Identifying Skills in Mutual Funds using Fund Holdings and Firm Earnings

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Abstract

The literature initially approaches the topic of managerial skill in mutual fund industry by scrutinizing the fund returns. As a classic example, Jensen (1968) uses the intercept in a regression of fund return on a return of a market portfolio vis-à-vis CAPM to capture the ability of mutual funds to beat the market, i.e. to capture fund managers' skills. His result, which shows stark underperformance of actively managed funds against the market portfolio, has sparked a lively debate in the literature on the topic. While various measures of fund performance have been invented over time , the use of the intercept in a regression of fund return in excess of a risk-free rate on some benchmark portfolios to capture fund outperformance has become a normative practice, so much so that it has been termed Jensen alpha or even referred to simply as alpha. However, as prominence invites scrutiny, a number of criticisms have been directed at the use of alpha to measure performance and managerial skill. Fund holdings data, by connecting fund data to the data at the security level for the respective fund, has opened up a level of granularity that enables researchers to come up with innovative performance measures and to explore aspects of the topic that are otherwise unapproachable with fund returns data alone. This paper combines fund holdings data and firm earnings announcements to identify managerial skills at two levels, namely individual fund level and the mutual fund industry in aggregate. To identify managerial skill at individual fund level, I partially follow the approach by Jiang and Zheng (2018) (JZ) who invents a measure of managerial skill, termed AFP. However, the result in this paper shows that the significance in their paper is sensitive to the sample period or to the choice of a benchmark factor model. To identify skill in the industry as a whole, I attempt to analyze whether the aggregated active investment decisions across all funds can predict future earnings surprises of a firm. Under the chosen empirical setting, no evidence is found to support the hypothesis that the mutual fund industry can predict earnings better than analyst forecasts.

Table of Contents

1. Introduction

According to Chen, Jegadeesh and Wermers (2000), by 2000, the U.S. mutual fund industry managed over $5.5 trillion, out of which $3 trillion is managed by equity funds. A substantial portion of this amount is spent on actively managed funds whose managers are expected to possess superior stock picking skill to outperform passive investment strategies. More importantly, the amount of money spent on active funds is far larger than that spent on the passive, index fund counterparts.

In contrast to investors who appear to trust actively managed funds as can be deduced from such figures, academics have been on the fence for decade, erring on the side of caution when it comes to the ability of actively managed funds to beat the market. In a classic example, Jensen (1968) used a dataset of 115 open end mutual funds from 1955-64 to find evidence of superior fund managerial skill to outperform the market. The fund performance measure used was the alpha in the regression of funds' returns in excess of the risk-free rate, on the risk-free-rate-adjusted-market return. He concluded that the funds in the sample on average do not outperform a fund that passively invests and holds a market portfolio; and that not one individual fund could outperform a randomly selected portfolio. This result holds both before and after expenses. Using a more comprehensive dataset of all funds with continuous records between 1982 and 1991 in another classic paper, Malkiel (1995) reached the same conclusion that in the aggregate, funds underperformed benchmark portfolios both before and after management expenses, again using CAPM-alpha as fund performance measure.

In fact, many of the earlier research on skill in mutual fund industry assessed fund skills by measuring fund performance using the regression intercept vis-à-vis the two cited classics in the previous paragraph, more prominently known in the literature as *alpha*. However, this performance measure is itself not without criticisms (see Roll (1978), Dybvig and Ross (1985a, 1985b), Berk and Green (2004), and Berk and Binsbergen (2014)). These criticisms are briefly summarized here at the risk of oversimplification. Roll (1978) argues that a truly diversified market portfolio is realistically infeasible to arrive at. Dybvig and Ross (1985a, 1985b) argues that even if a fund manager can make use of his or her superior information in an optimal fashion, the fund risk-return profile can still plot above, on or below the Security Market Line, and outside, on or inside the efficient frontier – any constellation has a positive probability of occurrence. Berk and Green (2004) argue that under the assumptions that investors are rational, financial markets are competitive, and the supply of fund manager skill is bounded, the net alpha never captures managerial skill, but rather reflects the equilibrium of the competition among investors. A positive net alpha indicates that the market is not competitive, and a negative net alpha indicates existence of irrational investors who commit extraneous amount of money to actively managed funds. Berk and Binsbergen (2014) proves mathematically that gross alpha can measure [proxy for] fund manager skill only if fund managers set their fees such that the asset under management of all funds is exactly $1 [identical].

With that said, the earlier results on mutual fund underperformance, notably the seminal Jensen (1968), had set off a lively debate in the literature on the topic of skill in mutual fund industry, evident in the abundant research on the topic that employ various methods to assess mutual fund skill from different angles.

For instance, the aforementioned *alpha* is inevitably not the only return-based measure of fund performance and, by extension, of managerial skill. Among the most classic portfolio performance measures are Sharpe Ratio (Sharpe (1966)), Treynor Ratio (Treynor (1965)), and Information Ratio.

$$Sharpe\ Ratio\colon \frac{E\left[R_{p,t}\right] - R_f}{\sigma_p} \qquad (1)$$

$$Treynor\ Ratio\colon \frac{E\left[R_{p,t}\right] - R_f}{\beta_p} \qquad (2)$$

$$Information\ Ratio\colon \frac{\alpha_p}{\sigma(\varepsilon_{p,t})} \qquad (3)$$

Some other return-based performance measures in the literature include measures that are based on lower partial moments such as Omega by Shadwick and Keating (2002), Sortino ratio by Sortino and Van der Meer

(1991), Upside potential ratio by Sortino, Van der Meer, and Plantinga (1999), and Kappa by Kaplan and Knowles (2004); or measures that are based on value at risks such as excess return on value at risk (see Dowd (2000)), Conditional Sharpe ratio (see Agarwal and Naik (2004)), or Modified Sharpe ratio by Gregoriou and Gueyie (2003). One does not need to be inundated by these numerous ratios to identify fund manager skill, however, as Eling (2008) makes the case that Sharpe ratio is generally sufficient for fund evaluation. Neither does one have to be limited by either alpha or Sharpe ratio when it comes to using fund return to measure performance; there exist innovative return-based performance measures in the literature that depart from the normative alpha and Sharpe ratio. For instance, Amihud and Goyenko (2013) introduce a novel return-based measure of skill which is the R^2 from a regression of a fund's returns on a multifactor benchmark model. High value of this measure implies higher selectivity, and they found that this measure can significantly predict performance.

The objective of this paper is to use mutual fund holdings and firms' earnings announcement to identify skills in mutual fund industry. This paper is not the first to incorporate fund holdings in assessing fund performance and thereby identifying managerial skills. A noteworthy but by no means comprehensive list includes Grinblatt and Titman (1989, 1993), Grinblatt, Titman and Wermers (1995), Daniel, Grinblatt, Titman and Wermers (1997), Wermers (1999, 2000, 2002, 2004), Chen, Jegadeesh and Wermers (2000), Ferson and Khang (2002), Ali, Durtschi, Lev and Trombley (2004), Kacperczyk, Sialm and Zheng (2006), Kacperczyk and Seru (2007), Cremers and Petajisto (2009), Baker, Litov, Wachter and Wurgler (2010), Petajisto (2013), and most recently Jiang and Zheng (2018) (hereafter referred to as JZ) whose methodology this paper attempts to partially follow to identify managerial skill at individual fund level.

Perhaps one of the most important advantages of holdings data is that, by connecting fund data to the data at the security level for the respective fund, it inherently opens up an expansive level of granularity. Such granularity in turn enables researchers to explore aspects of the research question regarding mutual fund managerial skill that are otherwise unapproachable with fund return data alone. A selected few of these aspects or papers whose methodology innovatively utilizes fund holdings data are briefly discussed.

A fund manager may possess superior information regarding a subset of securities that share certain characteristics in common, such as growth stocks, value stocks, stocks that belong in the same sector, etc.; and the manager would naturally orient the style of the fund towards the domain of his expertise. However, the style of the fund might shift drastically within a short period of time. An otherwise value manager may invest heavily in growth stocks in the technology sector before and during the dotcom bubble in the late 1990s. Ferson and Schadt (1996) finds that inference made about managerial ability is highly sensitive to the shifting in style or factor loadings of a professionally managed portfolio. Using portfolio holdings of U.S. equity mutual funds, Wermers (2002) decomposes a fund style drift into components that are attributable to either passive management or active management and documents substantial style drift between 1975 to 2002.

Active management differs from passive management in that fund managers of active funds would adjust their portfolios such that the portfolio weights would differ from those of certain benchmarks in an attempt to earn higher returns. Since regular portfolio adjustment would incur higher expenses such as transaction costs, active management is only justified if the fund managers possess superior private information as opposed to public information that is widely available to the market. Put differently, a skilled fund manager would rely more on superior private information and less on publicly available information to adjust his or her portfolio weights. Based on this premise, Kacperczyk and Seru (2007) devise a metric that captures the sensitivity of the change in fund portfolio holdings to the change in public information which is proxied by change in analysts' recommendations. To be more specific, the metric, termed RPI – reliance on public information – is the unadjusted R^2 of the following regression:

$$\Delta Holding_{s,f,t}\ (in\ \%) = \beta_{0,t} + \beta_{1,t}\Delta Re_{s,t-1} + \beta_{2,t}\Delta Re_{s,t-2} + \beta_{3,t}\Delta Re_{s,t-3} + \beta_{4,t}\Delta Re_{s,t-4} + \varepsilon_{f,t}\ , \qquad (4)$$

wherein the dependent variable is the percentage change in holding of security s by fund f at time t, and the independent variables are the changes in the recommendation of the consensus forecast of security s from one, two, three and four periods prior. Intuitively, RPI measures the extent to which the manager of fund f adjusts holdings on security s based on public information about security s. Based on the line of reasoning above, this metric is hypothesized to decrease in the fund manager's skill. Kacperczyk and Seru (2007) indeed finds evidence confirming this hypothesis; their results hold for both return-based performance measures such as FF alpha or Carhart alpha or holding-based measures such as CS, CT, and AS from Daniel et al. (1997) (see discussion below). Their result bolsters the stance that skill exists in mutual funds and some managers are more skilled than others.

Grinblatt and Titman (1989) pioneers the use of fund portfolio holdings to measure fund performance. For each fund at each month, they attempt to reconstruct the fund portfolio using holdings data on NYSE- and AMEX-listed stocks. The monthly excess returns of the stocks are then multiplied by their respective weights in the portfolio and summed up to form the "hypothetical" monthly excess return of the fund. The returns actually earned by investors and reported by funds are net of transaction costs and miscellaneous expenses. Grinblatt and Titman (1989) argues that, if fund managers do possess superior information, then from an economic standpoint the managers can extract rent in the form of perquisites through incurring higher expenses or in the form of higher fees to the investors (see Admati and Pfleiderer (1989) for a model wherein this happens). This implies that the net returns earned by investors and reported by funds in equilibrium cannot be higher than the returns of the market portfolio; hence the underperformance result reported by Jensen (1968) and various papers that employ data on fund returns alone. This "hypothetical" return, on the other hand, is a proxy for gross return, i.e. return that does not have transaction costs, fees, or other expenses deducted. Running several regressions of this "hypothetical" excess returns in a CAPM fashion to compute the pre-cost alpha of a manager, each regression with a different proxy for the market portfolio, Grinblatt and Titman (1989) find significantly positive risk-adjusted gross returns, i.e. pre-cost alphas, for some funds.

The result in Grinblatt and Titman (1989) provided an important perspective at the time of its issuance as the literature since Jensen (1968) had been filled with evidence of mutual fund underperformance, but their performance measure – pre-cost alpha – is subject to the same criticisms for alpha as outlined above. That said, their pioneering use of holdings data has given rise to an abundance of holdings-based performance measures, and the measures by Daniel, Grinblatt, Titman, and Wermers (DGTW 1997) are among the most widely cited in the literature that make use of fund holdings to overcome the drawbacks of alpha.

Instead of using as benchmark return the expected return from a multi-factor models such as Fama and French's (1993) three-factor model or Carhart's (1997) four-factor model, DGTW (1997) form benchmark portfolios by sorting the universe of stocks in the data into three quintile groupings based on the respective firm's size, book/market ratio, and holding return of the previous year, resulting in 5 x 5 x 5 = 125 passive benchmark portfolios. Each stock is then mapped to one of these benchmark portfolios along the dimensions of size, b/m ratio and holding return in the past year. The benchmark portfolio return is the value-weighted average return across all constituent stocks. Having the benchmark return for each stock at each time period in place, DGTW (1997) proceeds to decompose fund return into three components: characteristic selectivity (CS) measure, characteristic timing (CT) measure, and average style (AS) measure. The three components are the timeseries averages of the monthly measures displayed below:

$$CS_t = \sum_{j=1}^{N} \tilde{w}_{j,t-1} \left(\tilde{R}_{j,t} - \tilde{R}_t^{b_{j,t-1}} \right) \tag{5}$$

$$CT_t = \sum_{j=1}^{N} \left(\tilde{w}_{j,t-1} \tilde{R}_t^{b_{j,t-1}} - \tilde{w}_{j,t-13} \, \tilde{R}_t^{b_{j,t-13}} \right) \tag{6}$$

$$AS_t = \sum_{j=1}^{N} \tilde{w}_{j,t-13} \tilde{R}_t^{b_{j,t-13}} \tag{7}$$

To calculate the CS measure for a fund at month t, a stock's return at month t in excess of the month t return of the benchmark portfolio to which the stock is mapped from month t – 1 is multiplied by the weight from month t – 1 of that stock. Summing up such excess returns for all stocks yields the CS measure for the respective fund at month t. The CS measure of a fund is then the timeseries average across all months that the fund exists. A positive and significant CS measure indicates that the fund manager has selectivity ability, i.e. the fund manager on average can pick stocks that earn higher return than return of stocks that share the same size, book-to-market ratio and holding return in the past year. A CS measure of 0 indicates that the fund portfolio can be replicated by purchasing stocks that share the same size, book-to-market ratio and past year holding return.

CT measure captures the performance driven by market timing ability of the fund manager. The weight of stock j at month t - 13 is multiplied with the month t return of the benchmark portfolio mapped to the stock from month t - 13. This product is subtracted from the product between the weight of the stock at month t - 1 and the month t return of the benchmark matched at month t - 1. The CT measure of a fund is again the timeseries average across the months that the fund exists. As an example, a fund may increase the weights of small stocks in anticipation that the size effect will be unusually strong in the following month, in which case the CT measure of the fund in the following month will be high if the anticipation materializes.

The average style captures the performance of the fund attributable to the tendency to hold stocks with certain characteristics. The weight of the stock at month t - 13 is multiplied by the month t return of the benchmark portfolio mapped to the stock from month t - 13. DGTW (1997) posits that by lagging the weight and the benchmark matching by one year, the return attributable to market timing ability is eliminated. The gross return of a fund in a given month is equal to the sum of all these three measures in that month, i.e. Gross $Return_t = CS_t + CT_t + AS_t$.

One could observe from the formulae for all three measures by DGTW (1997) that the measures typically involve the product between the weight and the return, which can be intuitively understood as the comovement between returns and weights. In his literature review on using fund holdings data to evaluate performance, Wermers (2006) encapsulates portfolio holdings measures (PHM) as being grounded in covariance between lagged weights and current returns, succinctly expressed in the following equation:

$$\begin{aligned} PHM_t &= cov\left(\tilde{w}_{t-1}, \tilde{R}_t\right) = E\left\{\tilde{w}_{t-1}\left[\tilde{R}_t - E\left(\tilde{R}_t\right)\right]\right\} \\ &= E\{[\tilde{w}_{t-1} - E(\tilde{w}_{t-1})]\tilde{R}_t\} \\ &= E\left\{[\tilde{w}_{t-1} - E(\tilde{w}_{t-1})]\left[\tilde{R}_t - E\left(\tilde{R}_t\right)\right]\right\} \qquad (8) \end{aligned}$$

The covariance per se and the different expansions allow researchers to come up with different holdings-based performance measure. In fact, the AFP measure by JZ is a variant of the term after the third equality in the PHM_t formula – it is the empirical analog of the following covariance measure: $Cov\left(w_{i,t} - w_{i,t}^b, CAR_{i,t}\right) = E\left[\left(w_{i,t} - w_t^b\right) x\ CAR_{i,t}\right]$. More details on the derivation of this AFP measure is provided in Section 3.

This paper is not the first, too, to combine mutual fund holdings with data on firms' earnings announcement to meet this objective. Baker, Litov, Wachter and Wurgler (2010) combined these two types of data to construct measures of trading skill and found that the average fund's recent purchases significantly outperform its recent sells around the next earning announcement, and that this result accounts for a substantial fraction of the total abnormal returns to fund trades estimated in the extant literature.

This paper will combine these two types of data to identify fund managers' skills at two levels, namely at individual fund level and at the level of mutual fund industry as a whole. For the former, I partially follow JZ by computing the measure AFP for each fund, the measure being the covariance between the active investment decisions and the cumulative abnormal returns during a three-day window around future earnings announcement. The measure is intended to capture the fund manager's ability to adjust portfolios in anticipation of future earnings announcements. If the active investment decision is proxied by the difference between the portfolio weights and the weights of the respective stocks in a benchmark index, the AFP is referred to as index-based AFP. If the active investment decision is proxied by the change in weight relative to a previous period (accounting for passive weight change due to price changes), the AFP is referred to as trade-based AFP. The purpose of the analysis is to evaluate whether funds with high AFP value outperform. In a univariate analysis where funds are sorted into decile portfolios based on their AFP, the result for index-based AFP is ostensibly consistent with JZ in the full sample. But when the sample is split into overlapping and non-overlapping period, the significance remains in the former but disappears in the latter. This shows that the result is sensitive to sample period. The result for trade-based AFP is plainly insignificant, regardless of whether the active weight changes are relative to three months, six months or twelve months prior. In a multivariate analysis using panel data regressions wherein the dependent variable is the fund alpha from a factor model and the independent variables include AFP and a number of fund characteristics. Insofar as index-based AFP is concerned, the result for alpha from Carhart's (1997) four-factor model is significant and hence consistent with past result in JZ. However, I extend the analysis using alpha from Fama-French's (1993) model, and the result becomes sensitive to whether standard errors are clustered at fund or at time level. Therefore, I conclude that the result from the multivariate analysis is sensitive to the choice of benchmark, in this case the factor model used. As before, the result for trade-based AFP is insignificant. The strong discrepancy in trade-based AFP result between this paper and JZ prompts future research on the difference in fund holdings data between CRSP and Thompson and the implications thereof. The reason is because CRSP (which this paper uses) contains holdings data for both equity and non-equity holdings data, while Thompson only contains holdings data for common equity.

To identify skill in mutual fund industry in aggregate, I attempt to analyze whether the aggregated active investment activities in the industry can predict future earnings surprises. To this end, I regress future earnings surprises on active weight changes for the respective stock, aggregated across all funds. The active weight changes are relative to three months, six months, and twelve months prior. Under this empirical setting, there is no evidence of skill in the industry as a whole.

Hereafter the paper is structured as follows. Section 2 describes the data and the data work. Since this paper attempts to identify managerial skill at individual fund level and at the level of mutual fund industry as a whole, Section 3 and Section 4 will be dedicated to each level, respectively. Section 3 and Section 4 each will outline motivation, formulate hypothesis, describe the empirical model, and interpret the empirical result. Section 5 concludes.

2. Data

This paper makes use of multiple sources of data. More importantly, the mutual fund portfolio holdings data and the estimated portfolio weights are rather different from the extant literature. For this reason, this section is dedicated to describing the data and the data work.

This section has two sub-sections, one for data on mutual fund portfolio holdings and the other for other data and data work used in the paper, particularly the construction of the proxy for S&P 500 index.

2.1 Mutual Fund Portfolio Holdings

The analysis in the paper requires the use of the constituent weights of the mutual funds' portfolios; and to the best of my knowledge, this paper is the first to use portfolio holdings data for mutual funds from the Center for Research in Security Prices (henceforth CRSP) Survivor-Bias-Free U.S. Mutual Fund Database to estimate the weightings of the portfolio constituents. In contrast, most of the papers using holdings data cited in the introduction obtain portfolio holdings data for mutual funds from Thompson Reuters's CDA/Spectrum Mutual Fund Holdings Database (hence from Thompson holdings data), including the paper by JZ (which this paper attempts to partially replicate) in which the sample period spans from the first quarter of 1984 to the second quarter of 2014. In fact, a typical procedure would be to match fund holdings from Thompson data to the data on fund characteristics and returns and stock return data from CRSP (see Wermers (2000), Kacperczyk, Sialm, and Zheng (2005), and JZ). In addition, the sample period in this paper ranges from the first quarter of 2001 to the last quarter of 2018. As such, the use of CRSP fund holdings data to estimate portfolio weights, together with the sample period, constitute deviation from and thereby contribution to the extant literature.

Deviations from the literature warrant full clarity and transparency, thus the data per se and the data work is described in detail in Appendix A.5.

Table 1. Descriptive Statistics

A. Summary statistics of fund characteristics

	Mean	SD	25th pctl	Median	75th pctl
Number of funds	6409				
Net Asset Value ($ million)	53,86	65,28	17,88	34,57	64,96
Total Net Asset ($ million)	1059,23	3649,35	46,3	186,7	723,7
Expense (%)	1,37	5,66	0,6	1,01	1,30
Turnover (%)	98,96	480,75	16	51	95
Age	16,33	12,67	7,25	14,25	21,75
Quarterly Return (%)	2,13	8,50	-1,42	3,04	6,94

B. Average Spearman cross-sectional correlation coefficients

	NAV	TNA	Age	Expense	Turnover	Returns
Net Asset Value	1	0,48	0,07	0,23	0,17	0,04
Total Net Asset	0,48	1	0,27	-0,05	0,05	0,02
Age	0,07	0,27	1	-0,27	-0,27	0,02
Expense (%)	0,23	-0,05	-0,27	1	0,55	-0,01
Turnover (%)	0,17	0,05	-0,27	0,55	1	0,01
Quarterly Return (%)	0,04	0,02	0,02	-0,01	0,01	1

Table 1 shows the descriptive statistics for the set of 6409 unique mutual funds selected using the filters detailed above. Panel A presents summary statistics for the set of funds. Net asset value is the fund's underlying assets (including cash) minus its liabilities (expenses, fees, etc.) divided by the number of shares outstanding. Total net asset is the difference between total assets and total liabilities (in millions). Since each share class of a fund may have a different expense ratio, the expense ratio for a fund is the TNA-weighted mean across all share classes. Age is the time difference between the inception of the first share class of a fund to the date of the latest TNA. Quarterly return is the holding period return within a quarter, net of all expenses. Panel B presents the timeseries average of the Spearman correlation coefficients of the variables of interest.

Table 1 furnishes descriptive statistics on the sample of mutual funds. Panel A shows the summary statistics for the selection of mutual funds resulting from the aforementioned fund filters. An average fund in this [JZ's] paper manages $1,06 [1,39] billion of assets, is 16,33 [15,7] years old and earns an average quarterly return of 2,13% [2,39%]; the fund incurs an annual expense of 1,37% [1,23%] and turns over 98,96% [86,08%] of the portfolio on average per year. It can be observed that these figures are relatively consistent with JZ and by extension with the literature.

Panel B shows the timeseries average of the Spearman correlation coefficients of a set of variables of interest. The correlation coefficient of 27% between age and total net assets indicates that bigger funds are likely to be older. The coefficient of 0,55 between turnover and expense indicates the unsurprising positive correlation between turning over the portfolio and incurring expenses. This positive correlation is also reflected in the observation that older funds are less likely to both turn over their portfolios and incur expenses, as shown by the coefficient of -27%. A negative correlation between TNA and expense indicates that bigger funds would incur lower expenses. Again, this result is in line with that in JZ.

2.2 Other Data and Proxy for S&P 500 Index

The analysis will require the calculation of the cumulative abnormal returns of common stocks three days around quarterly earnings announcement. To this end, the stock return is obtained from CRSP Daily Stock File, and firms' quarterly earnings announcement dates are obtained from COMPUSTAT. To merge the stock return from CRSP to the firm's earning announcement dates from COMPUSTAT, I use the Linking Table from CRSP/COMPUSTAT Merged Database (CCM), available on WRDS. The link types used are LC, LU and LS. The daily abnormal return is the difference between the return of the security and the return on S&P 500 index of the same day. To obtain 3-day CAR, I sum the daily abnormal return from 1 trading day before the earning announcement to 1 trading day after the earning announcement. This means that if the earning announcement takes place on Monday, the CAR is calculated as the sum of the stock returns on Friday of the previous week, said Monday and Tuesday of the same week.

This paper will also work on earnings surprises which are calculated from analysts' forecasts and earning actuals from Institutional Brokers' Estimate System (henceforth I/B/E/S). The detailed description of this dataset and the data work is available in Appendix A.6.

Another data required is the historical weights of the constituents of the index S&P 500. Due to data unavailability, I resort to construct a proxy for the index. Historical index constituents are obtained from COMPUSTAT. The table from COMPUSTAT actually contains data on many different indexes. The S&P 500 Index can be identified by setting the value of the variable *spmi* to 10. This data allows for identifying the constituents of S&P 500 index at any particular date. The constituents are then merged to Security Daily data also from COMPUSTAT to obtain common shareholdings and stock price. These two variables enable the calculation of market value of any given constituent, of the total market value of S&P 500 at any given date, and consequently the weight of the constituent at any given date, i.e. the proxy for S&P 500 index.

I then use the Linking Table from the aforementioned CCM to map the computed constituent weights to stock return from CRSP, which allows me to compute the monthly return for the proxy. To compare the return of this proxy against the return of the actual index and thereby to assess the validity of this constructed proxy, I map this proxy to the composite index return data on the S&P 500 from "Index File on the S&P 500" from CRSP.

Since whenever mapping across databases takes place, it is virtually invariably the case that some observations will fail to be matched. Table 2 – Panel A shows the number of stocks in the proxy before and after mapping to CRSP stock data. It is indeed the case that after mapping, some stocks are dropped from the proxy. The lower bound of the number of stocks dropped in a year is 0, i.e., all stocks are mapped successfully. The upper bound of the number of stocks dropped in a year is 13 which takes place in 2016. It is noteworthy that the last four years in the sample period have among the largest number stocks dropped, namely 9, 13, 8, and 4, respectively. Therefore, particular attention needs to be paid when comparing the returns between the proxy and the de facto index in these four years.

Table 2 – Panel B compares the raw moments of the two timeseries and the Figure 1 illustrates the two timeseries of returns. It can immediately be seen that the mean of the proxy is relatively larger than the mean of the actual S&P 500 index. However, the two timeseries have a Pearson correlation coefficient of 0.995 (untabulated), indicating that the they comove quite closely, a fact that can also be observed in Figure 1. Upon an inspection of Table 2 – Panel B, we can see that the two timeseries have rather similar standard deviations. It can be observed from both Table 2 – Panel B and Figure 1 that the

difference between the timeseries are driven mostly by the downside of the de facto returns. To address the concern of high number of stocks dropped out in the last four years of the sample period, one can intuit from Figure 1 that the proxy tracks the actual index no less closely than the other years. In a nutshell, the proxy follows the actual index relatively closely, even though its return is slightly biased upwards.

Table 2: Comparison between the proxy and the de facto S&P 500 index

Panel A: The number of stocks in the proxy for S&P 500 index before and after mapping to CRSP stock data

Year	Before	After
2001	528	526
2002	525	523
2003	512	512
2004	522	520
2005	519	517
2006	534	529
2007	540	538
2008	538	537
2009	533	527
2010	525	519
2011	525	518
2012	521	521
2013	520	520
2014	519	518
2015	533	524
2016	544	531
2017	541	533
2018	536	532

Panel B: The raw moments of the Returns on the S&P 500 and on the Proxy thereof.

(in %)	Proxy	S&P 500
Mean	1.07	0.4
STD	4.16	4.21
Min	-14.86	-16.94
25%	-1.16	-1.68
50%	1.19	0.71
75%	3.4	2.97
Max	11.54	10.77

Panel B shows the raw moments of the return on the proxy of the S&P 500 index and the composite index return on the S&P 500 index taken from CRSP. The proxy is constructed by obtaining the list of the index’s constituents from COMPUSTAT, calculating the weight as the percentage of the market value (number of common shares outstanding * stock price) out of the total market value, and finally mapping to stock return from CRSP to calculate the value-weighted returns.

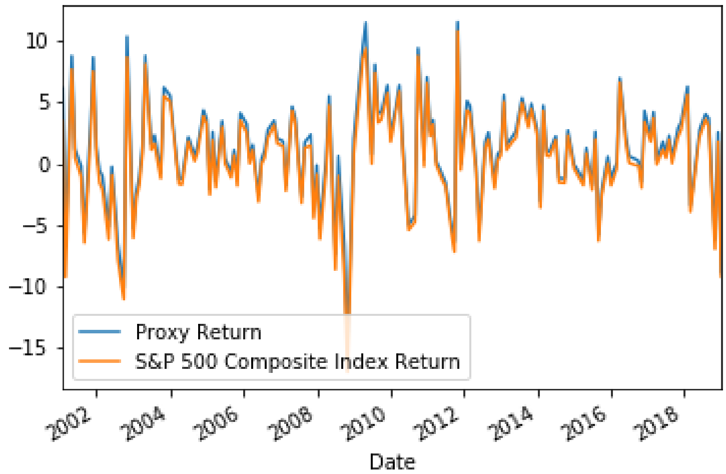

Figure 1. Returns on the S&P 500 Index and on the proxy thereof
The proxy is constructed by obtaining the list of the index's constituents from COMPUSTAT, calculating the weight as the percentage of the market value (number of common shares outstanding * stock price) out of the total market value, and finally mapping to stock return from CRSP to calculate the value-weighted returns.

3. Active Fundamental Performance

In this section, I attempt to identify managerial skill at individual fund level. To this end, I partially follow and replicates the methods and results by Jiang and Zheng (2018) (JZ). In their paper, they devise a measure of mutual fund managers' skills and name it AFP, i.e. Active Fundamental Performance. I then analyze whether AFP can actually capture managerial skill by looking at the correlation between AFP measure and performance of a fund. I first do a univariate analysis wherein the funds are sorted into decile portfolios and then analyze the performance of these portfolios. I then do a multivariate analysis wherein I run panel data regressions of fund alpha from factor models on fund AFP, controlling for fund characteristics that may affect the dependent variable.

In Subsection 3.1, I briefly explain the theoretical underpinning of the measure. In Subsection 3.2, I show how AFP is computed and how AFP portfolios are formed. In Subsection 3.3, I formulate the hypothesis. In

Subsection 3.4 and 3.5, I explain the empirical models used, elaborate the hypothesis in light of the specified empirical models, and display and analyze the empirical results.

3.1 Theoretical Foundation

In this subsection, I briefly walk through the derivation of the measure AFP originally derived by JZ. The authors start with the covariance between fund portfolio weight of a particular stock and the stock's future return, namely Cov($w_{i,t}$, $R_{i,t}$). Intuitively, the weight of a particular asset in the portfolio reflects the fund manager's decision to buy, sell or avoid this asset in anticipation of its future returns; and a positive value of this covariance indicates that the fund manager was on average purchasing the stock at the right time to earn the positive subsequent return and selling the stock at the right time to avoid the negative subsequent return, and a negative value of this covariance indicates that the fund manager was on average selling the stock before the stock earns positive returns and buying the stocks before returns of the stock go down.

It follows that aggregating this covariance measure across all securities in the fund portfolio furnishes an indication whether the fund manager was on average making the right investment decision to capture the future positive return and to avoid the future negative return, i.e. an indication of the skill of the fund manager. The appeal of this aggregated covariance measure is formally derived by Grinblatt and Titman (1993) and Lo (2008) as shown in Equation (9):

$$\underbrace{\sum_{i=1}^{N} Cov\left(w_{i,t}, R_{i,t}\right)}_{\text{Active}} = \sum_{i=1}^{N} E\left(w_{i,t}\ x\ R_{i,t}\right) - \sum_{i=1}^{N} E\left(w_{i,t}\right) x\ E\left(R_{i,t}\right) = \underbrace{E\left(R_{p,t}\right)}_{\text{Total}} - \underbrace{\sum_{i=1}^{N} E\left(w_{i,t}\right) x\ E\left(R_{i,t}\right)}_{\text{Passive}} \qquad (9)$$

Equation (9) intuitively shows that the active return of a fund, captured by the aggregated covariance between security holdings and the future returns of the respective securities, is the difference between the total portfolio return and the passive return of the portfolio.

Having shown the theoretical underpinning of their paper, JZ proceeds to introduce two innovations to this aggregated covariance measure.

The first innovation is to use the cumulative abnormal return (CAR) three days around a firm's earning announcement. This innovation is motivated by the studies on the relation between asset prices and information releases, e.g. Savor and Wilson (2013, 2014, 2016). In essence, returns within the short window around earning announcements have high information-to-noise ratio as price movements are highly driven by firm fundamental information. In addition to the informative returns, this innovation also exploits the large cross-section of earning announcements. These two advantages contribute to the increase in the power of the aggregated covariance measure in assessing fund managers' ability.

The second innovation is to use adjusted portfolio weights, rather than raw portfolio weights in the aggregated covariance measure; this innovation reveals active strategic decision of mutual fund managers. There are two way to adjust the portfolio weights. The first way is to measure the change in the portfolio weights relative to the past portfolio weights of the fund, i.e. to measure fund trades. The second way is to measure the deviations of the fund portfolio weights from a benchmark's weights. Since fund performance is commonly evaluated in the literature by being benchmarked against an index, it follows naturally that the portfolio weights can be adjusted against an index's weights. The practice of benchmarking fund portfolio weights against benchmark index weights was pioneered by Cremers and Petajisto (2009) and Petajisto (2013) who termed the deviation of the weights "Active Share".

Incorporating these two innovations in the aggregated covariance measure gives rise to Equation (10):

$$\begin{aligned}\sum_{i=1}^{N} Cov\left(w_{i,t} - w_{i,t}^{b}, CAR_{i,t}\right) \\ &= \sum_{i=1}^{N}\left\{E\left[\left(w_{i,t} - w_{t}^{b}\right) x\ CAR_{i,t}\right] - E\left(w_{i,t} - w_{t}^{b}\right) x\ E\left(CAR_{i,t}\right)\right\} \\ &= \sum_{i=1}^{N}\left\{E\left[\left(w_{i,t} - w_{t}^{b}\right) x\ CAR_{i,t}\right] - 0\ x\ E\left(CAR_{i,t}\right)\right\} \\ &= \sum_{i=1}^{N} E\left[\left(w_{i,t} - w_{t}^{b}\right) x\ CAR_{i,t}\right] \qquad (10)\end{aligned}$$

Taking the sample analog of Equation (10) yields the fund performance measure AFP introduced by JZ:

$$AFP_{j,t} = \sum_{i=1}^{N_j} \left(w_{i,t}^{j} - w_{i,t}^{b_j} \right) CAR_{i,t}, \qquad (11)$$

where $AFP_{j,t}$ is the the AFP measure of mutual fund j in quarter t; $w_{i,t}^{j}$ is the weight of security i in the portfolio of fund j in quarter t; $w_{i,t}^{b_j}$ is the weight of security i in fund j's benchmark portfolio in quarter t; $CAR_{i,t}$ is the cumulative abnormal return 3 days around the quarterly earnings announcement of firm i for quarter t. The daily abnormal return is the difference between the return of the security and the return on S&P 500 index of the same say. To obtain 3-day CAR, I sum the daily abnormal return from 1 trading day before the earning announcement to 1 trading day after the earning announcement. This means that if the earning announcement takes place on Friday, the CAR is calculated as the sum of the stock returns on Thursday of the same week, said Friday and Monday of the next week.

Having explained the derivation of the measure AFP by JZ, the next subsection will detail how to go about computing AFP and forming AFP portfolios.

3.2 Computing AFP and Construct AFP Portfolios

Figure 2 below illustrates the timeline whereby the AFP is calculated and used for analysis. In each quarter, the last holding data of a security by a fund is used. The benchmark weight can either be the weight of the same security in S&P 500 index proxy (index-based AFP) or the previous weight of this security by the fund (trade-based AFP), i.e. the lagged weight. Weights from the previous 3 months, 6 months, and 12 months (*) are used to compute trade-based AFP. The weight difference is then multiplied by the cumulative return 3 days around the date of the earning announcement. Please note that only earning announcement takes place within two months after a quarter end is considered. Earning announcement that takes place in the 3rd month after a quarter end is disregarded. The inclusion of the earnings in the first two months and the omission of the earnings in the 3rd month following a quarter are justified by two counterbalancing considerations. The first consideration is that the closer the earnings announcements to the reported holdings data, the less interim trade would occur and the more accurate AFP would be. Some results in the literature lends support to this consideration. Kacperczyk, Sialm and Zheng (2006) show that unobserved actions of mutual funds can persistently create or destroy value. Elton et al. (2010) find that quarterly reporting, as opposed to more frequent reporting, misses about 18% of the mutual fund trades. This consideration is counterbalanced with another consideration, which is to include more earnings announcements into the sample to increase the efficient use of data.

Once AFP has been calculated at a quarter end at month t (t can be 3, 6, 9 or 12), the funds are sorted into decile portfolios by their respective AFP measures. The decile portfolios are then held from month t+3 to month t+5. The portfolio return is then computed as the equally weighted returns of all funds in the portfolio. On a relevant note, the analysis requires the calculation of the risk-adjusted returns of the decile portfolios using factor models such as the three-factor model in Fama and French (1993). To this end, the holding returns of the factor-mimicking portfolios are calculated by the same approach for calculating holding returns for AFP decile portfolios; that is, by being held from t + 3 to t + 5.

As a concrete example, AFP is calculated for each fund at the end of the second quarter, i.e. at the end of June. In calculating the AFP of the fund, the active weight of each security is calculated by the difference between the last holding data of the security in that quarter and the benchmark weight. The cumulative abnormal returns are calculated for earning announcements that take place in July and August. Earnings announcements in September are disregarded. The funds are then sorted into decile portfolios, each of which is then held from September to the end of November. The factor-mimicking portfolios in a factor models are also held from September to the end of November. This way, in a regression of the Fama-French's (1993) three-factor model to estimate risk-adjusted return for a decile portfolio, the return (in excess of a risk-free rate) of the decile portfolio constructed by fund AFP at the end of June and held from September to November is aligned with the returns from holding factor-mimicking portfolios from September to November.

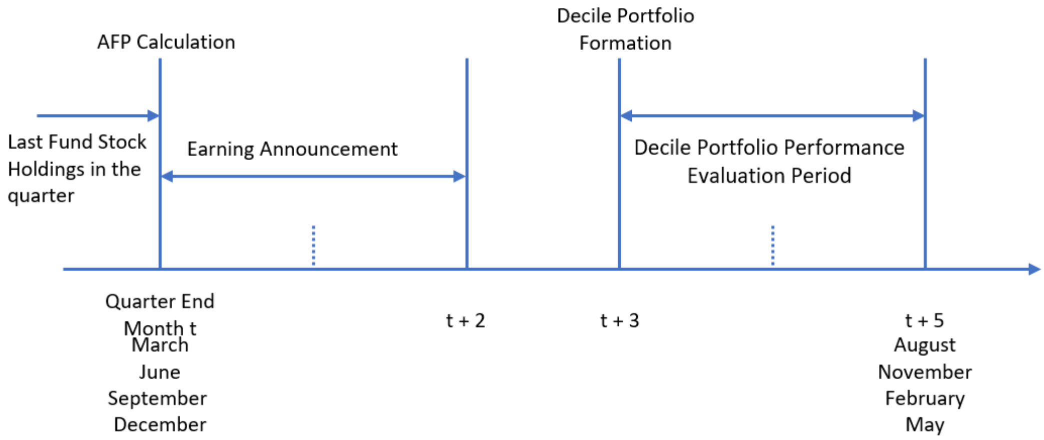

Figure 2. Timeline of AFP Computation and AFP Portfolio Construction

Some notes on how to calculate the weight difference in the computation of trade-based AFP are in order. For the trade-based AFP, the weight difference is the change in portfolio weights from a previous period, accounting for mechanical change in portfolio weight due to changes in stock prices. In other words, the weight difference is not simply the difference between the weights in the current period and the weights from a previous period, since this difference can be due to changes in stock prices, hence not attributable to fund managers' active investment decisions. To account for this, the weight difference is computed as the difference between current weight and the passive portfolio weight inferred from a previous period. The general expression of the active weight is shown in Equation (12):

$$w_{i,t}^{t-h} = \frac{n_{i,t-h}p_{i,t}}{\sum_{j=1}^{N^{p-h}} n_{j,t-h}p_{j,t-h}}, \qquad (12)$$

where $w_{i,t}^{t-h}$ is the passive portfolio weight at quarter t, inferred from the portfolio holding at quarter t-h $n_{i,t-h}$. $p_{i,t}$ is the price of security i at quarter t. $p_{j,t-h}$ is the price of security j at quarter t – h. Put differently, the passive weight of security i at quarter t inferred from its holding in quarter t – h is calculated by shifting the price from quarter t back to quarter t – h, calculating the market value at t – h using the price from t and the number of shares held at t - h, and then dividing by the total market value of the fund at t – h. The analysis in this paper reports results for trade-based AFP computed from weight changes from the previous 1, 2 and 4 quarters.

In the next subsection, I formulate hypothesis and introduce the tests used to assess the power of AFP in capturing mutual fund managers' skills.

3.3 Hypothesis Development

The objective of this section is to use funds' holdings and firms' earnings to identify managerial skill for individual mutual funds. This subsection has introduced the measure AFP, derived by JZ in order to capture mutual fund managers' ability, or the lack thereof, to make strategic investment decisions to take advantage of the returns around earnings announcements. If this measure can indeed do so, then funds that have high value for this measure should outperform funds with low value of this measure.

> *Hypothesis 1: AFP is a measure of fund skill. Mutual funds that have high value on the AFP measure have high positive returns. Mutual funds that have higher value on the AFP measure outperform mutual funds that have lower value on the AFP measure.*

Two tests will be done to test this hypothesis in the two following subsections. The first test is a univariate analysis in which funds are sorted into decile portfolios as described in Section 3.2. The funds in the high AFP portfolios, i.e. funds with the highest [lowest] AFP measure, are hypothesized to be actively managed by skilled [unskilled] managers. That is, the portfolios of funds with high AFP should outperform the portfolio of funds with low AFP. The second test is a multivariate analysis using panel data regressions of the fund risk-adjusted returns on the fund AFP, controlling for fund characteristics and time fixed effect. The risk-adjusted return of the fund is the fund alpha from a three-year rolling-window timeseries regression of the fund net returns in factor models as in Carhart (1997) and Fama-French (1993). The coefficient of AFP is hypothesized to be significantly positive.

The univariate test is described and implemented in Section 3.4, and the multivariate test in Section 3.5.

3.4 Univariate analysis – AFP Decile Portfolios

The first is a univariate analysis using portfolios of funds constructed based on their AFP measures. The decile portfolio construction is explained in subsection 3.2. As a reminder, at a quarter end at month t (t = 3, 6, 9 or 12), I compute the AFP measures for the funds and sort them into decile portfolios, which are held from month t+3 to t+5. The return on the portfolio is the equally weighted returns of all component funds.

If AFP can indeed capture fund managerial skills, then the high AFP decile portfolio should outperform the low AFP decile portfolio. The first simple measure of portfolio performance is the average return. In addition, I also estimate the risk-adjusted return on the portfolio as per the Jensen's alpha from the time-series regressions, according to the Capital Asset Pricing Model(CAPM), Fama-French (1993)'s three-factor model, Carhart's (1997) four-factor model, and Pastor and Stambaugh's (2003) five-factor model. For example, the Pastor and Stambaugh's alpha is the intercept from the following timeseries regression:

$$R_{p,t} - R_{f,t} = \alpha_p + \beta_m\left(R_{m,t} - R_{f,t}\right) + \beta_{smb}SMB_t + \beta_{hml}HML_t + \beta_{umd}UMD_t + \beta_{liq}LIQ_t \qquad (13)$$

In equation (13), $R_{p,t}$ is the return of the decile portfolio p, $R_{f,t}$ is the risk-free rate, $R_{m,t}$ is the return on a market portfolio, SMB_t is the return on the portfolio mimicking the size effect, HML_t is the return on the portfolio mimicking the value effect, and UMD is the return on the return difference between stocks with high and low past year return, and LIQ_t is the liquidity risk factor. The data on market portfolio, risk-free rate, SMB and HML is taken from the data library available on Kenneth French's personal website. The liquidity factor LIQ is taken from Lubos Pastor's personal website. All these factors have data available on a monthly basis throughout the sample period. With regards to the notation t, even though t indeed indicates month t, the data for this regression is not strictly monthly return at month t, but rather holding return from t + 3 to t + 5. The approach to calculate this holding return is described in Section 4.2, but is briefly re-explained here. At the end of a quarter, say month t (t can be 3, 6, 9, or 12), AFP is calculated for each fund, and decile portfolios are formed based on these fund AFP measures. The decile portfolios are then held from month t + 3 to month t + 5. To align the returns on the right-hand side of equation (13), the returns on the independent variables are also held from month t + 3 to month t + 5. In short, the return at month t is actually the return from holding the portfolio from month t + 3 to t + 5.

With these AFP portfolio performance measures in place, I formulate the hypothesis 1 in more detail.

> *Hypothesis 1a: The average return of the highest AFP portfolio is statistically significant and positive. The average return of the higher AFP portfolio is statistically significantly higher than the average return of the lower AFP portfolio, i.e. the higher AFP portfolio outperforms the lower AFP portfolio.*
>
> *Hypothesis 1b: Conditional on Hypothesis 1a, the CAPM-alpha, FF-alpha, Carhart-alpha, Pastor and Stambaugh-alpha of the higher AFP portfolio are statistically significantly higher than those of the lower AFP portfolio. That is to say, the outperformance of the high AFP portfolio over the low AFP portfolio cannot be explained away by the risk factors in the chosen factor models.*

The empirical result for the univariate analysis using AFP decile portfolio is shown in Table 3 in four panels, each for a different way to compute the AFP measure. Panel A reports result for index-based AFP, Panel B [C] [D] reports result for trade-based AFP where the weight difference is between current weight and the weight of one, two, or four quarters prior. The returns are net of all expenses. Table 3 reports both average returns of the AFP decile portfolios and the risk-adjusted returns based on the CAPM, the Fama and French's (1993) three-factor model, the Carhart's (1997) four-factor model, and the Pastor and Stambaugh's (2003) five-factor model.

Focus our attention first on the result for index-based AFP. The highest [lowest] decile portfolio, i.e. the mutual funds with the highest [lowest] AFP measures, earns on average 2,49% [1,42%] in the quarter following portfolio formation. Although the average difference of 99 bps between the highest and the lowest decile portfolios is clearly untrivial, it is not statistically significant. That being said, the lowest decile portfolio earns on average a return of 1,42%, but it is insignificant. The highest decile portfolio earns on average a return of 2,49% which is significant at 5% level. Therefore, given the choice between taking a long position in the lowest portfolio and in the highest portfolio throughout the sample period, the highest portfolio is the better choice. More importantly, in untabulated result, I compare the returns earned by the second highest decile portfolio (the 9th portfolio in Table 3) and the lowest decile portfolio. The difference is positive and significant at 5% level. This lends support to the notion that mutual funds with high AFP measure indeed outperform those with low AFP measure.

The alpha is negative for all decile portfolios, regardless of which factor model is accounted for. This indicates that common risk factors in the literature can explain away the significantly positive returns even for the decile portfolio whose constituent mutual funds have the highest AFP measures. However, it cannot be concluded from this result that the portfolios of funds with high AFP cannot earn positive risk-adjusted returns. Here we must distinguish the difference between the returns earned by mutual fund investors, which is net of all costs and expenses, and the returns that the portfolio of the fund can earn on the merits of the component securities alone, i.e. gross returns. Grinblatt and Titman (1989) argues that if fund managers do have skills, they will extract rent by charging investors higher fees or by obtaining perquisites through higher expenses, and Admati and Pfleiderer (1989) provides the conditions under which this holds true. Therefore, the negative alpha reported in Table 3 does not necessarily indicate that even the funds with high AFP cannot earn positive risk-adjusted return. To answer that question, gross return is needed.

That said, the risk-adjusted performance reported in Table 3 allows us to compare the funds. The difference in the alpha between the portfolio of funds with the highest AFP measures and one with the lowest AFP measures is significant and positive in all factor models used. This shows that any outperformance from the high-AFP funds over the low-AFP funds cannot be explained away by the common risk factors.

The result for index-based AFP is relatively in line with the result in JZ. Even though the difference in average return between the highest and lowest AFP portfolios is insignificant, the difference (unreported) between the second highest and the lowest AFP is significant and positive, lending support to hypothesis (1a). Moreover, the difference in risk-adjusted returns between the highest and lowest AFP portfolios is positive and significant for all factor models used, a result that corroborates the hypothesis (1b), (1a) and thereby (1).

That said, in light of the insignificant difference in average return between the highest and lowest portfolios, a discussion on the differences between this paper and JZ is in order.

There is an important difference in the computation of trade-based AFP. This paper uses S&P 500 index as the only benchmark to calculate the active weight. The disadvantage of this is that S&P 500 index contains a rather limited number of stocks. As can be seen from the index-based results, the direction of the index-based result is quite in line with the hypothesis in that the difference in average return is positive but insignificant. A potential reason for this is that due to the limited number of stocks in the chosen index, a substantial portion of the dataset is rendered unused, thereby decreasing the power of the AFP measure. In contrast, JZ, following Cremers and Petajisto (2009), uses a universe of 19 different benchmark indexes, namely S&P500, S&P 400, S&P 600, S&P 500/Barra Value, S&P 500/Barra Growth, Russell 1000, Russell 2000, Russell 3000, Russell Midcap, value and growth variants of the four Russell indexes, Wilshire 5000, and Wilshire 4500. For each fund-quarter, they use the index that minimize the distance between the current portfolio weights and the benchmark index weights. With such a diversity of indexes, it is inevitable that they can make more efficient use of their data and thereby increase the power of the AFP measure, which in turn potentially drive the significance in the difference in average return.

Another difference is the sample period. The sample period in JZ paper is from the first quarter of 1984 to the second quarter of 2014, whereas the sample period of this paper is from the first quarter of 2001 to the last quarter of 2018. The same analysis as in Table 3 is performed separately on two subsets of the dataset; one is from 2001Q1 up to 2014Q4 which overlaps with JZ, and the other is from 2015Q1 up to 2018Q4. The results are reported in Table A.1 and A.2 in the Appendix. The difference in average return between the highest and the lowest portfolios is still positive and insignificant. Importantly, the significant difference in risk-adjusted returns, i.e. alpha, between the high and the lowest portfolios persists in the overlapping sample period, but disappears in the non-overlapping period after 2014. Therefore, in spite of strong evidence in favour of index-based AFP in JZ, the analysis here shows that results for index-based AFP is sensitive to the sample period used. Next, we look at the result for trade-based AFP.

The result for trade-based AFP in Panel B, C and D in Table 3 unequivocally provides evidence against AFP. The insignificant return difference between the high and low portfolios notwithstanding, the difference in risk-adjusted returns, i.e. alpha, is insignificant for all models used, regardless of whether AFP is computed by lagging weight one quarter, two quarter or four quarters back. Table A.1 and A.2 in the Appendix show that similar results are found for both overlapping and non-overlapping periods.

In JZ paper, the magnitude of the result for index-based AFP is larger than the result for trade-based AFP; the difference in average return of the high and low index-based [trade-based] AFP portfolios 23 [12] bps. The authors attribute such difference to the fact that index-based AFP contains information on both short-term and long-term strategic investments of the fund managers, whereas trade-based AFP only accounts for short-term investment decisions. That said, the downright insignificant result for trade-based AFP in this paper makes for a huge discrepancy between the two papers.

Unfortunately, the cause for such a huge discrepancy between this result and the trade-based result in JZ has not been identified. Therefore, this paper can only attempt to make a shot in the dark. The first potential cause is that the significant result in JZ is driven by the non-overlapping period in their sample period, i.e. 1984Q1 to 2000Q4. The second potential cause has to do with the choice of database for fund holdings data. This paper uses fund holdings data provided by CRSP, and the data contains holdings information on both equity and non-equity securities. On the contrary, the Thompson database which JZ as well as the majority of the extant literature use only has holdings data on equity securities. Ignoring other securities while computing the portfolio weights can have major implications on the result. Indeed, Elton, Gruber and Blake (2011) find that the difference in alpha owing to not taking into account the non-common-equity portion of a portfolio (e.g. futures, options, preferred stocks, and bonds) is large on average and very large for individual funds. Since the use of holdings data in the extant literature is mostly confined to Thompson database (in fact to the best of my knowledge, this paper is the only one that use fund holdings data from CRSP), future research can attempt to identify whether incorporating holdings data on non-common-stock securities drive any other past results.

In a nutshell, this univariate analysis on AFP decile portfolios shows that the evidence for Hypothesis (1a, 1b and thereby 1) is inconclusive. The result for index-based AFP is significant in the full sample and ostensibly lends support to the said hypothesis. But when the sample is split into two periods, one overlaps with JZ and one doesn't, only the overlapping subperiod stays significant; the result in non-overlapping is insignificant. The result for trade-based AFP is unequivocally insignificant

The next subsection will perform a multivariate analysis with predictive panel data regressions.

3.5 Multivariate Analysis - Predictive Panel Regressions

This subsection tests Hypothesis (1) with a multivariate analysis by running panel data regressions of risk-adjusted returns of funds on their AFP, controlling for time fixed effect and other fund characteristics that may affect the dependent variable such as fund size, age, expense ratio, and turnover ratio. The risk-adjusted returns of a fund are the fund alpha, the differences between the fund net returns and the expected returns of the fund computed using Carhart's (1997) and Fama-French's (1993) factor models. The factor loadings are estimated by rolling-window timeseries regression of fund net returns on factor-mimicking portfolios in the previous three years. With the setting of the analysis in place, Hypothesis (1) can be elaborated as follows:

> *Hypothesis 1c: The coefficient of AFP in the panel data regression is significant and positive.*

The result is displayed in Table 4. Panel A displays results for index-based AFP; Panel B displays results for two-quarter trade-based AFP, i.e. AFP is measured by the product of the 3-day CAR around earnings announcements and the weight changes relative to two quarters earlier, controlling for any passive weight change due to changes in price. In each panel, the four columns on the left calculate alpha from Carhart's (1997) four-factor model (Carhart alpha), and the four columns on the right calculate alpha from Fama-French's (1993) three-factor model (FF alpha).

While JZ only performs similar analysis using Carhart's four-factor model, this paper uses Fama-French's model to evaluate whether the result is sensitive to the choice of factor models used.

The result in Panel A shows that AFP can significantly explain the Carhart alpha at 1% level. For every unit increase in AFP, a fund can earn an additional 10,68% in Carhart alpha. One standard deviation in the sample distribution of AFP is 0,0035 (untabulated), which translates into a Carhart alpha of 3,7 bps. The 1% significance persists whether the standard errors are clustered at fund level or at time (quarter) level. After controlling for fund characteristics that may affect risk-adjusted of the funds, the magnitude of the coefficient for AFP becomes even bigger. One standard deviation in AFP now translates into a Carhart alpha of 3,86 bps. In overall, the evidence strongly supports the hypothesis that funds with high AFP, a measure intended to measure managerial skills, on average can earn higher Carhart alpha. This result is consistent with the result in JZ.

However, JZ only implement this analysis for the four-factor model from Carhart (1997). Given that the dependent variable is the Jensen's alpha from a multi-factor model that has received numerous criticisms outlined in the introduction in Section 1, I additionally conduct the analysis on the three-factor model from Fama-French (1993) to observe whether the result is sensitive to the choice of benchmark models in calculating risk-adjusted returns. The result, displayed in the four columns on the right-hand side in Table 4, shows that the magnitude of the coefficient becomes smaller almost by half. More importantly, its significance is sensitive to whether the standard errors are clustered by funds or by firms. This means that the result is sensitive to whether the unexplained portions of the FF alpha are correlated across observations within funds or within quarters. The former means that the FF alpha of a given individual fund has portions that cannot be explained by AFP (and the controls), and these portions are correlated across time. The latter means that at each quarter in the sample, the FF alpha of funds in that quarter have unexplained portions that are correlated. If the structure of the data follows the former case, then the coefficient of AFP is significant and positive, lending support to Hypothesis 1c. If the structure of the data follows the latter case, the coefficient of AFP is no longer significant, indicating that the result is sensitive to the factor model employed. JZ clusters standard errors by funds, with a simple justification that "because the residuals might correlate within funds". They do include a footnote, however, which says that their result is robust to clustering standard errors by both fund and time.

In a nutshell, as far as index-based AFP is concerned, the evidence using Carhart alpha strongly corroborates Hypothesis (1c) and thereby Hypothesis (1), that funds with higher AFP can earn higher returns and by extension AFP is a measure of managerial skill. However, the evidence using FF alpha is not without loose end. If the standard errors are clustered at all but singularly time level as per the true structure of the data, then the evidence using FF alpha is also significant and supportive of Hypothesis (1). If standard errors are clustered at time level in the true structure of the data, then the result is not robust to the choice of benchmark model, lending support to the criticisms to Jensen alpha outlined in the introduction. Since the result for Carhart alpha holds when standard errors are clustered at either fund or time level and FF alpha does not, I conclude that the result is sensitive to the factor model used and thus the evidence from this multivariate analysis on index-based AFP is not strong enough to support Hypothesis (1c) and thereby Hypothesis (1).

Next, we look at the result for trade-based AFP. For regressions where the calculation of trade-based AFP uses the active portfolio weight change relative to one quarter and to four quarters prior, the result (reported in Table A.3 in the Appendix) is plainly insignificant. For regressions where the calculation of trade-based AFP uses the active portfolio weight change relative to two quarters prior, the result is somewhat mixed; it is reported in Table 4 Panel B.

At first inspection, one could immediately see that the negative sign of all the coefficient for AFP is evidence against Hypothesis (1c). When the standard errors are clustered at fund level (columns (1), (3), (5), and (7)), the evidence is significant at 5% level. When the standard errors are clustered at time level (the other columns), the evidence is insignificant or weekly significant. In overall, trade-based AFP either provides no evidence, or even evidence against the hypothesis that AFP captures managerial skills. This result is in stark contrast to JZ who find significant result in support of AFP when using either index-based AFP or trade-based AFP where the active portfolio weight changes are relative to four quarters prior.

As mentioned above, Thompson database only contains holdings data for common equity, whereas CRSP contains holdings data for all securities. To the best of my knowledge, the majority of the extant literature that use fund holdings data obtain the data from Thompson. The stark discrepancy in the result for trade-based AFP between this paper and JZ prompts future research on the difference in fund holdings data between CRSP and Thompson and the implications thereof on both past and future research that employs fund holdings data.

Table 3. AFP Decile Portfolio – Univariate Analysis 2001Q1 – 2018Q4

A. Decile portfolio formed according to the index-based AFP. Sample period 2001Q1-2018Q4

	Low	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**High**	**High-Low**
					Net Return						
Average Return	1,42	2,13	2,4	2,25	2,22	2,21	2,55	2,59	2,64	2,49	0,99
	(0,98)	(1,9)	(2,04)	(2,05)	(2,07)	(2,15)	(2,35)	(2,55)	(2,27)	(2,16)	(1,4)
CAPM α	-2,02	-1,18	-0,55	-0,56	-0,4	-0,45	-0,24	-0,03	-0,09	-0,4	1,43**
	(-4,3)	(-2,91)	(-1,79)	(-2,39)	(-1,97)	(-2,36)	(-0,89)	(-0,11)	(-0,27)	(-0,75)	(2,11)
Carhart α	-2,02	-1,22	-0,64	-0,65	-0,46	-0,55	-0,32	-0,08	-0,16	-0,15	1,62**
	(-4,11)	(-2,91)	(-2,04)	(-3,02)	(-2,57)	(-3,13)	(-1,21)	(-0,29)	(-0,52)	(-0,32)	(2,46)
Fama-French α	-2,02	-1,18	-0,61	-0,61	-0,44	-0,5	-0,31	-0,11	-0,22	-0,48	1,32*
	(-4,22)	(-2,84)	(-2)	(-2,92)	(-2,48)	(-2,82)	(-1,21)	(-0,42)	(-0,71)	(-0,94)	(1,97)
Pastor-Stambaugh α	-1,98	-1,2	-0,64	-0,65	-0,46	-0,56	-0,32	-0,06	-0,18	-0,17	1,58***
	(-4,59)	(-2,81)	(-2,04)	(-3,08)	(-2,63)	(-3,19)	(-1,21)	(-0,24)	(-0,56)	(-0,35)	(2,68)

B. Decile portfolio formed according to the 3-month trade-based AFP. Sample period 2001Q1-2018Q4

	Low	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**High**	**High-Low**
					Net Return						
Average Return	1,24	2,33	2,94	1,28	1,89	2,25	2,32	2,12	1,82	1,31	-0,18
	(0,95)	(1,73)	(2,36)	(0,91)	(1,45)	(1,91)	(1,83)	(1,46)	(1,09)	(0,89)	(-0,22)
CAPM α	-1,48	-0,68	-0,36	-0,81	-0,62	-0,5	-0,5	-0,72	-0,65	-1,99	-0,6
	(-2,23)	(-1,26)	(-0,67)	(-2,15)	(-1,81)	(-1,59)	(-1,3)	(-1,45)	(-1)	(-2,2)	(-0,73)
Carhart α	-1,5	-0,68	-0,28	-0,86	-0,6	-0,53	-0,66	-0,81	-0,78	-2,16	-0,52
	(-2,4)	(-1,39)	(-0,69)	(-2,79)	(-2,13)	(-1,92)	(-1,92)	(-1,97)	(-1,37)	(-2,54)	(-0,64)
Fama-French α	-1,52	-0,71	-0,44	-0,84	-0,51	-0,42	-0,49	-0,75	-0,52	-1,91	-0,48
	(-2,5)	(-1,47)	(-1,02)	(-2,78)	(-1,84)	(-1,53)	(-1,46)	(-1,9)	(-0,92)	(-2,37)	(-0,6)
Pastor-Stambaugh α	-1,51	-0,73	-0,34	-0,84	-0,59	-0,53	-0,68	-0,79	-1,01	-2,27	-0,55
	(-2,39)	(-1,46)	(-0,83)	(-2,82)	(-2,07)	(-1,89)	(-1,94)	(-1,9)	(-1,8)	(-2,67)	(-0,67)

C. Decile portfolio formed according to the 6-month trade-based AFP. Sample period 2001Q1-2018Q4

	Low	2	3	4	5	6	7	8	9	High	High-Low
						Net Return					
Average Return	1,74	1,51	1,65	1,66	1,57	2,03	1,74	1,6	2,59	1,75	0,1
	(1,29)	(0,86)	(1,18)	(1,29)	(1,23)	(1,48)	(1,34)	(1,12)	(1,64)	(1,18)	(0,12)
CAPM α	-1,75	-0,63	-0,98	-0,6	-0,85	-0,31	-0,59	-1,19	-0,23	-1,4	-0,27
	(-2,83)	(-0,89)	(-2,58)	(-1,53)	(-2,3)	(-0,57)	(-1,64)	(-2,98)	(-0,38)	(-1,63)	(-0,31)
Carhart α	-1,56	-0,63	-0,97	-0,57	-0,78	-0,34	-0,58	-1,24	-0,45	-1,35	-0,27
	(-2,43)	(-1,06)	(-2,86)	(-1,8)	(-2,35)	(-0,65)	(-1,85)	(-3,32)	(-0,85)	(-1,65)	(-0,31)
Fama-French α	-1,72	-0,68	-0,97	-0,5	-0,73	-0,31	-0,52	-1,19	-0,57	-1,47	-0,22
	(-2,82)	(-1,15)	(-2,93)	(-1,56)	(-2,21)	(-0,61)	(-1,68)	(-3,28)	(-1,1)	(-1,84)	(-0,26)
Pastor-Stambaugh α	-1,49	-0,65	-0,97	-0,57	-0,78	-0,35	-0,58	-1,24	-0,44	-1,36	-0,29
	(-2,35)	(-1,07)	(-2,85)	(-1,78)	(-2,33)	(-0,68)	(-1,84)	(-3,34)	(-0,82)	(-1,64)	(-0,34)

D. Decile portfolio formed according to the 12-month trade-based AFP. Sample period 2001Q1-2018Q4

	Low	2	3	4	5	6	7	8	9	High	High-Low
						Net Return					
Average Return	1,05	1,87	0,86	1,25	1,73	1,42	1,72	1,65	2,78	1,58	0,61
	(0,78)	(1,14)	(0,58)	(0,93)	(1,32)	(1,08)	(1,28)	(1,15)	(1,64)	(1,04)	(0,69)
CAPM α	-1,69	-0,7	-1,1	-0,54	-0,42	-0,79	-0,77	-0,71	-0,03	-1,1	0,23
	(-2,77)	(-1,07)	(-2,26)	(-1,35)	(-1,06)	(-2,04)	(-1,7)	(-1,67)	(-0,03)	(-1,23)	(0,24)
Carhart α	-1,6	-0,97	-1,07	-0,46	-0,4	-0,64	-0,78	-0,76	0,13	-0,76	0,48
	(-2,72)	(-1,65)	(-2,58)	(-1,49)	(-1,21)	(-1,84)	(-2,03)	(-1,93)	(0,2)	(-0,92)	(0,5)
Fama-French α	-1,62	-0,9	-1,01	-0,41	-0,36	-0,65	-0,73	-0,65	0,02	-0,97	0,28
	(-2,83)	(-1,53)	(-2,44)	(-1,32)	(-1,1)	(-1,9)	(-1,93)	(-1,7)	(0,03)	(-1,18)	(0,3)
Pastor-Stambaugh α	-1,62	-0,94	-1,11	-0,49	-0,41	-0,63	-0,78	-0,72	0,12	-0,76	0,49
	(-2,76)	(-1,59)	(-2,67)	(-1,58)	(-1,22)	(-1,79)	(-2,02)	(-1,87)	(0,17)	(-0,91)	(0,52)

Table 3 shows the empirical result for the univariate analysis using AFP decile portfolios. There are four panels, each for a different way to compute the AFP measure. Panel A reports result for index-based AFP, Panel B [C] [D] reports result for trade-based AFP where the weight difference is between current weight and the weight of one, two, or four quarters prior. The returns are net of all expenses. Each panel reports both average returns of the AFP decile portfolios and the risk-adjusted returns based on the CAPM, the Fama and French's (1993) three-factor model, the Carhart's (1997) four-factor model, and the Pastor and Stambaugh's (2003) five-factor model. t-statistics are reported in parenthesis. For the last column, symbols are employed to make statistically significant results salient; *, ** and *** indicate statistical significance at 10%, 5% and 1% levels, respectively.

Table 4. AFP Panel Data Regression – Multivariate Analysis

A. Index-Based AFP

	Carhart Alpha				FF Alpha			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
AFP	0,1068***	0,1068***	0,1103***	0,1103***	0.055***	0.055	0,05***	0,05
	(7,02)	(3,59)	(6,74)	(3,60)	(3,47)	(1,19)	(2,78)	(0,94)
log(TNA)			0,0001***	0,0001**			0,0001***	0,0001*
			(2,69)	(2.00)			(2,61)	(1,88)
log(Age)			-0,0003***	-0,0003			-0,0004***	-0,0004*
			(-2,88)	(-1,47)			(-3,02)	(-1,68)
Expense (%)			-0,0006	-0,0006			-0,002	-0,002
			(-0,59)	(-0,44)			(-1,55)	(-1,4)
Turnover (%)			-0,00	-0,00			0,00	0,00
			(-0,82)	(-0,52)			(0,80)	(0,63)
1st Order Lag			0,027**	0,027			0,03***	0,03
			(2,54)	(1,23)			(4,58)	(1,45)
No. Observations	56705	56705	40886	40886	56705	56705	40886	40886
No. Funds	4312	4312	3746	3746	4312	4312	3746	3746
No. Quarters	49	49	48	48	49	49	48	48
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund Cluster	Yes	No	Yes	No	Yes	No	Yes	No
Quarter Cluster	No	Yes	No	Yes	No	Yes	No	Yes

B. Trade-based AFP - Active portfolio weigh change relative to two quarters prior

	Carhart Alpha				FF Alpha			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
AFP	-0,07**	-0,07	-0,0656*	-0,0656	-0,08**	-0,08	-0,0861**	-0,0861*
	(-2,55)	(-1,58)	(-1,68)	(-1,20)	(-2,48)	(-1,63)	(-2,12)	(-1,68)
log(TNA)			0,0001***	0,0001**			0,0001***	0,0001*
			(2,80)	(2,05)			(2,67)	(1,89)
log(Age)			-0,0003***	-0,0003			-0,0004***	-0,0004*
			(-2,82)	(-1,42)			(-3,14)	(-1,74)
Expense (%)			-0,0005	-0,0005			-0,0019	-0,0019
			(-0,55)	(-0,40)			(-1,50)	(-1,36)
Turnover (%)			-0,00	-0,00			0,00	0,00
			(-0,91)	(-0,57)			(0,69)	(0,55)
1st Order Lag			0,02**	0,02			0,03***	0,03
			(2,55)	(1,23)			(4,82)	(1,50)
No. Observations	57699	57699	41072	41072	57699	57699	41072	41072
No. Funds	4426	4426	3781	3781	4426	4426	3781	3781
No. Quarters	49	49	48	48	49	49	48	48
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund Cluster	Yes	No	Yes	No	Yes	No	Yes	No
Quarter Cluster	No	Yes	No	Yes	No	Yes	No	Yes

Table (4) shows the empirical results for panel data regressions. The dependent variables are the fund alpha from Carhart's (1997) four-factor model in columns (1), (2), (3), and (4) and Fama-French's (1993) three-factor model in columns (5), (6), (7) and (8). The alpha is estimated by three-year rolling-window timeseries regressions on the factor models. The main independent variable is AFP, measured for each individual fund at each quarter. Panel A shows the result for index-based AFP; Panel B shows the result for two-quarter trade-based AFP, i.e. AFP calculated by active weight changes relative to two quarters prior. The regressions control for the first order lag of the dependent variable and fund characteristics such as fund size (TNA), age, expense ratio, and turnover ratio. Fund FE is included for all regressions. Clustering is done alternatively at fund level and at time (quarter) level. t-statistics are present in parentheses. *, ** and *** indicate statistical significance at 10%, 5% and 1% levels, respectively.

4. Forecasting Firms' Earning Surprises with Mutual Funds Holdings

The objective of this paper is to use fund holdings and firm earnings to identify managerial skills in mutual fund industry. The analysis done in the previous section combines these two types of data to identify managerial skills via the measure AFP following JZ. Since AFP is measured for each individual fund, AFP allows for identifying skill at individual fund level.

In this section, I combine the two data types to identify skill at the aggregate mutual fund industry level, rather than at individual fund level. More specifically, I analyze whether active investment decisions of all funds in the sample, reflected in the aggregated changes in their portfolio weights relative to one, two or four quarters prior, can predict earnings surprises of one, two, of four quarters ahead. In an additional analysis, I analyze whether the intensity of mutual fund trading, measured by the square of the said portfolio weight changes, can predict earnings surprises.

The earnings surprises are calculated as the deviation between the earnings actuals and the mean of the analyst forecasts. Fund managers may adjust their portfolio weights in anticipation of future earnings; they will add more [reduce] weights to stocks that they expect to earn positive [negative] earnings surprise – in effect drive stock price up [down]. If the aggregated active portfolio adjustments in the industry can significantly predict future earnings surprise, then I deduce that in the aggregate the mutual fund industry can predict firms' future earnings better than do the analysts. I also conjecture that a significant portion of the financial market relies on analyst forecasts to make investment decisions. Consequently, if mutual fund managers can predict firms' earnings better than analysts and profit from own predictions, then they should outperform the significant portion of the financial market. Put differently, I make the following assumption: if in aggregate mutual fund managers can predict earnings better than analysts, then it is an indication that skill exists in the mutual fund industry. With this assumption in mind, I formulate the hypothesis:

Hypothesis 2: In aggregate, the mutual fund industry can predict firms' future earnings better than analysts.

I perform the analysis by running the following regressions:

$$\begin{aligned} Unexpected\ Earning_{i,t+k} \\ &= \beta_1 Aggr.Active\ Weight_{i,t-3} \\ &+ \beta_2 Aggr.Active\ Weight_{i,t-6} \\ &+ \beta_3 Aggr.Active\ Weight_{i,t-12} + \varepsilon_{i,t} \end{aligned} \tag{14}$$

$$\begin{aligned} Unexpected\ Earning_{i,t+k} \\ &= \beta_1 \left(Aggr.Active\ Weight_{i,t-3}\right)^2 \\ &+ \beta_2 \left(Aggr.Active\ Weight_{i,t-6}\right)^2 \\ &+ \beta_3 \left(Aggr.Active\ Weight_{i,t-12}\right)^2 \\ &+ \varepsilon_{i,t} \end{aligned} \tag{15}$$

$$where\ Aggr.Active\ Weight_{i,t} = \sum_{j=1}^{n} (w_{j,t}^{i} - w_{j,t-l}^{i})$$

Aggregated active weight $Aggr.Active\ Weight_{i,t-3[6][12]}$ for security i at month t is the change in the security i's weight in fund j relative to the weight from the previous three [six][twelve] months, aggregated across n funds j for security i. Active weight is the difference between contemporaneous weight and the passive weight inferred from past holdings according to Equation (12). $Unexpected\ Earning_{i,t+k}$ is the earning surprise for stock i at month t + k, measured by the difference between the average of analysts' forecasts and the earnings actual. Analysts forecasts and earnings actuals are obtained from I/B/E/S. Details about the data per se and the data work are provided in Appendix A.6.

With Equation (14) and (15) in place, I elaborate Hypothesis 2 as follows:

Hypothesis 2a: The aggregated active investments by fund managers can predict earnings surprises

In the regression analysis for Equation (14), I alternatively control for firm fixed effect, time fixed effect, and alternatively cluster standard errors by firm and by time. The dependent variables chosen are the earnings surprises whereby the period between actuals and forecasts are either three months or twelve months apart. The result for twelve-month [three-month] earnings surprises is displayed in Table 5 [Table A.4]. It can be seen immediately that none of the coefficients in Table 5 and Table A.4 are statistically significant. This insignificant result indicates that the sum of the active weight changes for a stock cannot predict the respective firm's future earnings surprises.

Table 5. Predicting earnings surprises one year ahead using active investment decisions

	UE12M	UE12M	UE12M	UE12M
Aggr. Active Weight 3M	171,88	171,88	415,42	415,42
	(0,37)	(0,32)	(0,86)	(1,25)
Aggr. Active Weight 6M	-641,31	-641,31	58,68	58,68
	(-0,79)	(-0,86)	(0,70)	(0,58)
Aggr. Active Weight 12M	-280,97	-280,97	-261,7	-261,7
	(-0,60)	(-0,39)	(-0,94)	(-1,1)
No. Observations	161507	161507	161507	161507
No. Firms	7364	7364	7364	7364
No. Quarters	61	61	61	61
Firm FE	No	No	Yes	Yes
Quarter FE	Yes	Yes	No	No
Firm Cluster	Yes	No	Yes	No
Quarter Cluster	No	Yes	No	Yes

Table 5 reports the results for four regressions following Equation (14). The dependent variable is the earnings surprises for the earnings actuals from one year ahead. The independent variables are the active investments aggregated across all funds in the sample. The active investments are the changes in the weights for the common stock of the respective firm relative to three months, six months, or twelve months prior. Firm FE, Time FE are alternatively controlled for. Standard errors are alternatively clustered at fund and time levels.

The regression analysis result for Equation (15) is displayed in Table 6. As before, the dependent variable is the unexpected earnings whereby the earnings forecasts and actuals are three months apart (Panel A) or twelve months apart (Panel B). The independent variables are the squares of the aggregated active weights, which can be interpreted as the intensity in aggregated active investments for the respective stock. The active weights are calculated as the portfolio weight change from three months, six months and twelve months prior, accounting for mechanical weight change due to changes in stock prices following Equation (12). Firm fixed effect and time fixed effect are alternatively included, and standard errors are alternatively clustered at firm level or at time (quarter) level.

An initial inspection shows that the intensity in active weight change relative to six months prior does not have any predictive power in all settings. As for the other two independent variables, their predictive powers are sensitive to model specifications. When firm effect is included and the residuals are at correlated across time for each fund (so that standard errors are clustered at fund level), the intensity of aggregated active weight changes relative to the previous 3 months can predict earnings surprises for earnings actuals both three months or one year ahead. More specifically, higher level of intensity in active investment relative to three months prior predicts higher earnings surprises three months ahead and lower earnings surprises one year ahead (third column in Panel A and B, respectively). When time fixed effect is included and the residuals are correlated among firms at each quarter (so that standard errors are clustered at time level), then the intensity in active investment relative to one year prior can predict higher unexpected earnings for the announcements in the next quarter (second column Panel A).

As Petersen (2009) remarks: “[..]estimates that are robust to the form of dependence in the data produce unbiased standard errors and correct confidence intervals; estimates that are not robust to the form of dependence in the data produce biased standard errors and confidence intervals that are often too small”. Therefore, whether the results in the second column or the third column (for both panels) holds depends on the structure of the data; this means that we can’t draw any definitive conclusion from the result in Table 6.

Furthermore, in view of some significant results in Table 6, it is worthwhile to discuss the potential economic interpretation of the predictive power of the intensity in active investments. Since it is the square of the aggregated active weight change, its value can be driven either by many funds making active investments of the same sign into the stock, or by many funds making active investments of opposites signs into the same stock. If the former scenario is the case, then we might also observe significant result for Equation (14). Given that some results for the square of the aggregated active investments are significant (Equation (15) and Table 6) but none of the results for the aggregated active investments are significant (Equation (14) and Table 5), it is likely that the value of the square of the aggregated weight change is driven by many funds making large active decisions in opposite signs, meaning that the funds have strongly different opinions about the future earnings of the stock and make strong active investments accordingly. In other words, there is a large dispersion among mutual funds in their forecasts about the future earnings of the firms, which in turn implies that the future earnings being concerned is difficult for the mutual fund industry to forecast. The earnings surprise in the dependent variable for Equations (7) and (8), after all, is a proxy for how difficult it is for analysts to make forecasts about the firms' earnings. Consequently, because the result in Table (5) is insignificant, the square of aggregated active investments becomes a proxy for how difficult it is for the mutual fund industry to forecast earnings, and the significant results in Table (6) then go to show that the degree of forecasting difficulty in the mutual fund industry can predict the degree of forecasting difficulty among the analysts. The positive signs of the coefficients in Table 6 then suggest general difficulty in forecasting earnings, because the positive coefficient can be interpreted that the higher dispersion in forecasts among mutual funds, the higher the errors from the analysts' forecasts. The negative signs then suggest that the forecasting ability of mutual fund industry is weaker than that of the analysts, because it can be interpreted that the higher the dispersion in forecasts among mutual funds, i.e. the more difficult it is for the mutual fund industry as a whole to accurately predict the earnings, the less errors from the analysts' forecasts, i.e. the less difficult it is for the analysts to predict the earnings more accurately.

That said, the negative coefficient in the third column in table 6 Panel B shows that the dispersion in opinions among the funds in the last three months can not predict earnings surprises twelve months ahead as well as analysts. However, funds are likely to adjust their portfolios in anticipation of earnings announcements three months ahead than one year ahead. As such, this result does not necessarily suggest higher forecasting difficulty in mutual fund industry compared to the analysts. The significant results in Panel A, if the respective models are correct, only show that it is generally difficult for both mutual fund industry and the analysts to forecast future firm earnings. In other words, the significantly negative coefficient in Panel B should not be interpreted as mutual fund industry having lesser skill than the analysts; and the significantly positive coefficients in Panel A do not provide evidence that mutual fund industry has better skill than the analysts.

Table 6. Predicting earnings surprises using intensity in active investment decisions

A. Earnings surprises for actuals one quarter ahead

	UE3M	UE3M	UE3M	UE3M
(Aggr. Active Weight 3M)^2	-0,02	-0,02	0,00007***	0.00007
	(-0,75)	(-0,89)	(3,7)	(0,48)
(Aggr. Active Weight 6M)^2	-0,005	-0,005	-0,00002	-0.0
	(-1,15)	(-1,54)	(-0,09)	(-0,06)
(Aggr. Active Weight 12M)^2	0,19	0,19***	-0,0014	-0,0014
	(0,81)	(3,64)	(-0,76)	(-0,77)
No. Observations	161507	161507	161507	161507
No. Firms	7364	7364	7364	7364
No. Quarters	61	61	61	61
Firm FE	No	No	Yes	Yes
Quarter FE	Yes	Yes	No	No
Firm Cluster	Yes	No	Yes	No
Quarter Cluster	No	Yes	No	Yes

B. Earnings surprises for actuals four quarters ahead

	UE12M	UE12M	UE12M	UE12M
(Aggr. Active Weight 3M)^2	-0,07	-0,07	-0,0002***	-0,0002
	(-0,77)	(-0,8)	(-5,86)	(-0,40)
(Aggr. Active Weight 6M)^2	-0,03	-0,03	-0,0003	-0,0003
	(-0,64)	(-0,64)	(-1,11)	(-0,29)
(Aggr. Active Weight 12M)^2	-0,06	-0,06	0,0012	0,0012
	(-0.09)	(-0,08)	(0,91)	(0,29)
No. Observations	161507	161507	161507	161507
No. Firms	7364	7364	7364	7364
No. Quarters	61	61	61	61
Firm FE	No	No	Yes	Yes
Quarter FE	Yes	Yes	No	No
Firm Cluster	Yes	No	Yes	No
Quarter Cluster	No	Yes	No	Yes

Table 6 shows the results from the regressions following Equation (15). The dependent variable is the earnings surprises for the earnings actuals from one quarter ahead for Panel A and one year ahead for Panel B. The independent variables are the square of the active investments aggregated across all funds in the sample. The active investments are the changes in the weights for the common stock of the respective firm relative to three months, six months, or twelve months prior. Firm FE, Time FE are alternatively controlled for. Standard errors are alternatively clustered at fund and time levels. *** indicates statistical significance at 1% level.

5. Conclusion

The literature initially approaches the research questions regarding mutual fund performance and by extension managerial skill by scrutinizing the fund returns. As a classic example, Jensen (1968) uses the intercept in a regression of fund return on the return of a market portfolio vis-à-vis CAPM to capture the ability of mutual funds to beat the market, i.e. to capture fund managers' skills. His result, which shows stark underperformance of actively managed funds against the market portfolio, has sparked a lively debate in the literature on the topic. While various measures of fund performance have been invented over time (e.g. Sharpe ratio), the use of the intercept in a regression of fund return in excess of a risk-free rate on some benchmark portfolios (see e.g. Fama-French (1993) and Carhart (1997)) to capture fund outperformance has become a normative practice, so much so that it has been termed Jensen alpha or even referred to simply as alpha. However, as prominence invites scrutiny, a number of criticisms have been directed at the use of alpha to measure performance and managerial skill, notably Roll (1978), Dybvig and Ross (1985a, 1985b), Berk and Green (2004), Berk and Binsbergen (2014). Fund holdings data, by connecting fund data to the data at the security level for the respective fund, has opened up a level of granularity that enables researchers to come up with innovative performance measures and to explore aspects of the topic that are otherwise unapproachable with fund returns data alone. Pioneering the use of fund holdings data to evaluate mutual fund performance, Grinblatt and Titman (1989) computes "hypothetical returns" from equity holdings of funds to proxy for gross returns of the funds. They argue that if fund managers do have skills, they would have extracted economic rent and consequently the net returns, which had been widely used at the time to document underperformance of funds, cannot reflect managerial skills. They then proceed to compute the fund Jensen alpha using the gross return and find evidence of managerial skills. Even though their result is similarly subject to the aforementioned criticisms directed at alpha, their use of fund holdings and their findings provided an important perspective at the time. Since then, many holdings-based performance measures have been invented to measure fund performance and identify managerial skills.

This paper combines fund holdings data and firm earnings announcements to identify managerial skills at two levels, namely individual fund level and the mutual fund industry in aggregate. To identify managerial skill at individual fund level, I partially follow the approach by Jiang and Zheng (2018) (JZ). I compute the AFP measure, which is computed by first multiplying the active weight of a component stock by the cumulative abnormal returns on the stock during a three-day window around the next earnings announcements. The AFP measure of a fund is the sum of such product across all component stocks in the fund's portfolio. The active weight is measured either as the difference between the weight of the stock in the portfolio and in a benchmark index, in which case the measure is referred to as index-based AFP; or between the current weight and the weight of a previous period, in which case the measure is referred to as trade-based AFP. The AFP measure is intended to capture the ability of mutual fund managers to make active investment decisions in anticipation of upcoming earnings announcements. However, in contrast to JZ, the results in this paper provides mixed evidence that index-based AFP can capture managerial skills, and no evidence whatsoever in favour of trade-based AFP. The result in a univariate analysis wherein funds are sorted into decile portfolios whose performance are in turn evaluated, the result for index-based AFP is ostensibly consistent with that in JZ in the full sample. When the sample is split into overlapping and non-overlapping periods, however, only the result in overlapping period is significant. This shows that the result in JZ is not robust to more recent sample period. In another multivariate analysis using panel data regressions, I regress funds' alpha from Carhart's (1997) four-factor model on the funds' index-based AFP and other characteristics as JZ does. I also extend the analysis by using funds' alpha from Fama-French's (1993) three-factor model. The result using Carhart alpha is consistent with the previous result in JZ, but the result using Fama-French Alpha is sensitive to whether the standard errors are clustered at fund or time level; this sensitivity doesn't happen for Carhart alpha. In a nutshell, the result for index-based AFP is sensitive to sample period in the univariate analysis and to the factor model used to calculate alpha in the multivariate analysis, and the result for trade-based AFP is plainly insignificant. I conclude that the evidence in this paper is not strong enough to support the hypothesis that AFP can capture managerial skill.

To identify the existence of skill in the mutual fund industry as a whole, I analyze whether the active portfolio weight changes aggregated across all funds in the sample can predict future unexpected earnings. More specifically, for each firm, I calculate the aggregated active weight changes made by all funds relative to one quarter, two quarters and four quarters prior. I then regress unexpected earnings on these variables. If one of the coefficients is significantly positive [negative], that means that on average the mutual fund industry in aggregate can adjust portfolio weights to capitalize [avoid] on future positive [negative] unexpected earnings; that is, on average the mutual fund industry can predict earnings better than analysts' forecasts. The empirical result shows that none of the coefficient is significant, however. It is unclear whether the result indeed reflects the lack of predictive power of the aggregated active investment in the industry in forecasting unexpected earnings, or whether the empirical setup fails to capture it.

As a concluding remark, I would like to bring attention back to the trade-based AFP result wherein the result in this paper stands in sharp contrast to that in JZ. While the driver behind the discrepancy in result is unclear, one important difference between the two papers is the source of fund holdings data. This paper obtains fund holdings data from CRSP which contains holdings on both equity and non-equity securities. On the contrary, JZ obtains holdings data from Thompson database, which only contains holdings data on common equity. This can have major implications on the weights estimated for the fund portfolio constituents. For instance, Elton, Gruber and Blake (2011) find that the difference in alpha owing to not accounting for the non-common-equity portion of a portfolio is large on average and very large for individual funds. To the best of my knowledge, this paper is the only one using fund holdings data from CRSP; the majority of the extant literature that work with holdings data obtain the data from Thompson database. This prompts future research on the difference in fund holdings data between CRSP and Thompson and the implication thereof on both past and future research that employs fund holdings data.

6. Appendix

Table A.1. AFP Decile Portfolio – Univariate Analysis 2001Q1 – 2014Q4

A. Decile portfolio formed according to the index-based AFP. Sample period 2001Q1-2014Q4

	Low	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**High**	**High-Low**
					Net Return						
Average Return	1,55	2,87	2,88	2,54	2,54	2,5	2,94	2,89	2,66	2,69	1,03
	(0,83)	(2)	(1,92)	(1,87)	(1,91)	(1,99)	(2,19)	(2,29)	(1,81)	(1,94)	(1,26)
CAPM α	-2,13	-0,79	-0,26	-0,36	-0,14	-0,22	0,04	0,16	0,01	-0,26	1,69
	(-4,08)	(-1,64)	(-0,78)	(-1,38)	(-0,73)	(-1,29)	(0,13)	(0,49)	(0,03)	(-0,42)	(2,48)
Carhart α	-2,12	-0,83	-0,41	-0,46	-0,22	-0,32	-0,01	0,19	0	0,11	1,98
	(-3,86)	(-1,66)	(-1,29)	(-2,13)	(-1,65)	(-2,26)	(-0,05)	(0,77)	(0,01)	(0,2)	(3,06)
Fama-French α	-2,15	-0,8	-0,4	-0,46	-0,23	-0,3	-0,06	0,09	-0,12	-0,34	1,61
	(-4,04)	(-1,62)	(-1,28)	(-2,2)	(-1,69)	(-2,15)	(-0,23)	(0,37)	(-0,33)	(-0,56)	(2,35)
Pastor-Stambaugh α	-2,15	-0,78	-0,42	-0,47	-0,24	-0,33	-0,01	0,19	0,01	0,11	2,02
	(-4,45)	(-1,49)	(-1,3)	(-2,21)	(-1,81)	(-2,42)	(-0,05)	(0,77)	(0,03)	(0,2)	(3,56)

B. Decile portfolio formed according to the 3-month trade-based AFP. Sample period 2001Q1-2014Q4

	Low	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**High**	**High-Low**
					Net Return						
Average Return	1,41	3,63	3,57	1,91	2,42	2,78	2,92	2,63	2,7	1,79	0,04
	(0,86)	(2,29)	(2,42)	(1,17)	(1,61)	(2,03)	(2)	(1,62)	(1,39)	(0,98)	(0,04)
CAPM α	-1,38	0,27	-0,09	-0,41	-0,43	-0,35	-0,32	-0,5	-0,11	-1,72	-0,42
	(-1,78)	(0,5)	(-0,13)	(-1,18)	(-1,33)	(-1,18)	(-0,79)	(-1,03)	(-0,15)	(-1,63)	(-0,43)
Carhart α	-1,45	0,13	-0,29	-0,46	-0,32	-0,35	-0,49	-0,59	-0,29	-2,22	-0,45
	(-2,07)	(0,26)	(-0,61)	(-1,87)	(-1,36)	(-1,34)	(-1,26)	(-1,45)	(-0,41)	(-2,22)	(-0,49)
Fama-French α	-1,49	0,1	-0,41	-0,47	-0,32	-0,28	-0,33	-0,58	-0,02	-1,92	-0,43
	(-2,2)	(0,21)	(-0,81)	(-1,95)	(-1,42)	(-1,12)	(-0,92)	(-1,53)	(-0,03)	(-2,06)	(-0,48)
Pastor-Stambaugh α	-1,45	0,19	-0,39	-0,46	-0,31	-0,35	-0,51	-0,56	-0,48	-2,33	-0,45
	(-2,07)	(0,36)	(-0,81)	(-2,08)	(-1,31)	(-1,32)	(-1,32)	(-1,37)	(-0,7)	(-2,37)	(-0,49)

C. Decile portfolio formed according to the 6-month trade-based AFP. Sample period 2001Q1-2014Q4

	Low	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**High**	**High-Low**
					Net Return						
Average Return	1,98	2,52	2,26	1,98	1,99	2,2	1,83	1,66	2,38	3,05	1,16
	(1,21)	(1,11)	(1,28)	(1,25)	(1,3)	(1,35)	(1,15)	(1,01)	(1,33)	(1,74)	(1,26)
CAPM α	-1,65	0,4	-0,42	-0,26	-0,49	-0,22	-0,54	-0,94	-0,29	-0,19	0,72
	(-2,41)	(0,51)	(-1,08)	(-0,58)	(-1,24)	(-0,38)	(-1,49)	(-2,29)	(-0,44)	(-0,21)	(0,74)
Carhart α	-1,1	0,27	-0,44	-0,27	-0,47	-0,28	-0,52	-0,95	-0,5	-0,2	0,55
	(-1,56)	(0,41)	(-1,38)	(-0,8)	(-1,3)	(-0,49)	(-2,1)	(-2,64)	(-0,87)	(-0,23)	(0,55)
Fama-French α	-1,55	0,17	-0,49	-0,24	-0,46	-0,29	-0,49	-0,97	-0,62	-0,36	0,66
	(-2,28)	(0,25)	(-1,54)	(-0,72)	(-1,29)	(-0,52)	(-2,03)	(-2,78)	(-1,11)	(-0,42)	(0,69)
Pastor-Stambaugh α	-1,07	0,21	-0,45	-0,26	-0,45	-0,24	-0,51	-0,93	-0,49	-0,19	0,59
	(-1,52)	(0,32)	(-1,46)	(-0,76)	(-1,24)	(-0,43)	(-2,07)	(-2,68)	(-0,86)	(-0,22)	(0,64)

D. Decile portfolio formed according to the 12-month trade-based AFP. Sample period 2001Q1-2014Q4

	Low	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**High**	**High-Low**
					Net Return						
Average Return	1,09	2,65	1,13	1,14	1,89	1,93	2,04	2,1	2,64	2,2	1,21
	(0,66)	(1,25)	(0,62)	(0,68)	(1,2)	(1,23)	(1,35)	(1,25)	(1,32)	(1,18)	(1,15)
CAPM α	-1,62	0,11	-0,83	-0,46	-0,22	-0,4	-0,33	-0,19	0,07	-0,45	0,74
	(-2,16)	(0,15)	(-1,49)	(-1,16)	(-0,6)	(-0,98)	(-0,76)	(-0,45)	(0,08)	(-0,45)	(0,68)
Carhart α	-1,58	-0,35	-0,79	-0,44	-0,23	-0,38	-0,43	-0,34	0,2	-0,2	0,96
	(-2,14)	(-0,52)	(-1,72)	(-1,41)	(-0,75)	(-1,16)	(-1,13)	(-0,98)	(0,28)	(-0,21)	(0,85)
Fama-French α	-1,64	-0,34	-0,77	-0,41	-0,23	-0,41	-0,44	-0,27	0,02	-0,46	0,74
	(-2,27)	(-0,52)	(-1,69)	(-1,33)	(-0,75)	(-1,26)	(-1,18)	(-0,78)	(0,03)	(-0,5)	(0,66)
Pastor-Stambaugh α	-1,58	-0,35	-0,85	-0,47	-0,24	-0,35	-0,43	-0,27	0,19	-0,2	0,95
	(-2,14)	(-0,52)	(-1,84)	(-1,5)	(-0,74)	(-1,07)	(-1,12)	(-0,79)	(0,27)	(-0,21)	(0,84)

Table A.2. AFP Decile Portfolio – Univariate Analysis 2015Q1 – 2018Q4

A. Decile portfolio formed according to the index-based AFP. Sample period 2015Q1 - 2018Q4

	Low	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**High**	**High-Low**
					Net Return						
Average Return	1	0,23	1	1,32	1,25	1,27	1,35	1,66	2,58	1,88	0,88
	(0,69)	(0,15)	(0,67)	(0,82)	(0,78)	(0,79)	(0,84)	(1,1)	(1,63)	(0,92)	(0,59)
CAPM α	-1,1	-2,07	-1,24	-1,19	-1,23	-1,23	-1,15	-0,65	-0,43	-1,12	-0,23
	(-1,34)	(-3,02)	(-1,83)	(-2,26)	(-2,21)	(-2,16)	(-1,97)	(-1,05)	(-0,59)	(-1,17)	(-0,15)
Carhart α	-1,27	-2,22	-1,36	-1,31	-1,26	-1,33	-1,25	-0,73	-0,8	-1,25	-0,19
	(-1,64)	(-2,97)	(-1,76)	(-2,56)	(-2,26)	(-2,42)	(-2,3)	(-1,33)	(-1,22)	(-1,15)	(-0,11)
Fama-French α	-1,07	-2,12	-1,29	-1,18	-1,14	-1,18	-1,1	-0,55	-0,39	-1,2	-0,33
	(-1,21)	(-2,82)	(-1,73)	(-2)	(-1,88)	(-1,87)	(-1,7)	(-0,82)	(-0,48)	(-1,15)	(-0,2)
Pastor-Stambaugh α	-1,29	-2,2	-1,33	-1,32	-1,25	-1,31	-1,24	-0,73	-0,98	-1,18	-0,09
	(-1,61)	(-2,82)	(-1,66)	(-2,43)	(-2,13)	(-2,29)	(-2,18)	(-1,26)	(-1,6)	(-1,09)	(-0,05)

B. Decile portfolio formed according to the 3-month trade-based AFP. Sample period 2015Q1 - 2018Q4

	Low	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**High**	**High-Low**
					Net Return						
Average Return	0,72	-1,34	0,69	-1,19	-0,25	0,19	-0,27	0,11	-1,51	-0,1	-0,82
	(0,38)	(-0,57)	(0,32)	(-0,44)	(-0,1)	(0,09)	(-0,11)	(0,03)	(-0,49)	(-0,04)	(-0,51)
CAPM α	-1,64	-3,21	-1,26	-2,32	-1,3	-1,03	-1,25	-1,49	-2,55	-2,63	-1,2
	(-1,19)	(-2,89)	(-1,63)	(-1,94)	(-1,12)	(-0,97)	(-1,07)	(-0,97)	(-2,27)	(-1,41)	(-0,67)
Carhart α	-1,44	-3,22	-0,87	-2,27	-1,21	-1,01	-1,1	-1,24	-2,2	-2,22	-0,99
	(-0,96)	(-3,88)	(-1,45)	(-2,18)	(-1,14)	(-1,05)	(-1,2)	(-0,8)	(-1,83)	(-1,13)	(-0,48)
Fama-French α	-1,32	-2,73	-0,83	-2,22	-1,16	-0,83	-1,06	-1,28	-2,31	-2,07	-0,95
	(-0,91)	(-2,75)	(-1,66)	(-1,77)	(-0,92)	(-0,79)	(-0,99)	(-0,9)	(-1,79)	(-1,09)	(-0,49)
Pastor-Stambaugh α	-1,43	-3,25	-0,93	-2,26	-1,13	-1,03	-1,13	-1,15	-2,62	-2,29	-1,06
	(-0,9)	(-3,63)	(-1,5)	(-1,92)	(-0,97)	(-0,97)	(-1,09)	(-0,66)	(-2,24)	(-1,12)	(-0,49)

C. Decile portfolio formed according to the 6-month trade-based AFP. Sample period 2015Q1 - 2018Q4

	Low	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**High**	**High-Low**
					Net Return						
Average Return	1,03	-0,82	0,08	0,7	0,16	1,46	1,46	1,37	3,5	-2,14	-3,17
	(0,43)	(-0,31)	(0,04)	(0,34)	(0,07)	(0,59)	(0,67)	(0,48)	(1,01)	(-0,81)	(-1,94)
CAPM α	-2,21	-3,36	-2,59	-1,76	-2,13	-0,68	-0,77	-2,64	-0,46	-5,09	-3,1
	(-1,5)	(-2,71)	(-3,03)	(-2,3)	(-2,37)	(-0,45)	(-0,75)	(-2,1)	(-0,24)	(-2,43)	(-1,73)
Carhart α	-1,77	-3,29	-2,79	-1,77	-1,58	-1,48	-0,45	-2,58	-0,27	-4,22	-2,66
	(-1,39)	(-3,45)	(-3,95)	(-2,6)	(-1,93)	(-0,86)	(-0,38)	(-2,33)	(-0,15)	(-2,15)	(-1,34)
Fama-French α	-1,53	-2,97	-2,53	-1,52	-1,47	-1,41	-0,42	-2,56	0,12	-4,14	-2,82
	(-1,14)	(-2,61)	(-2,93)	(-1,63)	(-1,47)	(-0,86)	(-0,34)	(-1,5)	(0,08)	(-2,22)	(-1,47)
Pastor-Stambaugh α	-1,75	-3,26	-2,81	-1,74	-1,55	-1,38	-0,38	-2,96	-2,01	-4,38	-2,83
	(-1,31)	(-3,32)	(-3,85)	(-2,4)	(-1,75)	(-0,75)	(-0,3)	(-2,69)	(-0,83)	(-2,34)	(-1,52)

D. Decile portfolio formed according to the 12-month trade-based AFP. Sample period 2015Q1 - 2018Q4

	Low	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**High**	**High-Low**
					Net Return						
Average Return	0,94	0,13	0,08	1,57	1,28	-0,45	0,3	-0,09	3,42	-0,2	-1,13
	(0,44)	(0,05)	(0,03)	(0,74)	(0,53)	(-0,22)	(0,1)	(-0,04)	(1,22)	(-0,08)	(-0,7)
CAPM α	-2,13	-2,84	-2,01	-0,83	-1,2	-2,19	-3,42	-3,03	-0,31	-3	-1,08
	(-2,11)	(-2,26)	(-1,99)	(-0,73)	(-1,05)	(-2,27)	(-2,6)	(-2,7)	(-0,13)	(-1,51)	(-0,6)
Carhart α	-1,73	-2,94	-2,09	-0,48	-1	-2,42	-2,38	-3,79	0,02	-2,42	-0,9
	(-1,88)	(-2,92)	(-2,23)	(-0,53)	(-1,08)	(-1,76)	(-2,71)	(-2,51)	(0,01)	(-1,16)	(-0,44)
Fama-French α	-1,64	-2,71	-1,77	-0,25	-0,79	-2,19	-2,07	-3,57	0,61	-2,36	-0,93
	(-1,83)	(-1,88)	(-1,73)	(-0,27)	(-0,74)	(-1,55)	(-1,33)	(-2,35)	(0,26)	(-1,2)	(-0,48)
Pastor-Stambaugh α	-1,72	-2,96	-2,06	-0,5	-1,04	-2,45	-2,2	-3,83	0,34	-2,46	-0,94
	(-1,78)	(-2,74)	(-2)	(-0,51)	(-1,03)	(-1,85)	(-2,2)	(-2,1)	(0,27)	(-1,13)	(-0,44)

Table A.3. AFP Panel Data Regression – Multivariate Analysis

A. Trade-based AFP - Active portfolio weigh change relative to one quarter prior

	Carhart Alpha				FF Alpha			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
AFP	-0,03	-0,03	0,0028	0,0028	-0,05	-0,05	-0,015	-0,015
	(-1,19)	(-0,88)	(0,08)	(0,07)	(-1,69)	(-1,10)	(-0,46)	(-0,36)
log(TNA)			0,0001**	0,0001**			0,0001***	0,0001*
			(2,76)	(2,01)			(2,61)	(1,84)
log(Age)			-0,0003***	-0,0003			-0,0004***	-0,0004*
			(-2,76)	(-1,38)			(-3,07)	(-1,7)
Expense (%)			-0,0006	-0,0006			-0,0019	-0,0019
			(-0,62)	(-0,47)			(-1,55)	(-1,45)
Turnover (%)			-0,00	-0,00			0,00	0,00
			(-0,87)	(-0,56)			(0,71)	(0,56)
1st Order Lag			0,027**	0,027**			0,03***	0,03
			(2,56)	(1,24)			(4,78)	(1,49)
No. Observations	57691	57691	41062	41062	57691	57691	41062	41062
No. Funds	4426	4426	3783	3783	4426	4426	3783	3783
No. Quarters	49	49	48	48	49	49	48	48
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund Cluster	Yes	No	Yes	No	Yes	No	Yes	No
Quarter Cluster	No	Yes	No	Yes	No	Yes	No	Yes

B. Trade-based AFP - Active portfolio weigh change relative to four quarters prior

	Carhart Alpha				FF Alpha			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
AFP	0,0081	0,0081	0,013	0,013	0,019	0,019	0,0186	0,0186
	(0,29)	(0,31)	(0,41)	(0,38)	(0,60)	(0,53)	(0,47)	(0,4)
log(TNA)			0,0001***	0,0001**			0,0001***	0,0001*
			(2,79)	(2,04)			(2,64)	(1,87)
log(Age)			-0,0003***	-0,0003			-0,0004***	-0,0004*
			(-2,83)	(-1,42)			(-3,15)	(-1,75)
Expense (%)			-0,0005	-0,0005			-0,0019	-0,0019
			(-0,56)	(-0,41)			(-1,52)	(-1,37)
Turnover (%)			-0,00	-0,00			0,00	0,00
			(-0,90)	(-0,41)			(0,70)	(0,55)
1st Order Lag			0,02**	0,02			0,03***	0,03
			(2,55)	(1,23)			(4,8)	(1,49)
No. Observations	57669	57669	41053	41053	57669	57669	41053	41053
No. Funds	4426	4426	3777	3777	4426	4426	3777	3777
No. Quarters	49	49	48	48	49	49	48	48
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund Cluster	Yes	No	Yes	No	Yes	No	Yes	No
Quarter Cluster	No	Yes	No	Yes	No	Yes	No	Yes

Table A.4. Predicting earnings surprises three months ahead using active investment decisions

	UE3M	UE3M	UE3M	UE3M
Aggr. Active Weight 3M	168,97	168,97	72,38	72,38
	(0,57)	(0,35)	(0,82)	(1,12)
Aggr. Active Weight 6M	-74,47	-74,47	-9,66	-9,66
	(-0,10)	(-0,10)	(-0,2)	(-0,22)
Aggr. Active Weight 12M	-333,28	-333,28	-13,71	-13,71
	(-0,92)	(-0,50)	(-0.38)	(-0,25)
No. Observations	161507	161507	161507	161507
No. Firms	7364	7364	7364	7364
No. Quarters	61	61	61	61
Firm FE	No	No	Yes	Yes
Quarter FE	Yes	Yes	No	No
Firm Cluster	Yes	No	Yes	No
Quarter Cluster	No	Yes	No	Yes

A.5. Mutual fund data description

I obtain mutual fund data from four different tables from CRSP Mutual Fund database, downloaded from WRDS. The first table, referred to as Fund Summary on WRDS, contains numerous variables on fund characteristics at share class level, of which the ones relevant to this paper are the CRSP objective code, the date the fund-share class was first offered, the date of the latest available net asset value (NAV), the percentage of common stocks in the portfolio (per_com), quarterly data on NAV, total net asset (TNA), turnover ratio and expense ratio. There are two primary fund filters, the first of which is filter by funds' investment strategies. To this end, there is a number of variables available on CRSP, namely Strategic Insight Objective Code, Wiesenberger Objective Code, Lipper objective Code, policy, and the aforementioned CRSP Objective Code. With the exception of CRSP Objective Code, these other codes have different validity periods. For example, Wiesenberger Objective Code is available up to 1993, while Lipper Objective Code begins in 1998. To reconcile all these objective codes, according to the CRSP US Mutual Fund Guide available on WRDS, CRSP Objective Code maps these codes into a continuous series, hence used for the first fund filter. A fund is chosen for the analysis if it has one of the following objective codes: EDYG, EDYI, EDYB, EDCM, EDCI, EDCS, representing equity, domestic funds whose investment strategies focus on Growth (EDYG), Income (EDYI), Growth & Income (EDYB), Mid-cap (EDCM), Micro-cap (EDCI), or Small-cap (EDCS) stocks. Additionally, I remove funds whose names contain “Index”, “S&P”, “DOW”, “Wilshire”, ‘Russell”, “Balanced”, and “International”. This filter implies the exclusion of any non-US funds and any funds whose investment strategies focus on fixed income assets. As a second fund filter, only funds for whom common stocks constitute between 95 and 100 percent of the total holdings at a particular quarter; that is, funds with per_com values between 95 and 100. The reason is that, even though only domestic equity funds are selected from the first filter, i.e. funds that focus on domestic equity as the primary part of their strategies, these funds can still have holdings in foreign equity or other fixed-income assets. Plus, the analysis will focus on holdings in common stocks rather than alternatives such as preferred stocks.

The second table from CRSP Mutual Fund database is the Portfolio Holdings, aptly named on WRDS. The table contains variables related to a fund’s portfolio holdings, such as security identifiers (name, permno, cusip), number of shares (nbr_shares) of the respective security, market value of the holdings of the respective security (market_val), the security’s percentage of total net asset (percent_tna), period end date of the reported holding (report_dt), date of bond maturity and coupon date if the security is a fixed-income asset. I obtain mutual fund portfolio holdings from the first quarter of 2001 to the last quarter of 2018 from this table.

One apparent candidate for the portfolio weights is the variable percent_tna, a security’s percentage of the fund’s total net asset. However, as mentioned above, this paper estimates the fund portfolio weights rather than uses this variable which was obtained directly from the data source. There are two main reasons. The first reason is missing data. Roughly 4% of the observations from the raw data do not have percent_tna. Second, after summing up the percent_tna for a fund-quarter, the percent_tna of the securities do not add up to 100%. The summed percent_tna for a random fund-quarter can range anywhere between less than -100 and more than 100.

Due to these two reasons, this paper will estimate the portfolio weights with the raw data obtained from this second table.

Some data work is done before the weight is estimated. First, I remove all fund-quarter whose summed percent_tna is zero, and then I keep only the fund-quarters whose summed percent_tna fall between 5th percentile and 95th percentile, which corresponds to the summed percent_tna between 83 and 102 percent, respectively. Second, I calculate the total market value of a fund-quarter. As a reminder, market_val variable is the market value of the holding of a security for a fund-quarter. I then calculate the weight of a security for a fund-quarter by dividing the security's market value by the total market value of the fund-quarter. In other words, contrary to percent_tna which by definition is the security's percentage of total net asset, the estimated weight of a fund-quarter-security is the percentage of the market value of the holding of a security out of the total market value of the fund, as shown in the equation below.

$$w_{i,t}^{f} = \frac{n_{i,t}^{f} * \ p_{i,t}}{\sum_{j=1}^{N} n_{j,t}^{f} * \ p_{j,t}}$$

$w_{i,t}^{f}$: $weight\ of\ security\ i\ for\ fund\ f\ at\ time\ t$

$p_{i,t}$: $price\ of\ security\ i\ at\ time\ t$

$n_{i,t}^{f}$: $the\ number\ of\ security\ i\ held\ by\ fund\ f\ at\ time\ t$

The data renders this method not without imperfection. There are many observations wherein the market value of a security held is zero, even though the number of the respective security held is positive. To remedy this situation, for the common equity observations where the market value is 0 but the number of shares held is positive, I obtain stock price from CRSP and map to the corresponding observations via identifier *permno*. I then use multiply this stock price by the number of shares held to calculate the market value that is otherwise 0.

Permno is an important identifier for common stocks since it is used to map different datasets together. However, there are some observations where permno is missing, even though cusip, another security identifier, is available.

I download CRSP Stock Header table from WRDS which contains stock identifiers and the start dates and end dates of their availability. I then map permno from this table to the holdings dataset via cusip.

The third table from CRSP Mutual Fund Database is the Monthly Returns which contains monthly returns, total net asset (TNA) and net asset value (NAV). Monthly returns are computed as the percentage change in NAV from one month to the next, taking into account reinvested dividends; and NAVs are exclusive of all management expenses and 12b-fees, front and rear loads.

The data from this table is on a share class level. In order to calculate the monthly returns for the funds, I first map share class identifier crsp_fundno to fund identifier crsp_portno using the fourth table named Fund-Portfolio Map on WRDS. The monthly return is then calculated as the weighted returns across share classes of a fund, the weight being the TNA of the respective share classes. At times there is missing data on the total net assets. For a fund-month, if there is TNA data for some share classes and not others, I assign the lowest available TNA to the share classes with missing TNA. For the fund-months where none of the share classes have data on TNA, I compute equally weighted returns instead of TNA-weighted returns.

A.6 Description of data obtained from I/B/E/S and the data work

This appendix describes the data and the procedure to calculate earnings surprises for the analysis in Section 4. Analyst forecasts and earnings actuals are obtained from the Institutional Brokers' Estimate System, commonly known as I/B/E/S. The main variables downloaded are firm identifiers (TICKER, CUSIP, C(ompany)NAME), analyst identifier (ESTIMATOR), the forecasted value (VALUE), the announcement date of the forecast (ANNDATS), the announcement of the forecast period end date (FPEDATS), the corresponding earnings actual (ACTUAL), the announcement date of the actual (ANNDATS_ACT).

I make an assumption that the forecast period end date (FPEDATS) allows me to deduce the fiscal calendar of the firm. For instance, if the FPEDATS ends in the end of month 3, 6, 9, or 12, I assume that the fiscal calendar of the firm coincides with the standard calendar. If the FPEDATS ends in month 1, 4, 7 or 10 [2, 5, 8, or 11], I assume the firm's fiscal calendar starts in February

[March]. I then make an adjustment to align the fiscal calendar of the whole dataset. For FPEDATS that ends in month 1, 4, 7 or 10 [2, 5, 8, or 11], I lag all the date variables back by one month [two months], including FPEDATS, ANNDATS and ANNDATS_ACT.

Additionally, there's a forecast period indicator (FPI) which indicates the period of the earnings actual the forecast is for. An FPI value of 6, 7, 8 or 9 shows that the forecast is made for the earnings actual one, two, three, or four quarters ahead, respectively. There are more values that an FPI can have, but the analysis of this paper requires the calculation of unexpected earnings one, two, and four quarters ahead, so I obtain data with FPI of 6, 7, 8 and 9 (8 is obtained but unused).

However, FPI doesn't always work as intended. Table A.6.1 below shows an example. The table displays the forecasts from analyst with code 282 for the company named "EP ENGR CORP" for its earnings announced on 28/10/2015. The table is sorted by FPI in ascending order, so that the forecasts closer to the announcements appear first. It could be noticed that there can be more than one row for each FPI. This means that the analyst can revise his or her forecast and the dataset will update the revision in a new row with an updated ANNDATS (date of the forecast announcement). More importantly, it could be noticed that the forecast of a given FPI may not necessarily stay within the quarter that it is intended to by the FPI. For example, there are two forecasts on 21/04 and 30/04, but the former has FPI of 8 and the latter has FPI of 7. The earnings actual is announced in quarter 4 of 2015, which means that forecast of FPI of 8 should be made three quarters prior, i.e. it should be in the first quarter of 2015. While the other observation with FPI of 8 falls within the first quarter, the second quarter gets into the second quarter.

Table A.6.1 Forecasts from analyst 282 for the earnings announcement of the company "EP ENGR CORP" on 28/10/2015

CNAME	ESTIMATOR	FPI	VALUE	FPEDATS	ANNDATS	ACTUAL	ANNDATS_ACT
EP ENGR CORP	282	6	0.19	30/09/2015	01/09/2015	0.26	28/10/2015
EP ENGR CORP	282	6	0.18	30/09/2015	19/08/2015	0.26	28/10/2015
EP ENGR CORP	282	7	0.13	30/09/2015	16/07/2015	0.26	28/10/2015
EP ENGR CORP	282	7	0.15	30/09/2015	30/04/2015	0.26	28/10/2015
EP ENGR CORP	282	8	0.11	30/09/2015	21/04/2015	0.26	28/10/2015
EP ENGR CORP	282	8	0.14	30/09/2015	19/02/2015	0.26	28/10/2015
EP ENGR CORP	282	9	0.25	30/09/2015	19/12/2014	0.26	28/10/2015
EP ENGR CORP	282	9	0.22	30/09/2015	21/11/2014	0.26	28/10/2015

For each analyst, I keep only the observations that meets two criteria. First, the forecast announcement date must fall within the intended quarter. Second, because a forecast can be revised multiple time within a quarter, I keep the forecast closest to the quarter end. The analysis uses active investment activity relative to a past period to forecast earnings surprises one, two or four quarters ahead. These two criteria allow the fund managers to use the latest forecast within the intended quarter in anticipation of the intended actual as indicated by FPI. For example, for an earnings announcement in quarter 3 and in an observation with FPI of 7 (forecast intended for actual two quarters ahead), the filtering criteria make sure to only keep the last forecast in the first quarter. As such, in an empirical setting, the mutual fund industry can incorporate the analyst forecast in quarter 1 in active investment decision in anticipation of the earnings surprise in quarter 3.

The earnings surprise is then calculated as the difference between the actual and the mean of the analyst forecasts that are selected from the two criteria above.

To map the earnings surprises data to fund holdings data from CRSP, I use the IBES-CRSP Link Table furnished by WRDS to match permno to the corresponding observations. The Link Table has a scoring system to indicate the potential accuracy of the mapping. To make sure that I use mostly correct mapping, I keep only observations that have a mapping with a score of 1 or 2, out of 6 available scores.

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