characters. We take the simple average of the coefficient all through every month in the sample period.

$$r_{i,t} = a_t + b_t * \mathrm{character}_{i,t-1} + \varepsilon_{i,t}$$

$$B = \sum_{t=1}^{T} b_t$$

For portfolio analysis, we rank all resulting fund characters estimates into ten portfolios based on fund alpha, idiosyncratic risk, past return, funds' R square, Sharpe Ratio and Information Ratio, and winsorize the top and bottom 0.5% of the observations. We report the result for

[15] See Fama and MacBeth (1973) for more details.

both monthly and annually portfolio rebalance[16], and include these characters and ratios in cross-sectional regressions. Additionally the control variables in the predictive cross-fund regression are those that are commonly introduced by previous studies of fund performance: Amihud and Goyenko (2009) introduce fund age (year), expenses, the expenses ratio calculated in the latest fiscal year, Total Net Asset (TNAM hereafter), turnover, defined as the minimum of aggregated sales or aggregated purchases of securities divided by the average 12-month TNA of the fund, and managers' tenure[17] into this regression to check the robustness of our result. The predictors studied in this paper are alpha and idiosyncratic risk. They reflect mutual fund managers' investment skill and strategy.

Neither Sharpe Ratio nor Information Ratio exhibit significant predictive power in the whole sample. However they show clear predictive patterns in sub-samples. We divide the whole sample into three categories by funds' investment objectives: Aggressive Growth, Growth, Growth and Income. And Fama-MacBeth's technique is employed in each category to study the predictive power of Sharpe Ratio and Information Ratio: R square measures the selection sensitivity, alpha proxy the past performance, Sharpe Ratio and Information Ratio combine profit earning and risk controlling, thus are the fundamental predictor in this paper. Our argument is that these ratios may proxy fund managers' investment skills.

One contribution of this paper is that we reveal the predictive power of fund alpha conditional on funds' idiosyncratic risk level. We further re-do our portfolio analysis and divide the sample into 5*5 portfolios classified by funds' alpha*idiosyncratic risk. The low and high idiosyncratic risk groups indeed show inverse pattern on the predictive power of past alpha. In addition, we employ Fama-MacBeth technique in each of the sub-samples, and

[16] Monthly rebalance requires to renew the portfolio formation in each month, and to hold the new portfolio for one month. Annually rebalance only renew the portfolio at the end of year, and holds the portfolio for the next 12 months.
[17] It counts the years since current manager took his position.

the inverse factor loadings strengthen our findings that the predictive power of alpha has changed fundamentally from low idiosyncratic risk funds to high idiosyncratic risk funds.

In the end we conclude our findings that fund alpha may represent the investment capability for funds with low idiosyncratic risk, which indicates that high alpha and low idiosyncratic risk funds may possess superior ability to select the stocks, while low alpha and low idiosyncratic risk funds keep their underperformance comparing with benchmark. In the other way, it is hard to identify the investment capability for high idiosyncratic risk funds. It is still an open question on how to separate the active management from risk expanding simply due to interest conflicts. To assess the capability of fund managers, we apply Barras, Scaillet and Wermers (2010)'s technique for three sub-groups: low alpha and low idiosyncratic risk funds, high alpha and low idiosyncratic risk funds, and high idiosyncratic risk funds. We document that the proportion of zero-alpha fund is highest among high idiosyncratic risk funds.

5. Result and Analysis

We summarize the basic sample statistics in table 1. Most funds charge reasonable expenses ratios around 1.1%, and Aggressive Growth funds in average charge higher expenses over Growth, Growth and Income funds. Fund alpha is negative in average calculated with past 3 years excess returns, this result is consistent with a lot of previous empirical findings (e.g. Amihud and Goyenko (2009) document negative fund alpha with daily data). However, the average raw return for mutual fund is significantly positive, and mutual funds will typically profit 0.5% per month. The ratio of idiosyncratic risk over the return volatility is around 1/3 for most of funds in our sample. And a majority of funds usually rebalance all the positions they hold in 3 to 4 months. It should be noticed that in each month we remove the observations with lowest 1% TNAM, to make sure that our result is not driven by some extremely small institutes.

[Insert table 1 here]

5.1 The prediction of Sharpe Ratio and Information Ratio

We paint a brief portrait for the control variables in our sample by studying their correlations. Table 2 presents the Spearman correlation between the fund characters and variables. It is interesting to find that R square is negative correlated with excess return (mretn). This is consistent with Amihud's result which documents a negative relation between expected alpha and current R square. Table 2 presents the correlation for variable in the same month. There is no prediction pattern in the whole calculation. The correlation we present here is consistent with previous studies: the expenses ratio is positively correlated with mutual fund's turnover, and it is significant all through the sample period. Since aggressive growth funds are more likely to take active investment strategies, and in average they charge higher expense ratio for their management. The age of the funds is positive correlated with fund's total net asset, which means the older the fund is, the larger it should be. Besides that, fund's TNA is negatively correlated with turnover ratio and past returns, but positively related with R square, which reveals that bigger funds tend to converge to passive investment strategies, thus have worse performance comparing with smaller funds, which have the incentive to employ more aggressive strategies. Therefore the positive correlation with R square is intuitive that larger funds may prefer the stable investment strategies which put more weight on market portfolio.

[Insert table 2 here]

5.1.1 Predictive power in full sample

To examine the predictive power of fund characters, we employ the investment based strategy. In each month we single sort the sample on past characters and hold the portfolios for one month. Then we have 10 portfolios, which are ten continuous time series. We keep the equally weighted average returns as the mean performance of the portfolios, and introduce Carhart's 4 factors on monthly basis to compute the risk adjusted returns. Two methods are employed to form the portfolios: the one is to rebalance the portfolio in every month and hold the portfolio for future one month; the other is only to rebalance the portfolio at the end of each year, and to hold the portfolio for the future twelve months. The annually rebalance result is more consistent with result for Fama-MacBeth regression, in which many fund characters are only available in annual basis[18].

[Insert table 3 here]

Panel 1 reports the result for single sort on past alpha. It is consistent with previous research that 4 factor alpha does not predict future returns in ordinary linear settings. The return spread is only around 0.0013 per month, with its t-statistic 0.33. This pattern is stable whether we employ monthly or annually rebalance portfolios and is persistent across raw return and risk adjusted returns. In panel 2 we sort on past idiosyncratic risk, again we find that each group earns significant positive raw returns and none significant risk adjusted returns. The result does not change too much for yearly rebalance. The pattern for return spread is vague that semi-significant profit is documented by longing one share of the highest idiosyncratic risk portfolio and shorting one share of the lowest. And the result is the same when we turn to annually rebalancing. However, the risk adjusted return adds little to this finding. There is insignificant spread when we look at monthly/annually rebalanced alpha. Panel 3 sorts funds based on past R square. It is a contradiction that we do not find clear predictive power for R square[19]. We document positive prediction, and the t-statistic equals 1.45, which indicates semi significant relation. This pattern is reversed when we study the risk adjusted returns.

Similar patterns are observed when we sort the funds based on ratio1 and ratio2[20]. Averagely neither information ratio nor Sharpe ratio is clearly correlated with expected return in the whole sample. Therefore, an easy conclusion is that none of these fund characters has strong

[18] Fund expenses, total net asset is only available at the end of year for most of funds.
[19] Amihud and Goyenko (2009) document negative predictions for R square.
[20] Ratio1 is information ratio, which is alpha over idiosyncratic risk; ratio2 is alpha over return volatility.

predictive power for expected returns, including information ratio and Sharpe ratio. The factor loadings from Fama-MacBeth regression support similar patterns[21].

5.1.2 Predictive power in sub-samples

The first contribution of this paper is that we study fund characters' predictive power within sub-samples, which is categorized based on investment objective. Although little predictive power has been documented in full sample, information ratio and Sharpe ratio could still be useful in forecasting future performance in sub-samples. It is common that researchers find weak or minor evidence in the full sample, since it includes all types of institutions and a lot of investment strategies. The factor loadings may be negative for some specific institutions, while positive for some others. Therefore, the general picture is veiled by the co-existence of many different patterns. Therefore the helpful as well as critical routine to study the predictive power is to divide the full samples into different sub-samples, and find different patterns of prediction in sub-samples. This paper divides the sample based on their investment objectives (IOB hereafter). IOB is one of the most consistent characters of the mutual funds. It is stable all through many years in funds' life, thus it is reliable proxy for their investment strategies. The predictive power of information ratio and Sharpe ratio may vary across different investment objectives: funds which employ aggressive strategies pay more attention to investment opportunities instead of risk controlling. Actually they often manually expand risk exposure to bet for better expected returns. Meanwhile funds with passive strategies may prefer low risk bearing portfolios. So our hypothesis is that information ratio and Sharpe ratio predict returns positively in samples which employ less aggressive strategies, and negatively in aggressive samples.

[21] The result of Fama-MacBeth regression also finds little evidence for fund characters' predictive power. Therefore it is not reported in this paper. It is available upon request.

Previous researches typically categorize the fund investment objectives into three types: Aggressive Growth, Growth, Growth and Income. Aggressive Growth funds are actively managed to search investment opportunities, thus bear higher risk exposure. Growth, Growth and Income funds manage their portfolios to invest on valuable assets. Usually they pay more attention on risk controlling than Aggressive Growth funds, which earn profit by expanding risk exposure. In this paper we find comprehensive evidence that information ratio is useful in predicting expected returns for Growth, Growth and Income fund. Since these institutions combines their profit earning and risk management goals in their value investment. Instead, future returns are negatively predicted by information ratio for Aggressive Growth funds, to which risk controlling may border their profit earning plans.

[Insert table 4 here]

Model 4 introduces R square, information ratio and past risk adjusted returns into the regression[22]. R square, as mentioned in Amihud and Goyenko (2009), proxies the active management, thus adds value to the prediction of expected returns. We notice that none of the factors introduced is significant in predicting the expected return. Both R square and Information ratio are negatively correlated with future returns for funds with aggressive growth objective, but the absolute value of t-statistic does not exceed 2. Therefore we could only suggest that active management may possibly increase the performance, and information ratio is not very sound a proxy for the investment skills for aggressive growth funds. However, neither of these two hypotheses could be verified.

[22] The result is also available for regression on both predictive factors and fund characters. Since it is consistent with each other, we only report the result for regression on predictive factors. The full regression is available upon request.

Meanwhile the predictive power of information ratio is significant for Growth funds and Growth and Income funds. Although R square and past alpha still do not show clear predictive patterns under this setting: their t-statistics are less than 1 in average, the coefficients of information ratio are positive significant in both panel 2 and 3.

5.2 Conditional predictors for expected returns

5.2.1 Investment based analysis

The other contribution of this paper is that we find a conditional predictor for future performance. Although none of fund characters presents significant predictive power for all conditions, we do document some evidence by splitting the sample into two dimensions: past performance and past idiosyncratic risk exposure. Table 5 divides the whole sample into 5*5 portfolios based on past alpha and past idiosyncratic risk. We find that averagely funds with high idiosyncratic risk earn better performance over funds with low idiosyncratic risk. This is consistent with a lot of previous research. Also it is consistent with our single sort result. When we focus on the funds with low idiosyncratic risk, high alpha funds maintain the stable and premium performance over funds with low alpha, which maintain the stable but inferior performance. On the other hand, we have observed reverse pattern for funds with high idiosyncratic risk: funds with low alpha in the past 3 years generally outperform their counterparts with high alpha. Although these patterns are weaker when we consider the risk adjusted returns, we still find that the return spread is persistent. So we have the first hypothesis on the predictive characters: alpha could be a sound predictor conditioning on idiosyncratic risk exposure. Fund's alpha positively predicts future returns when low idiosyncratic risk is presented. Additionally, alpha may not predict expected returns quite well when funds show high idiosyncratic risk exposure. To be noticed, for low alpha funds, the group with low idiosyncratic consistently underperforms the peers with high idiosyncratic risk. However this pattern reverses for funds with high alpha: funds with low idiosyncratic risk outperform high idiosyncratic funds. So we have the second hypothesis: alpha may represent the investment capability for fund managers whose idiosyncratic risk exposure is low, and alpha is powerless to proxy investment ability for funds with high idiosyncratic risk.

[Insert table 5 here]

This finding is confirmed by annual rebalancing result in Table 6. Clear outperformance patterns are documented for funds with high alpha and low idiosyncratic risk over low alpha low idiosyncratic risk funds. The spread portfolio which takes long position on low idiosyncratic risk high alpha funds and short position on low idiosyncratic risk low alpha funds earns 0.75% per month. The t-statistics is 2.03, which indicates significant profit. Besides that, we also get some evidence in support of that fund with low alpha and low idiosyncratic risk is unskilled: funds with high idiosyncratic risk and low alpha maintain the better performance over low idiosyncratic risk and low alpha funds. This result is consistent whether we employ raw returns or risk adjusted returns: high idiosyncratic risk & low alpha portfolio outperforms low idiosyncratic risk & low alpha portfolios by 0.93% for raw returns, and 0.18% for risk adjusted returns. Both are significant in statistical point of view.

[Insert table 6 here]

5.2.2 Regression analysis

To test the two hypotheses mentioned above, we split the sample into two groups by two dimensions: panel 1 and panel 2 present the result for high alpha and low alpha groups respectively. We document clearly reversed patterns for the coefficient of idiosyncratic risk: it is quite significant that idiosyncratic risk predict negative expected returns within the group of high alpha funds: the coefficient of idiosyncratic risk is -0.0029 for models without controlling variables. And it is even more negative after controlling variables are introduced. In both models the t-statistics of the coefficients are negative significant. The reversal pattern is held for the coefficient of idiosyncratic risk for funds with low alpha. Again the t-statistics are significant. We then study the sub-sample of high and low idiosyncratic risk. And the result for two regressions in panel 3 and 4 are highly consistent with previous result for double sort: alpha is critical and reliable proxy for investment capability that it predicts the future return with high significance: for low idiosyncratic risk funds, the coefficient of alpha is positive significant whether controlling variables are introduced or not. The prediction role of alpha for high idiosyncratic risk funds is clouded by the extremely high risk exposure. May most of their superior (or inferior) performance be attributed to luck (or unlucky).

[Insert table 7 here]

5.2.3 Further evidence

To further shed some light on the differences between low and high idiosyncratic risk funds. Figure 1 is presented to show the distribution of expected returns for two groups.

[Insert figure 1 here]

The expected returns of high idiosyncratic risk funds are more diversified: the probability of quintile 1, 2, and quintile 24, 25 exceed 0.05, and quintile 11, 12, 13 are only around 0.03. It is more likely to witness extreme returns for high idiosyncratic risk funds: the likelihood of extreme values (quintile 1, 2, 24, 25) is 22.8%. While the likelihood of extreme values for low idiosyncratic risk is around 8.9%. The distribution of low idiosyncratic risk funds' expected returns is more converged to its mean value.

The distinctive patterns shown in figure 1 are intuitive: high idiosyncratic risk funds manually expand risk exposure to bet for better performance. However, their aggressive strategies may not realize the better performance for sure. Some of them may be lucky enough to get extremely positive returns, while still some funds will unfortunately to accept the truth that they may lose a lot on expanding risk exposures. In another way the extreme value for low idiosyncratic risk funds is very rare, which also indicates that the performance is quite stable among the low idiosyncratic risk funds.

To verify the hypothesis that low idiosyncratic risk funds' performance is truly more stable than high idiosyncratic risk funds, this paper plots the change of distribution of fund alpha in figure 2.

[Insert figure 2 here]

Panel 1a, b, c, d present the alpha distribution for low idiosyncratic risk funds, and panel 2a, b, c, d show this distribution for high idiosyncratic risk funds. Panel 2 pictures the drift of the alpha distribution after 1 year. We find that most of the low idiosyncratic risk funds stay in the same quintile after one year. 53% funds in the quintile 1 remain their rankings after one year. And similar patterns are founded for funds in quintile 2, 3, 4, 5. However, fewer high idiosyncratic risk funds stay in the same quintile after one year: only 32% funds in quintile 1 keep their rankings in one year time. Again the same result is held for quintile 2, 3, 4, 5. Panel 2 shows alpha switch distribution in two years' time. The distribution for three years is presented in panel 3. Shown in panel 3b, we find that most of high idiosyncratic risk funds in quintile 1 have changed their rankings to quintile 5, and most of funds in quintile 5 have moved to quintile 1. This finding strengthens our conclusion that low idiosyncratic risk funds' expected returns are more stable comparing with high idiosyncratic risk funds.

Since low idiosyncratic risk funds' performance is more reliable, we could place more credit on their past performance when we study the mutual funds' investment capabilities. In another word, alpha could predict expected returns positively for funds with low idiosyncratic risk. This idea is similar with Barras, Scaillet and Wermers (2010) which divide the funds into three groups: unskilled, zero-alpha and skilled. In their paper, they indicate that there are three distributions in association with three types. And funds' performance will be more consistent with their true distributions when they make this specification. They insist that a skilled fund is less likely to be identified as unskilled in their specifications comparing with in traditional hypothesis which assumes one general distribution for all the funds. The intuition of their story is that their division of the whole sample categories all funds into different types and funds' performance will be more stable conditional on their types. Therefore, their estimation of funds' performance is reduced biased estimation, and their test captures the true investment capability.

This paper employs the methodology developed in their paper: assumes that there are unskilled, zero-alpha and skilled funds. We further divide the sample into three groups: funds with low alpha low idiosyncratic risk, high alpha low idiosyncratic risk and high idiosyncratic risk, and study the proportion of unskilled, zero-alpha and skilled funds in these groups.

[Insert table 8 here]

The proportion of skilled funds is lowest for low idiosyncratic risk low alpha funds. And the skilled funds proportion is not significant from zero. However, for low idiosyncratic risk high alpha funds and high idiosyncratic risk funds, the proportion of skilled funds is about the same: much higher than that for low idiosyncratic risk low alpha funds. In the end, the proportion of zero-alpha fund is highest for high idiosyncratic risk funds.

5.3 Robust check

The patterns we find in section 5.2 are true for sample period from 1965 to 2007's observations on monthly basis. In each month, we calculate funds' past alpha and idiosyncratic risk with a regression for past 36 months' data. In this regression, past 36 months' excess returns regress on Carhart's four factors. Funds' alpha is the intercept of the regression; idiosyncratic risk is the standard deviation of the residuals.

However, one may argue that the pattern we document above is valid only with the specification of this paper. To verify the robustness of the findings, we specify a second setting on sample period and on portfolio construction. Amihud and Goyenko (2009) use daily data for each month in the period 1989-2007 to calculate funds' alpha and idiosyncratic risk. They specify the form of regressions to reveal that funds' R square is negatively predictive for expected returns. In the robust check, we employ the same method to calculate funds' alpha and idiosyncratic risk: In each year from 1999-2007[23], daily data is used to calculate the funds' alpha and idiosyncratic risk. After that, funds' alpha and idiosyncratic risk are ranked into 10 quintiles as in table 3. The result is shown in table 9.

[Insert table 9 here]

Model 1 presents the result for regular Carhart's regression. Because we use daily data and because some stocks that constitute the fund returns are slow to adjust to information, we use model 2 where the fund return is regressed on the current and one-lag returns of the benchmark indexed[24].

Yearly rebalance presents similar pattern as shown in table 3: none of fund alpha, idiosyncratic risk, Information ratio or Sharpe ratio shows clear predictive power for future returns. However, R square indeed predicts returns negatively. In both model 1 and 2, this pattern is robust for both raw returns and risk adjusted returns. This is consistent with Amihud and Goyenko (2009)'s result.

Similar with table 6, double sort result is presented in table 10.

[Insert table 10 here]

[23] Amihud's sample is constituted with two sectors: daily data for 1989-1998, which is from a private database from International Finance Centre in Yale Business School; and daily data for 1999-2007, which is available from CRSP's mutual fund file. Since the author of this paper only get access to CRSP, the sample in this paper is from 1999 to 2007.

[24] See Dimson (1979).

For low idiosyncratic risk funds, the return spread is still significant between the high alpha and low alpha funds: the raw return spread is 0.71%, and the t-statistic is 2.02; the risk adjusted return spread is 0.19%, t-statistic is 2.10. Besides that, little evidence is founded to support other patterns. The return spread is positive for high idiosyncratic risk fund; however it is extremely insignificant. For low alpha funds, the return spread between high idiosyncratic risk funds and low idiosyncratic risk funds is positive. But t-statistic is only 1.39 for raw return, 1.20 for risk adjusted return. Although little evidence can be revealed with this new setting, our basic patterns do not change: alpha indeed predict returns positively for low idiosyncratic risk funds.

6. Conclusion

In this paper, we suggest a new view on the role of alpha and idiosyncratic risk in predicting mutual funds' expected returns. The contribution of this paper is that we find predictive factors conditional on funds' idiosyncratic risks. Our empirical evidence supports that alpha is a sound predictor for funds with low idiosyncratic risk. The further implement is that it is easier for investors to learn about the investment capability for funds with low idiosyncratic risk. Their performance is more stable comparing with high idiosyncratic risk funds. Therefore their alpha may proxy capability quite well. However little evidence is documented on the return prediction for funds with high idiosyncratic risk (no matter their past returns are high or low). The predictive factors may be veiled by the high risk exposure. We replicate Barras, Scaillet and Wermers (2010)'s method, and prove that the ratio of zero-alpha fund is highest for high idiosyncratic risk funds; skilled fund proportion is lowest for low idiosyncratic risk low alpha funds.

Our work also reveals the role of information ratio in return prediction. For a long time investors measure the performance and capability of fund managers by information ratio. However many previous researches posit that high idiosyncratic risk represents active management of mutual funds, thus predicts better performance. The seemingly contradiction is reconciled after we split the sample into three groups based on their investment objectives. Idiosyncratic risk exposure may be a value added feature for Aggressive Growth funds, while for funds with more passive objectives; it may offset mutual fund managers' effort to earn a higher profit.

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Table 1: Summary statistics

Our sample covers the mutual fund data from January 1965 to December 2007. We download the data for mutual fund returns (meanret), expenses, turnover and management information for monthly pace. Age counts the number of years since the fund is tradable in public, and tenure is the years since the incumbent management has taken control. For each fund, at least 36 months returns is required to be included in our sample. Idiosyncratic risk in every month is computed by regressing past 36 month returns on Carhart(1997)'s 4 factors, and take standard deviation of the residuals as idiosyncratic risk. Alpha is computed as the intercept of this regression, and the rsqua represents R square of the estimation. At last, ratio1 equals to alpha over idiosyncratic risk, ratio2 equals to alpha over the return standard error for past 36 months. Ratio3 represents past mean return over idiosyncratic risk, and ratio4 equals to past mean return over price standard error in past 36 months.

	mean	median	maximum	minimum
expenses (%)	1.2	1.16	7.89	0.01
turnover(%)	81.24	58.9	3603	0.02
TNAM(million)	1298.539	253.5631	102231.9	15.1
age(year)	16.85163	11.78692	93	2
tenure(year)	7.294158	6	46	1
alpha	-0.00013	-0.00036	0.053831	-0.03757
idiosyncratic risk	0.016181	0.013577	0.261214	0.000195
meanret	0.00528	0.006152	0.057181	-0.04848
sigma	0.047446	0.04484	0.26471	0.000204
ratio1	-0.03507	-0.03181	1.276934	-1.52589
ratio2	-0.00576	-0.00938	0.817856	-1.47363
ratio3	0.147477	0.155609	0.876452	-1.47488
ratio4	0.483945	0.44428	7.78022	-5.63997
rsqua	0.852426	0.894139	0.999045	0.00963

Table 2: Spearman correlation for the statistics

We collect the data from CRSP mutual funds file. CRSP only report the fund returns and other information for different classes within the funds. So we take the value weighted average (weight on their Total Net Asset, TNAM hereafter) when computing the turnover, expenses, returns and other characters of the fund. For some funds with missing TNAM for their classes, we simply take these characters from the class with the highest TNAM. If none of the classes reports the TNAM, we take the simple average of all the classes. In the end, we include all the funds with a none-missing fundn_MSC, which is the unique identifier in MFLINK file in CRSP. This table presents a brief table on how these characters are correlated.

Spearman Correlation												
	ratio1	ratio2	ratio3	ratio4	TNAM	age	tenure	expenses	turnover	intercept	mretn	rsqua
ratio1	1	0.971545	0.269451	0.190274	0.085549	-0.05622	0.101369	-0.09648	-0.09471	0.953041	-0.01082	-0.16055
ratio2	0.971545	1	0.277067	0.207906	0.099996	-0.05746	0.095868	-0.10975	-0.10345	0.973054	-0.00928	-0.08728
ratio3	0.269451	0.277067	1	0.92922	0.115494	0.007259	0.093205	-0.12051	-0.1218	0.301488	0.134301	-0.0313
ratio4	0.190274	0.207906	0.92922	1	0.155362	0.016406	0.071594	-0.17769	-0.14781	0.238633	0.127904	0.243563
TNAM	0.085549	0.099996	0.115494	0.155362	1	0.35625	0.09771	-0.28466	-0.08221	0.098754	-0.00325	0.177323
age	-0.05622	-0.05746	0.007259	0.016406	0.35625	1	0.238353	-0.16876	-0.07159	-0.05112	-0.00014	0.037214
tenure	0.101369	0.095868	0.093205	0.071594	0.09771	0.238353	1	-0.10248	-0.27583	0.099464	0.003493	-0.06617
expenses	-0.09648	-0.10975	-0.12051	-0.17769	-0.28466	-0.16876	-0.10248	1	0.238198	-0.10572	-0.01146	-0.2392
turnover	-0.09471	-0.10345	-0.1218	-0.14781	-0.08221	-0.07159	-0.27583	0.238198	1	-0.10723	-0.00487	-0.13853
intercept	0.953041	0.973054	0.301488	0.238633	0.098754	-0.05112	0.099464	-0.10572	-0.10723	1	-0.01315	-0.08658
mretn	-0.01082	-0.00928	0.134301	0.127904	-0.00325	-0.00014	0.003493	-0.01146	-0.00487	-0.01315	1	0.018567
rsqua	-0.16055	-0.08728	-0.0313	0.243563	0.177323	0.037214	-0.06617	-0.2392	-0.13853	-0.08658	0.018567	1

Table 3: Single-sort result on past characters

We study all the domestic equity funds from 1965 to 2007. This table reports the result for portfolio analyze based on past characters. Idiosyncratic risk in every month is computed by regressing past 36 month returns on Carhart (1997)'s 4 factors, and take standard deviation of the residuals as idiosyncratic risk. Alpha is computed as the intercept of this regression, and the rsqua represents R square of the estimation. At last, ratio1 equals to alpha over idiosyncratic risk, ratio2 equals to alpha over the return standard error for past 36 months. For each panel we report the future one month returns in column 2. Column 4 presents the result for future one month alpha. The t statistics is listed right besides the estimations. In Column 2-5 we rebalance the portfolio in every month, and compute the expected returns for next month. Column 6-9 presents the result for annually rebalance, that is we only renew the portfolio at the end of a month, and keep the portfolio for a year. In every panel we report the result for ten subgroups and the spread between the top and bottom group. Panel 1 forms portfolios based on alpha computed by past 3 years' data, panel 2 on past idiosyncratic risk, panel 3 on past R square, panel 4 on past alpha/idiosyncratic risk, panel 5 on past alpha/sigma, panel 6 on past returns. To remove the impact of price volatility for extremely small funds, we remove the return observation for the smallest funds in every month (bottom 1% in TNAM). All the raw return and alpha are computed with equal weighted average method.

	Month				Year			
Panal 1: Single sort on alpha								
	ret	t-stat	alpha	t-stat	ret	t-stat	alpha	t-stat
1	0.0055	2.55	-0.0005	-0.45	0.0068	2.68	-0.0015	-1.2
2	0.0053	2.83	-0.0000	-0.05	0.0040	1.81	-0.0001	-0.06
3	0.0042	2.46	0.0012	1.38	0.0032	1.68	-0.0004	-0.57
4	0.0046	2.48	-0.0001	-0.16	0.0051	2.36	-0.0001	-0.2
5	0.0041	2.26	-0.0002	-0.23	0.0047	2.58	0.0004	0.5
6	0.0053	2.94	0.0006	0.96	0.0045	2.63	0.0004	0.63
7	0.0027	1.42	-0.0014	-2.10	0.0041	2.18	0.0004	0.6
8	0.0058	3.03	0.0014	1.96	0.0049	2.38	0.0002	0.4
9	0.0047	2.25	0.0001	0.10	0.0045	2.00	0.0002	0.26
10	0.0068	2.60	0.0006	0.57	0.0069	2.51	-0.0013	-1.43
spread	0.0013	0.33	0.0011	0.89	0.0002	0.12	0.0001	0.13
Panal 2: single sort on idiosyncratic risk								
1	0.0031	2.02	-0.0006	-0.7	0.0040	2.48	-0.0002	-0.25
2	0.0044	2.52	0.0003	0.65	0.0041	2.24	0.0000	0.03
3	0.0041	2.35	-0.0001	-0.26	0.0038	2.01	0.0001	0.17
4	0.0053	2.83	0.0007	1.30	0.0045	2.32	0.0003	0.45
5	0.0050	2.59	-0.0005	-0.77	0.0055	2.63	0.0007	1.01
6	0.0049	2.61	0.0007	0.88	0.0055	2.79	0.0004	0.64
7	0.0044	2.31	0.0016	1.67	0.0054	2.46	0.0004	0.59
8	0.0061	2.91	0.0023	2.03	0.0047	2.02	0.0014	1.12
9	0.0054	2.33	-0.0005	-0.49	0.0057	2.39	-0.0008	-0.7
10	0.0061	2.26	-0.0012	-0.89	0.0076	2.66	-0.0014	-1.09
spread	0.0030	1.40	-0.006	-0.75	0.0036	1.42	-0.0012	-0.7

Panal 3: single sort on R square								
1	0.0035	2.76	0.0004	0.44	0.0037	2.98	0.0009	0.95
2	0.0044	2.31	-0.0002	-0.17	0.0063	2.73	0.0007	0.65
3	0.0049	2.50	0.0007	0.80	0.0056	2.37	0.0007	0.73
4	0.0072	3.53	0.0008	1.07	0.0053	2.22	-0.0007	-0.94
5	0.0045	2.08	0.0000	0.04	0.0061	2.84	0.0008	1.21
6	0.0065	3.18	-0.0008	-1.20	0.0061	2.57	-0.0005	-0.70
7	0.0043	2.20	0.0006	0.96	0.0041	1.96	0.0007	0.95
8	0.0051	2.53	-0.0006	-0.97	0.0047	2.25	0.0000	-0.08
9	0.0042	2.18	0.0005	1.20	0.0030	1.47	-0.0001	-0.28
10	0.0048	2.34	0.0002	0.46	0.0055	2.63	0.0000	0.04
spread	0.0013	1.45	-0.0002	-0.29	0.0018	1.21	-0.0009	-1.05
Panal 4: Single sort on Ratio1								
1	0.0048	2.10	-0.0004	-0.47	0.0058	2.28	-0.0019	-3.25
2	0.0049	2.02	0.0006	0.80	0.0057	2.31	-0.0004	-0.5
3	0.0051	2.06	-0.0001	-0.16	0.0056	2.18	-0.0010	-1.86
4	0.0058	2.34	0.0010	1.14	0.0059	2.24	-0.0007	-1.54
5	0.0057	2.25	0.0004	0.49	0.0057	2.11	-0.0008	-1.36
6	0.0052	2.03	0.0002	0.37	0.0060	2.19	-0.0006	-1.12
7	0.0063	2.34	-0.0006	-0.72	0.0064	2.25	-0.0012	-2.88
8	0.0060	2.15	0.0005	0.74	0.0053	1.81	-0.0008	-1.59
9	0.0054	1.82	0.0003	0.42	0.0048	1.59	-0.0014	-2.57
10	0.0063	2.10	0.0000	0.04	0.0058	1.84	-0.0012	-1.73
spread	0.0015	1.05	0.0005	0.17	0.0000	0.02	0.0007	0.74
Panal 5: single sort on Ratio2								
1	0.0045	2.01	0.0006	0.52	0.0058	2.35	-0.0020	-3.2
2	0.0052	2.20	-0.0006	-0.65	0.0059	2.38	-0.0002	-0.3
3	0.0051	2.08	0.0009	1.12	0.0054	2.13	-0.0011	-1.81
4	0.0052	2.08	0.0011	1.63	0.0054	2.01	-0.0012	-2.51
5	0.0057	2.22	0.0003	0.52	0.0061	2.28	-0.0002	-0.33
6	0.0053	2.04	0.0007	1.13	0.0056	2.03	-0.0008	-1.65
7	0.0055	2.01	0.0005	0.73	0.0057	1.99	-0.0006	-1.4
8	0.0061	2.17	0.0003	0.37	0.0055	1.89	-0.0007	-1.51
9	0.0053	1.79	-0.0002	-0.22	0.0055	1.79	-0.0020	-3.08
10	0.0063	2.15	-0.0006	-0.54	0.0058	1.90	-0.0013	-2.02
spread	0.0017	0.88	-0.0012	-0.66	0.0000	0.00	0.0007	0.71

Table 4: Fama-MacBeth regression result for sub-samples.

This table presents the regression result for 3 sub-samples based on investment objectives. The database we download from CRSP includes three investment objective identifiers: sp_obj_cd, obj and icdi_obj_cd. We identify the funds as Aggressive Growth when OBJ="AGG", icdi_obj_cd="AG", icdi_obj_cd="AGG", sp_obj_cd="AGG", as Growth when OBJ="SCG", sp_obj_cd="SCG", OBJ="G", OBJ="G-S", OBJ="S-G", OBJ="GRO", OBJ="LTG", icdi_obj_cd="LG", sp_obj_cd="GRO", OBJ="MCG", as Growth and Income when OBJ="I", OBJ="I-S", OBJ="IEQ", OBJ="ING", icdi_obj_cd="IN", sp_obj_cd="ING", OBJ="GCI", OBJ="G-I", OBJ="G-I-S", OBJ="G-S-I", OBJ="I-G", OBJ="I-G-S", OBJ="I-S-G", OBJ="S-G-I", OBJ="S-I-G", OBJ="GRI", icdi_obj_cd="GI", sp_obj_cd="GRI". We only report the factor loadings without control variable in this table: alpha is the intercept of the Carhart's 4-factor regression, rsqua is the R square of the estimation. And ratio1 equals to alpha over idiosyncratic risk, ratio2 equals to alpha over the return standard error for past 36 months.

Panel 1: Aggressive Growth funds										
	model 1		model 2		model 3		model 4		model 5	
	coeff.	t-stat	coeff.	t-stat	coeff.	t-stat	coeff.	t-stat	coeff.	t-stat
rsqua			-0.0019	-0.43	-0.0021	-0.42	-0.0026	-0.62	-0.0025	-0.63
ratio 1							-0.0007	-0.189		
ratio 2									-0.0125	-0.86
alpha	0.102	0.92	0.095	0.9			0.187	0.95	0.372	1.31
Panel 2: Growth funds										
	model 1		model 2		model 3		model 4		model 5	
	coeff.	t-stat	coeff.	t-stat	coeff.	t-stat	coeff.	t-stat	coeff.	t-stat
rsqua			-0.003	-0.8	-0.0029	-0.72	-0.0022	-0.61	-0.0023	-0.69
ratio 1							0.0084	2.27		
ratio 2									0.039	2.58
alpha	0.114	0.94	0.086	0.77			-0.326	-1.26	-0.675	-1.68
Panel 3: Growth & Income funds										
	model 1		model 2		model 3		model 4		model 5	
	coeff.	t-stat	coeff.	t-stat	coeff.	t-stat	coeff.	t-stat	coeff.	t-stat
rsqua			0.0026	0.9	0.0028	0.94	0.0031	1	0.0021	0.71
ratio 1							0.0027	1.79		
ratio 2									0.00021	0.041
alpha	0.1	0.89	0.059	0.54			-0.12	-0.68	0.088	0.45

Table 5: Double-sort result on alpha and idiosyncratic risk, monthly rebalances

This table presents the result for double sort on past alpha and past idiosyncratic risk. Alpha is calculated as the intercept of Carhart's 4 factor regression; idiosyncratic risk equals the standard deviation of the regression residuals. In each month we split the whole sample into 5 subgroups based on past risk adjusted returns (alpha) and into 5 equal subgroups based on their past idiosyncratic risk exposure. Overall we have 25 portfolios. Again we eliminate the impact of extremely small funds by removing the bottom 1% TNAM funds. For each 5 portfolios with the same alpha, we also report the spread of returns for high idiosyncratic risk and low idiosyncratic risk. For each 5 portfolios with the same idiosyncratic risk, again the spread of returns is reported. Panel 1 presents the result for monthly raw return, which means we take the simple average of the returns at the end of each month, and hold the portfolio for a month. In Panel 2 risk adjusted returns are reported. We compute this by regressing the abnormal returns of each fund on Carhart (1997)'s 4 factors, and take the intercept of the regression.

Panal 1: future raw return

		idiosyncratic risk											
		Bottom	t-stat	2	t-stat	3	t-stat	4	t-stat	Top	t-stat	Top-Bot	t-stat
	Bottom	-0.0002	-0.12	0.0010	0.44	0.0038	1.71	0.0065	2.92	0.0081	3.23	0.0084	3.61
	2	0.0027	1.47	0.0035	1.78	0.0054	2.58	0.0068	3.06	0.0071	2.47	0.0044	1.98
alpha	3	0.0030	1.65	0.0038	1.98	0.0067	3.28	0.0061	2.52	0.0046	1.51	0.0016	0.70
	4	0.0047	2.41	0.0049	2.49	0.0034	1.54	0.0040	1.68	0.0037	1.15	-0.0010	-0.38
	Top	0.0071	2.97	0.0082	3.29	0.0062	2.49	0.0047	1.96	0.0000	-0.01	-0.0072	-2.83
	top-bot	0.0074	3.10	0.0072	2.97	0.0024	0.99	-0.0018	-0.79	-0.0081	-2.85		

Panal 2: future alpha

		idiosyncratic risk											
		Bottom	t-stat	2	t-stat	3	t-stat	4	t-stat	Top	t-stat	Top-Bot	t-stat
	Bottom	0.0031	0.83	0.0038	1.01	0.0050	1.52	0.0070	2.11	0.0085	2.22	0.0054	1.59
	2	0.0046	1.59	0.0047	1.60	0.0059	1.95	0.0071	2.20	0.0083	2.23	0.0037	1.40
alpha	3	0.0038	1.39	0.0045	1.64	0.0076	2.57	0.0077	2.25	0.0080	2.04	0.0042	1.17
	4	0.0050	2.00	0.0052	1.83	0.0048	1.44	0.0061	1.69	0.0056	1.19	0.0005	0.09
	Top	0.0073	3.13	0.0079	2.99	0.0066	2.11	0.0060	1.55	0.0033	0.55	-0.0040	-1.12
	top-bot	0.0041	1.22	0.0041	1.60	0.0016	1.29	-0.0010	-0.72	-0.0052	-1.57		

Table 6: Double-sort result on alpha and idiosyncratic risk, annually rebalance

This table presents the result for double sort on past alpha and past idiosyncratic risk. Alpha is calculated as the intercept of Carhart's 4 factor regression; idiosyncratic risk equals the standard deviation of the regression residuals. In each December we split the whole sample into 5 subgroups based on past risk adjusted returns and into 5 equal subgroups based on their past idiosyncratic risk exposure. Overall we have 25 portfolios. Again we eliminate the impact of extremely small funds by removing the bottom 1% TNAM funds. For each 5 portfolios with the same alpha, we also report the spread of returns for high idiosyncratic risk and low idiosyncratic risk. For each 5 portfolios with the same idiosyncratic risk, again the spread of returns is available. This table reports the result for annual rebalance. Comparing with table 4, we only renew the portfolio formation at December, and hold the portfolio for 12 months. Panel 1 presents the result for monthly raw return, which means we take the simple average of the returns for each month. In Panel 2 risk adjusted returns are reported. We compute this by regressing the abnormal returns of each fund on Carhart (1997)'s 4 factors, and take the intercept of the regression.

Panal 1: future raw return

						idiosyncratic risk							
		Bottom	t-stat	2	t-stat	3	t-stat	4	t-stat	Top	t-stat	Top-Bot	t-stat
	Bottom	-0.0004	-0.18	0.0010	0.49	0.0042	1.87	0.0066	2.82	0.0089	3.43	0.0093	2.33
	2	0.0028	1.53	0.0041	2.02	0.0054	2.44	0.0068	2.72	0.0075	2.63	0.0047	1.91
alpha	3	0.0031	1.63	0.0043	2.03	0.0065	3.34	0.0066	2.76	0.0044	1.43	0.0013	0.55
	4	0.0050	2.50	0.0050	2.36	0.0039	1.79	0.0046	1.83	0.0039	1.13	-0.0011	-0.35
	Top	0.0071	2.97	0.0077	3.17	0.0066	2.37	0.0051	2.15	0.0001	0.04	-0.0070	-1.98
	top-bot	0.0075	2.03	0.0066	2.18	0.0024	1.35	-0.0015	-0.87	-0.0088	-1.78		

Panal 2: future alpha

						idiosyncratic risk							
		Bottom	t-stat	2	t-stat	3	t-stat	4	t-stat	Top	t-stat	Top-Bot	t-stat
	Bottom	-0.0014	-0.87	-0.0010	-0.42	0.0001	0.08	0.0002	0.24	0.0004	0.29	0.0018	1.90
	2	-0.0007	-0.50	-0.0004	-0.19	-0.0017	-0.70	0.0007	0.68	0.0005	0.49	0.0013	0.98
alpha	3	0.0000	-0.02	-0.0001	-0.10	0.0002	0.09	0.0002	0.25	-0.0002	-0.10	-0.0002	-0.14
	4	-0.0002	-0.09	-0.0006	-0.19	0.0016	0.44	0.0004	0.50	-0.0008	-0.44	-0.0006	-0.39
	Top	0.0004	0.46	0.0006	0.60	-0.0007	-0.41	-0.0011	-0.79	-0.0009	-0.43	-0.0012	-1.11
	top	0.0018	1.75	0.0016	1.11	-0.0007	-0.44	-0.0014	-1.31	-0.00125	-0.99		

Table 7: The Fama-MacBeth Regression result for sub-samples based on past alpha and past idiosyncratic risk.

In the left part of the table, we report the Fama-MacBeth regression coefficient for both high past alpha and low alpha. In each month, we rank the fund alpha into 3 categories: High alpha, middle alpha and low alpha. This table only report the result for high/low alpha groups. Model 1 presents the result when we regress expected return on idiosyncratic risk alone. And model 2 introduces all the other controlling variables. Idiosyncratic risk is the standard deviation of the regression residuals from Carhart's 4 factor model. The fund characters are downloaded from CRSP mutual fund files: expenses proxy the 12-b-1 expenses ratio, age counts the years since the fund is tradable in the public, turnover is the proportion of the share holdings which are rebalanced. The coefficient of Log (TNAM) measures the sensitivity of expected returns on percentage change of Total Net Asset. The right side of the table presents the regression result for subsamples based on past idiosyncratic risk. We form 3 portfolios each month on past idiosyncratic risk exposure. This table only shortlists the coefficient for high/low idiosyncratic portfolios.

Panel 1: High alpha group					Panel 3: High idiosyncratic group				
	model 1		model 2			model 3		model 4	
	coeff.	t-stat	coeff.	t-stat		coeff.	t-stat	coeff.	t-stat
idio	-0.0029	-2.64	-0.0045	-3.08	alpha	-0.099	-1.1	-0.134	-1.44
expenses			-0.089	-2.76	expenses			-0.115	-2.39
age			2.86E-06	0.3	age			8.01E-06	-0.49
turnover			0.00042	1.2	turnover			-0.00053	-1.29
log(TNAM)			0.00105	2.39	log(TNAM)			0.00116	2.22
log(TNAM)*log(TNAM)			-0.000077	-2.44	log(TNAM)*log(TNAM)			-0.000092	-2.18
obj			0.0013	1.64	obj			0.00136	1.3
Panel 2: Low alpha group					**Panel 4: Low idiosyncratic group**				
	model 1		model 2			model 3		model 4	
	coeff.	t-stat	coeff.	t-stat		coeff.	t-stat	coeff.	t-stat
idio	0.0032	2.79	0.0042	3.14	alpha	0.123	3.35	0.078	2.69
expenses			-0.144	-3.75	expenses			-0.099	-4.68
age			-6.67E-06	-0.61	age			2.66E-06	0.38
turnover			-0.000057	-1.67	turnover			0.000095	0.37
log(TNAM)			0.0006	1.21	log(TNAM)			0.00059	1.88
log(TNAM)*log(TNAM)			-0.000034	-0.86	log(TNAM)*log(TNAM)			-0.000031	-1.33
obj			0.0013	1.33	obj			0.00079	1.17

Table 8: Proportion of unskilled, zero-alpha and skilled funds

Following Barras, Scaillet and Wermers (2010)'s method, this table presents the proportion of unskilled, zero-alpha and skilled funds for three groups: panel 1 shows the result for low idiosyncratic risk and low alpha funds, panel 2 for low idiosyncratic risk and high alpha funds, panel 3 for high idiosyncratic risk funds. In each panel, we report the estimated proportion of the significant funds in both left and right tail of the cross-sectional t-statistic distribution at three significance level (5%, 10%, 15%). In the leftmost columns, the significant group in the left tail is decomposed into unlucky and unskilled funds. In the rightmost columns, the significant group in the right tail is decomposed into lucky and skilled funds. Sigif is the proportion outside of the threshold, and it equals to the sum of unlucky and unskilled funds.

Panel 1: low idio & low alpha funds		unskilled 30.90%		zero-alpha 68.88%		skilled 0.22%		
		5%	10%	15%	15%	10%	5%	
	sigif(%)	14.40	20.71	29.04	6.11	4.10	2.05	sigif(%)
	unlucky(%)	1.96	3.93	5.88	5.88	3.93	1.96	lucky(%)
	unskilled(%)	12.44	16.78	23.16	0.23	0.17	0.09	skilled(%)
Panel 2: low idio & high alpha funds		unskilled 25.10%		zero-alpha 73.30%		skilled 1.60%		
		5%	10%	15%	15%	10%	5%	
	sigif(%)	12.75	17.99	24.24	7.45	4.94	2.28	sigif(%)
	unlucky(%)	1.96	3.93	5.88	5.88	3.93	1.96	lucky(%)
	unskilled(%)	10.79	14.06	18.36	1.57	1.01	0.32	skilled(%)
Panel 3: high idio funds		unskilled 23.75%		zero-alpha 74.74%		skilled 1.51%		
		5%	10%	15%	15%	10%	5%	
	sigif(%)	12.70	17.47	23.66	7.37	4.94	2.35	sigif(%)
	unlucky(%)	1.96	3.93	5.88	5.88	3.93	1.96	lucky(%)
	unskilled(%)	10.74	13.54	17.78	1.49	1.01	0.39	skilled(%)

Table 9: Single sort, yearly rebalance based on annualized alpha and idiosyncratic risks

We study the mutual fund data on daily basis for sample period 01/1999-12/2007. In each year, we calculate the fund alpha, idiosyncratic risk and so on with the daily return data in that year. The daily Carhart's 4 factors are also included to compute the risk adjusted returns. Alpha is the intercept for Carhart's 4 factor regression, and idiosyncratic risk is the standard deviation of regression residuals. R square measures the soundness of the estimation. Amihud and Goyenko (2010) argue that R square proxies active management, thus predict better performance in the future. Ratio1 is information ration, and equals to alpha over idiosyncratic risk. Ratio2 is alpha over return volatility. We require at least 50 observations for each fund per year to be eligible in our sample since it should meet the minimum requirement for the regressions. After the fund characters are calculated we build portfolios based on these characters in each year. All through years 1999-2006, we split the sample into ten sub-groups on their alpha, idiosyncratic risk, information ratio or R square, and hold the portfolios for the next 12 months. This table reports both portfolio raw return and risk adjusted return. Since many previous researches argue that some stocks which constitute fund returns are slow to adjust to daily information, we also use in practice the model where the current return is regressed on both current factor and lag one term factors. The result is reported on the right side of the table.

	Model1				Model2			
Panal 1: Single sort on alpha								
	ret	t-stat	alpha	t-stat	ret	t-stat	alpha	t-stat
1	0.0023	0.52	-0.0030	-1.99	0.0029	0.64	-0.0023	-1.39
2	0.0025	0.60	-0.0018	-1.68	0.0029	0.70	-0.0010	-0.84
3	0.0023	0.59	-0.0015	-1.97	0.0025	0.61	-0.0012	-1.32
4	0.0026	0.68	-0.0008	-1.11	0.0027	0.69	-0.0008	-1.10
5	0.0021	0.53	-0.0015	-2.67	0.0025	0.64	-0.0010	-1.48
6	0.0026	0.67	-0.0008	-1.30	0.0024	0.62	-0.0010	-1.67
7	0.0026	0.65	-0.0010	-1.59	0.0027	0.67	-0.0012	-1.87
8	0.0031	0.73	-0.0011	-0.03	0.0030	0.72	-0.0014	-1.72
9	0.0046	0.97	-0.0005	-0.47	0.0039	0.81	-0.0013	-1.16
10	0.0055	0.90	0.0003	0.17	0.0045	0.74	-0.0010	-0.57
spread	0.0031	0.91	0.0033	1.11	0.0016	0.44	0.0014	0.46
Panal 2: single sort on idiosyncratic risk								
1	0.0013	0.37	-0.0007	-1.92	0.0013	0.40	-0.0007	-1.86
2	0.0012	0.32	-0.0014	-3.76	0.0013	0.36	-0.0012	-3.28
3	0.0021	0.59	-0.0010	-2.08	0.0020	0.55	-0.0011	-2.36
4	0.0025	0.66	-0.0016	-2.86	0.0025	0.66	-0.0015	-2.67
5	0.0035	0.91	-0.0007	-0.94	0.0036	0.94	-0.0007	-0.97
6	0.0041	1.02	-0.0006	-0.85	0.0041	1.02	-0.0008	-0.95
7	0.0044	1.01	-0.0009	-1.01	0.0043	0.98	-0.0011	-1.30
8	0.0041	0.83	-0.0014	-1.36	0.0041	0.83	-0.0013	-1.25
9	0.0048	0.84	-0.0009	-0.66	0.0046	0.83	-0.0010	-0.78
10	0.0052	0.91	-0.0006	-1.68	0.0024	0.35	-0.0004	-1.58
spread	0.0040	0.88	0.0001	0.58	0.0011	0.25	0.0003	0.70

Panal 3: single sort on R square								
1	0.0056	1.58	-0.0001	-0.12	0.0054	1.54	-0.0003	-0.46
2	0.0061	1.43	-0.0005	-0.46	0.0062	1.45	-0.0003	-0.27
3	0.0049	1.11	-0.0010	-0.95	0.0046	1.04	-0.0014	-1.31
4	0.0042	0.90	-0.0017	-1.70	0.0043	0.93	-0.0012	-1.31
5	0.0036	0.80	-0.0010	-1.25	0.0034	0.78	-0.0012	-1.45
6	0.0024	0.53	-0.0018	-1.91	0.0023	0.51	-0.0019	-1.95
7	0.0020	0.46	-0.0011	-1.12	0.0020	0.46	-0.0011	-1.18
8	0.0010	0.24	-0.0017	-2.05	0.0011	0.26	-0.0016	-1.99
9	0.0006	0.14	-0.0014	-2.61	0.0007	0.17	-0.0012	-2.42
10	0.0006	0.15	-0.0012	-2.17	0.0007	0.17	-0.0011	-2.05
spread	-0.0050	-2.58	-0.0011	-2.20	-0.0047	-2.44	-0.0090	-2.03
Panal 4: Single sort on Ratio1								
1	0.0022	0.55	-0.0018	-1.66	0.0024	0.59	-0.0016	-1.31
2	0.0017	0.44	-0.0022	-2.46	0.0024	0.61	-0.0012	-1.06
3	0.0021	0.51	-0.0019	-2.20	0.0022	0.53	-0.0015	-1.79
4	0.0027	0.65	-0.0011	-1.22	0.0025	0.62	-0.0012	-1.35
5	0.0025	0.60	-0.0013	-1.90	0.0029	0.70	-0.0008	-1.00
6	0.0031	0.75	-0.0008	-1.08	0.0031	0.76	-0.0007	-1.09
7	0.0035	0.83	-0.0005	-0.78	0.0029	0.69	-0.0012	-1.80
8	0.0029	0.64	-0.0013	-1.59	0.0033	0.75	-0.0011	-1.28
9	0.0037	0.80	-0.0011	-1.13	0.0034	0.72	-0.0017	-1.48
10	0.0057	1.10	0.0003	0.21	0.0048	0.90	-0.0010	-1.65
spread	0.0035	1.18	0.0021	0.81	0.0024	0.73	0.0007	0.31
Panal 5: single sort on Ratio2								
1	0.0027	0.70	-0.0025	-1.82	0.0030	0.76	-0.0021	-1.41
2	0.0025	0.61	-0.0016	-1.62	0.0028	0.68	-0.0012	-1.06
3	0.0024	0.58	-0.0014	-1.47	0.0028	0.66	-0.0007	-0.66
4	0.0020	0.49	-0.0012	-1.68	0.0018	0.45	-0.0015	-1.98
5	0.0018	0.44	-0.0016	-2.52	0.0025	0.60	-0.0008	-1.14
6	0.0023	0.53	-0.0010	-1.47	0.0019	0.46	-0.0011	-1.66
7	0.0026	0.60	-0.0008	-1.12	0.0022	0.51	-0.0014	-2.03
8	0.0029	0.67	-0.0012	-1.43	0.0033	0.75	-0.0012	-1.44
9	0.0043	0.90	-0.0009	-0.88	0.0039	0.82	-0.0015	-1.35
10	0.0067	1.36	0.0006	0.47	0.0059	1.18	-0.0004	-0.25
spread	0.0040	1.33	0.0031	1.14	0.0030	0.94	0.0018	0.82

Table 10: Double sort, yearly rebalance based on annualized alpha and idiosyncratic risks

Similar with table 9 we calculate annualized fund alpha and idiosyncratic risk with the daily data in that year. Alpha equals to the intercept of the Carhart's 4 factor regression, and idiosyncratic risk is the standard deviation of the regression residuals. The sample is divided equally into 5*5 groups by their past alpha and idiosyncratic risk, and we hold the 25 portfolios for 12 months. Since the result for current factor regression and lag one term factor regression is consistent (as in table 9) we only report the result for current factor regression.

Panel 1: future raw return													
		idiosyncratic risk											
		Bottom	t-stat	2	t-stat	3	t-stat	4	t-stat	Top	t-stat	Top-Bot	t-stat
	Bottom	-0.0013	-0.36	0.0018	0.49	0.0038	0.99	0.0047	1.06	0.0027	0.62	0.0040	1.39
	2	-0.0008	-0.24	0.0017	0.45	0.0043	1.13	0.0042	0.92	0.0052	0.94	0.0060	1.33
alpha	3	0.0012	0.32	0.0012	0.31	0.0031	0.80	0.0034	0.78	0.0039	0.66	0.0027	0.72
	4	0.0021	0.60	0.0024	0.65	0.0023	0.57	0.0029	0.63	0.0041	0.71	0.0020	0.49
	Top	0.0058	1.52	0.0053	1.36	0.0052	1.26	0.0042	0.85	0.0038	0.57	-0.0020	-0.71
	top-bot	0.0071	2.02	0.0035	0.90	0.0014	0.17	-0.0005	-0.07	0.0011	0.55		
Panel 2: future alpha													
		idiosyncratic risk											
		Bottom	t-stat	2	t-stat	3	t-stat	4	t-stat	Top	t-stat	Top-Bot	t-stat
	Bottom	-0.0016	-1.74	-0.0016	-1.73	-0.0015	-1.50	-0.0017	-1.29	-0.0009	-0.69	0.0007	1.20
	2	-0.0011	-2.34	-0.0016	-2.66	-0.0012	-1.42	-0.0018	-1.50	0.0002	0.11	0.0013	1.94
alpha	3	-0.0012	-3.21	-0.0016	-2.81	-0.0009	-1.06	-0.0010	-1.16	-0.0011	-0.79	0.0001	0.49
	4	-0.0014	-2.74	-0.0013	-2.19	-0.0005	-0.68	-0.0018	-1.92	-0.0007	-0.51	0.0007	0.70
	Top	0.0003	0.32	-0.0008	-0.88	0.0004	0.42	-0.0001	-0.09	-0.0002	-0.10	-0.0004	-0.68
	top-bot	0.0019	2.10	0.0009	0.94	0.0019	1.18	0.0016	0.88	0.0007	0.39		

Figure 1: The distribution of expected returns

In each month we split the sample into two parts: high idiosyncratic funds and low idiosyncratic risk funds. We study the expected raw return for each group by plotting the distribution of future expected returns. Firstly, we rank all expected returns into 25 portfolios (expected return is the return in future one month). For each fund in each month, its return in next month is categorized into one of the 25 portfolios. For each of 25 portfolios, we can get the number of fund & month observations. Finally we normalize the distribution of expected returns by dividing the number of each portfolio on the total fund & month observations.

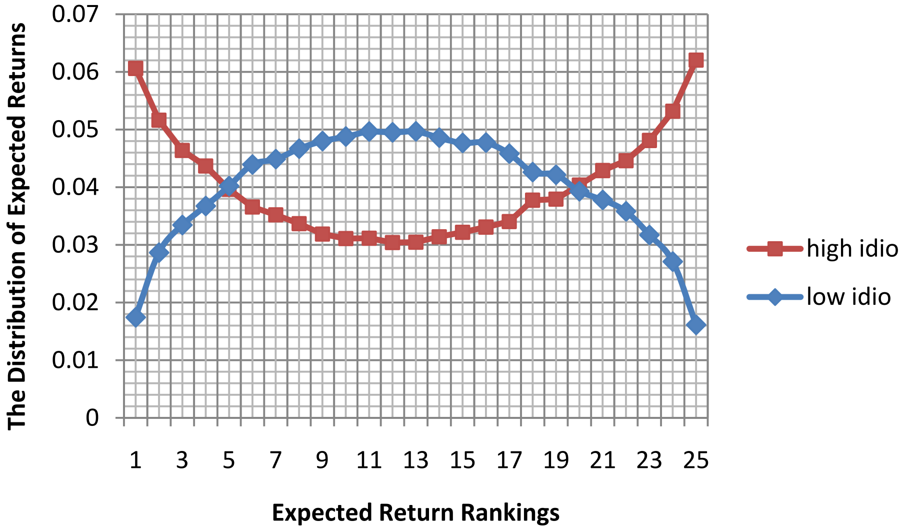
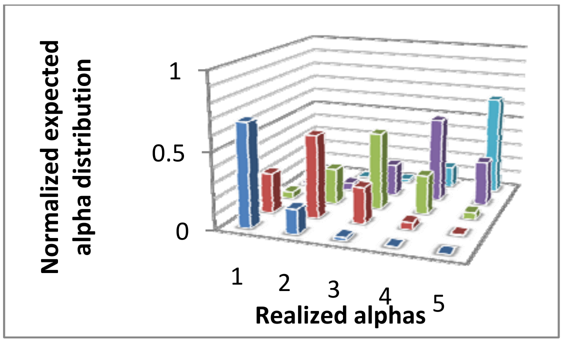


Figure 2: Expected alpha distribution

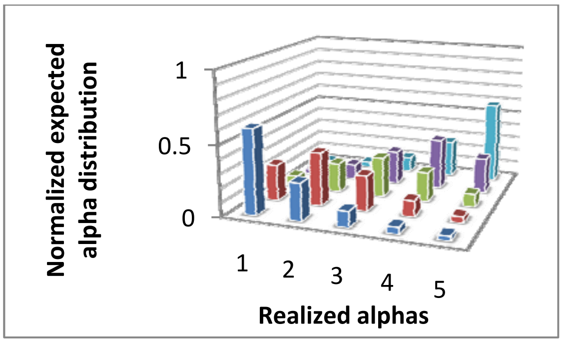
Panel a presents the drift of alpha distribution for low idiosyncratic risk funds. In each month, we match the realized alpha and expected alpha for each fund. Then, for each of the five rankings of realized alpha we have five expected alpha rankings. In the end, we normalized the distribution of expected alpha into 1.

Panel b presents the drift of alpha distribution for high idiosyncratic risk funds. In each month, we match the realized alpha and expected alpha for each fund. Then, for each of the five rankings of realized alpha we have five expected alpha rankings. In the end, we normalized the distribution of expected alpha into 1.

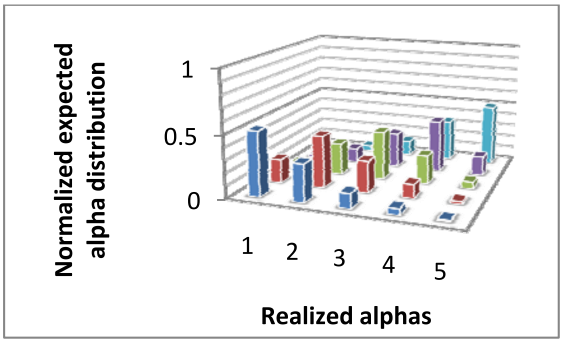
Panel 1a: Expected alpha distribution for low idiosyncratic risk funds in 6 months time span.



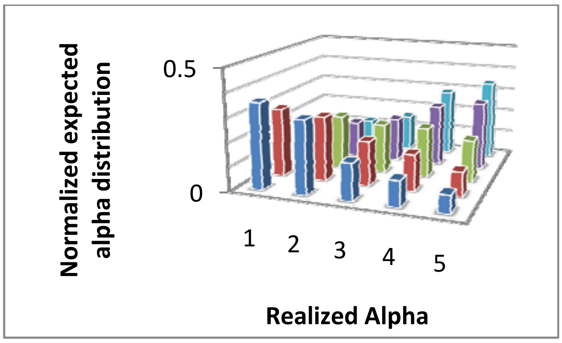
Panel 1b: Expected alpha distribution for high idiosyncratic risk funds in 6 months time span.



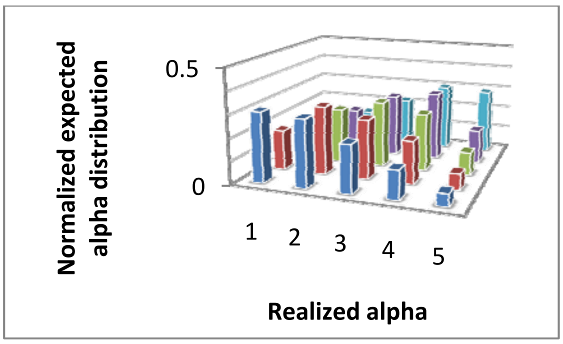
Panel 2a: Expected alpha distribution for low idiosyncratic risk funds in 1 year time span.



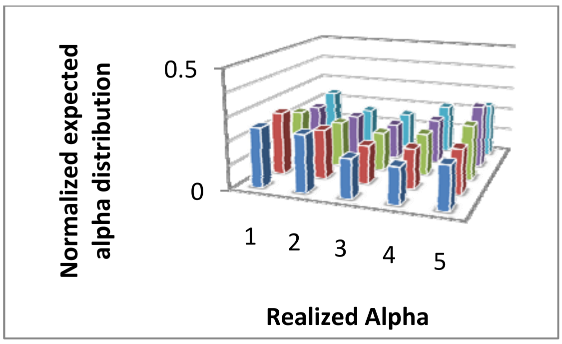
Panel 2b: Expected alpha distribution for high idiosyncratic risk funds in 1 year time span.



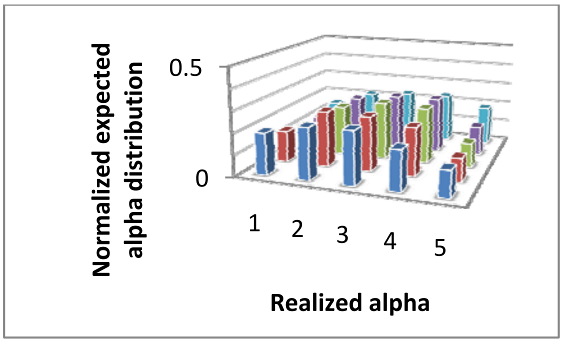
Panel 3a: Expected alpha distribution for low idiosyncratic risk funds in 2 years time span.



Panel 3b: Expected alpha distribution for high idiosyncratic risk funds in 2 years time span.



Panel 4a: Expected alpha distribution for low idiosyncratic risk funds in 3 years time span.



Panel 4b: Expected alpha distribution for high idiosyncratic risk funds in 3 years time span.