Aalto University
School of Business

Think you can choose your asset manager? Think again

Mutual fund investors' inability to distinguish fund managers' skill

Bachelor's Thesis
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1 Introduction

The main contribution of this thesis is to provide further evidence on mutual fund investors' inability to recognise real managerial skill. The findings contribute to the current understanding in three respect. First, the results continue to pile up on the increasingly established relationship between mutual fund flows and factor-related returns (FRRs), i.e., investors' tendency to merit fund managers' performance as alpha although it is attributable to factor exposures. Second, the results show that excessive fund flows have an impact on future expected fund underperformance measured in investors' net alpha. Third, the results provide an interesting piece of evidence suggesting that the root cause of the documented underperformance is driven by investors' unsophistication, culminating to their inability to recognise real managerial skill and confusing it with prior FRRs.

Mutual fund flows are among the most extensively researched areas in the field of finance. Under perfect markets assumption, little there is to research. Investors can distinguish funds' FRRs from managerial skill to uncover the true alpha of the funds, leading to all fund flows behaving rationally (Berk & Green, 2004). Those mutual funds that produce the highest risk-adjusted returns continuously attract the most fund flows, while those less successful funds encounter outflows other than the lost capital from poor investments. One could even argue, that under the perfect markets – or even highly efficient ones – such mutual funds were rare to exist, as outlier performers tend to converge towards each other over time.

Perfect capital markets, or even highly efficient ones, is a bold assumption in the mutual fund industry. One of the reasons why mutual funds have been so widely researched is that they hold a significant figure in financial assets, thus being an interesting platform to analyse market dynamics. Despite many market participants and strong liquidity of the sector, the mutual fund industry has displayed peculiar characteristics that even contradict with the Efficient Market Hypothesis (EMH). Although mutual fund managers are financial professionals that possess the financial rigour and sophistication to work as professional asset managers, mutual fund investors are not. For instance, as Yang (2020) points out, according to the Investment Company Institute (ICI), almost 94% of mutual fund assets in the United States were held by households in 2011. Assuming that ordinary household investors with little to no advanced financial training were able to distinguish factor-exposures – let alone to recognise systematically real managerial skill – is not a given. Therefore, financial economists have devoted justifiably a large number of hours studying the dynamics of mutual fund flows, how they react to swings in different market factors, and many peculiarities that prevail within the mutual fund industry.

Due to mutual investors' unsophistication, some mutual funds grow larger than is justified by the real skill of the fund managers, leading to lower investor returns net of fees for the subsequent periods. Several explanations have been proposed to elaborate that observation, including trading costs of funds, liquidity of funds' current positions, and higher managerial fees due to the increasing demand for their services. However, all previous research has overlooked the impact that the lack of investor sophistication has on their net returns, i.e., returns net of fees and other managerial expenses. Therefore, the main research question of this thesis is "Is documented expected fund underperformance ex-post excessive fund flows impacted by the investors' inability to distinguish managerial skill?" The main hypothesis is that yes, investors' inability to recognise real managerial skill directly impacts the documented relationship between unjustified fund size and future fund performance measured in investors' net alphas. The question is of particular interest, as it has numerous implications on several dimensions, including the EMH and the rationale for uninformed mutual fund investors to participate in the actively managed mutual fund industry as clients.

I will study the research question by running four analyses. First, I will analyse the impact of historical FRRs on mutual fund flows, controlling for real alpha. Second, I will analyse if the results of the first analysis hold during 2010-2019, characterised as an era of decreasing overall demand for the services of actively managed equity mutual funds, and higher returns than the long-term average due to inflated asset prices caused by highly regenerative monetary policy. Third, controlling for funds' assets under management (AUM), I show how mutual fund investors' net alphas are predictable by funds' excessive fund flows due to prior FRRs. Fourth, I will conduct a similar analysis on the same sub-sample period in 2010-2019 to see if the fund underperformance is stronger at times, when investors confuse even more easily managerial skill to other factors that impact the delivered net returns. Methodology and means to present the results are replicated from Yang's (2020) study *The mismatch between mutual fund scale and skill.*

2 Theoretical background

2.1 Mutual fund flows and investor sophistication

Mutual fund investors' sophistication can be deduced from mutual fund flows. Assuming that mutual fund investors are rationally using all the available information to make profit to the best of their abilities, the mutual fund flows are signs of investors' information interpretation processes. A wide range of research on mutual fund flows has uncovered, that investors are not behaving as expected in terms of their sophistication. The most fundamental established finding that casts doubts on investor sophistication is the uncovered relationship between common FRRs and mutual fund flows.

A wide range of academic research has found that common factors other than the market drive a material portion of mutual fund flows (Remolona, Kleiman & Gruenstein, 1997; Berk & van Binsberg, 2016; Ben-David, Li, Rossi & Song, 2018). According to these studies, investors attend most to the market factor. All other factor-exposures are misperceived as alpha by the investors (Barber, Huang & Odean, 2016; Chakraborty, Kumar, Muhlhofer & Sastry, 2018).

In addition to the above mentioned, further empirical evidence emerges regarding investor sophistication related to mutual fund flows. Friesen and Sapp (2007) find that from 1991 to 2004, equity fund investors' poor timing decisions alone reduced investors' average returns by 1.56% per annum. The provided explanation was investors' inability to time their investments in both actively managed funds as well as index funds, exhibiting investor return-chasing behaviour. Given the previously introduced research literature on FRRs and fund flows, it is possible that the poor timing is due to falsely interpreting FRRs as managerial alpha in actively managed funds. To conclude, these findings further support the view of mutual fund investors' inability to distinguish funds' managerial superiority.

Not only are mutual fund investors incapable of differentiating managerial skill from factor exposures, empirical evidence even implies that mutual fund investors can be plain fooled by cosmetics. Jain & Wu (2000) find that advertised funds attract significantly more money, although their performance is not superior during the post-advertisement period. Sirri & Tufano (2002) find similar results by showing how mutual funds' ability to attract funds appears to be most salient for funds that exert higher marketing effort, as measured by higher marketing expenses. Sirri & Tufano further show that fund inflows are also directly related to the size of the fund complex as well as the currently received media attention, both of which serve as a proxy for lower consumers' search costs. Solomon, Soltes & Sosyura (2014) also find evidence on advertising and media coverage of mutual funds impacting investors' capital allocation across mutual funds. Cooper, Gulen & Rau (2005), on the other hand, show that mutual funds can attract an average cumulative abnormal inflow of 28% just one year after repositioning their fund to reflect some current hot investment style, e.g., value or growth. Del Guercio & Tkac (2008) provide final hard-hitting evidence to strengthen the case against investors' rationality. According to their findings, Morningstar ratings have substantial independent influence in investment allocation decisions among retail mutual fund investors.

Consistently, it appears that the main conclusion for mutual fund flows is that they are characterised by unsophisticated and even irrational investor behaviour. According to the previous work in this field, investors can be influenced even by cosmetic effects. These findings challenge mutual fund investors' ability to analyse funds' factor-exposure and distinguish it from managerial skill systematically.

2.2 Mutual fund size and expected returns

Mutual funds' size has been argued to have a significant impact on funds' expected future performance. In the broad scheme of things, little evidence seems to suggest how fund performance can be estimated from the fund size. However, a wide variety of research work shows how the AUM of mutual funds has an inverse relationship with expected future fund investor returns. Berk & Green (2004) show by providing a theoretical model, how investors chase on historical returns by competitively supplying funds to managers. According to their model, investors reward fund managers' benchmark-winning performance by investing more capital into their funds. These fund managers, however, take advantage of the demand for their service by demanding themselves higher compensation, resulting in decreasing net returns on the scale to the point where investors' net expected returns fall back to the normal competitive levels going forward.

Berk & Green's (2004) theory has received support from the empirical work. Chen, Harrison, Huang & Kubik (2004) find that fund returns, both before and after fees and expenses, decline with fund size even after accounting for various performance benchmarks. However, unlike

Berk & Green, Hong, Huang & Kubik propose that these findings are driven by the liquidity of the investments and the subsequent price impact in the markets. Edelen, Evans and Kadlec (2009) find similar results in terms of the inverse relationship between fund size and future expected investor returns, but they propose trading costs as the source for diseconomies of scale. Zhu (2018) has further found a significant negative impact of fund size on future performance, indicating that future fund alpha and fund size are not independent measures.

Interesting view on mutual funds' expected performance is provided by Lou (2012) and Yang (2020), who both propose that the way mutual funds attract their flows impact their future expected performance. Yang states that instead of mutual funds' AUM per se, it is how these mutual funds attract those flows that determine the majority of funds' performance predictability in the future. He splits fund flows into justified flows and excessive flows, depending on whether these flows have been attracted by factor exposures or real alpha. Those flows attracted by high prior FRRs drive fund underperformance compared to its relevant benchmarks, while justified flows do not. Although these findings are interesting, they contradict the widely accepted theory provided by Berk & Green (2004), as the future expected returns for investors arguably fall below the normal competitive levels. Yang proposes, based on the research of Chen, Harrison, Huang & Kubik (2004), Pollet & Wilson (2008), Edelen, Evans & Kadlec (2013), and Pástor, Stambaugh & Taylor (2020), that the negative performance of active funds with higher prior FRRs is more significant among those funds that have higher trading costs. Yang concludes that by comparison, the trading costs have no predictive power for future return performance among those funds that have non-positive FRRs. Altogether, these findings are strong evidence of factor-related returns and the subsequent excessive fund flows driving the future expected fund underperformance compared to its benchmarks.

Interestingly, although such a broad front of empirical evidence exists on the inverse relationship between fund AUM and expected future returns, it appears to have little behavioural impact on fund managers. According to Pollet & Wilson (2008), asset growth has little effect on the behaviour of the typical mutual funds' fund managers. However, they do show that some of these funds diversify their portfolios in response to growth. This observation supports the theory of liquidity and price impact presented by Chen, Harrison, Huang, and Kubik (2004): the increased diversification can be considered as a consequence of too low liquidity to continue building positions in the current holdings. Yan (2008) has obtained similar supporting results.

To conclude, there is a strong case for AUM to have an impact on mutual funds delivered future returns. Some have successfully argued that the root cause in this phenomenon is not the AUM per se, but rather if the funds are attracted for the right reasons, i.e., managerial skill. Previous research proposes several explanations, including increasing funds' transaction costs, liquidity of current holdings, and an increase in managerial fees. However, none of the previous research work addresses the sophistication of investors that has a direct role to play in this equation. In this thesis, as I already established, I aspire to provide evidence on the impact that the investors' inability to distinguish managerial skill has on investors' net alphas.

3 Data and methodology

3.1 Mutual fund datasets

Mutual fund data comes from CRSP Survivor-Bias-Free U.S. Mutual Fund Database. The sample-set comprise mutual funds' monthly return data and quarterly fund summary data between 1992-2019. I dropped all data before 1992 because prior to that, all mutual funds did not report their returns monthly.

I clean the data with several procedures. First, I filter out all other mutual funds expect actively managed equity mutual funds, i.e., those that have ED-starting four-letter code describing the mutual funds' investment style in the database. I do this to differentiate funds where managerial skill should have an impact on fund performance. Then, for the same purpose, I filter out all index funds and exchange-traded funds (ETFs). I continue by filtering out all mutual funds that have never managed assets more than five million (U.S. dollars), or that do not have available monthly return data for at least 48 months straight, because those funds are not applicable for the chosen asset pricing model (see 3.3 Asset pricing model). Finally, I filter out all mutual funds that have no quarterly summary information for at least four years straight for the same reason. Eventually, the sample comprises a total of 14,804 mutual funds from 27 years. The data set is representative of the universe of the U.S. actively managed equity mutual funds, given the extended time horizon and broader inclusion of funds in the final sample compared to the preceding research in this field.

3.2 Asset pricing dataset

Factor data used in the asset pricing model is from Kenneth French's web site at Dartmouth, to which Wharton Research Data Services provided the access. The dataset comprises monthly returns of three Fama-French Portfolios, momentum (latest quarter), and a risk-free return. The three Fama-French Portfolios are the market-weighted portfolio, size-proxy portfolio (SMB), and value-proxy portfolio (HML). These factors capture a statistically significant portion of the variation of single stock returns (Fama & French, 1993), and thus, total gross returns of equity-focused mutual funds.

3.3 Asset pricing model

Measuring the risk-adjusted return of monthly mutual fund returns, I use a common four-factor model called Fama-French-Carhart model (FFC), a similar four-factor model that Carhart (1997) used in his research on persistence in mutual fund performance. I will not use a more complex asset pricing model, e.g., a seven-factor model with three industry factors used by Yang (2020) for the sake of avoiding over-fitting and maintaining the robustness of the findings. Thus, the asset pricing model takes the form of

$$(1)\quad r_{i,\tau} - r_{f,\tau} = \alpha_{i,t}^{FFC} + \beta_{i,t}\left(MKT_\tau - r_{f,\tau}\right) + \gamma_{i,t}SMB_\tau + \theta_{i,t}\, HML_\tau + \delta_{i,t}MOM_\tau + \varepsilon_{i,\tau},$$

$$\tau \in \left\{t - \frac{m}{12}, \ldots, t - \frac{1}{12}\right\}$$

where $r_{i,\tau}$ is the mutual fund i's monthly return in month τ, and $r_{f,\tau}$ stands for the risk-free rate of return at month τ. MKT_τ is the return of the value-weighted market portfolio, while SMB_τ, HML_τ and MOM_τ are the returns of the other factor portfolios adjusted by the value-weighted market return. $\beta_{i,t}, \gamma_{i,t}, \theta_{i,t},$ and $\delta_{i,t}$ are the fund exposures to each factor in the asset pricing model, namely the market, size, value, and momentum, respectively. $\varepsilon_{i,\tau}$ equals the noise term that is assumed to satisfy the standard assumptions of ordinary least square (OLS) method.

3.4 Factor-related returns

Using the OLS estimates for each month, $\gamma_{i,t}, \theta_{i,t}$ and $\delta_{i,t}$, derived from the equation (1), I determine the factor-related average monthly return over the 48 months regression period as

$$(2)\ \ \Delta_{i,t} = \frac{1}{m}\sum_{\tau=t-\frac{m}{12}}^{t-\frac{1}{12}}\left(\gamma_{i,t}SMB_{\tau} + \theta_{i,t}HML_{\tau} + \ \delta_{i,t}UMD_{\tau}\right),$$

where m equals the length of the regression period, and τ stands for each month involved in the regression period t. I specifically leave the market factor unconsidered, since market-factor-related returns have been shown not to have statistically significant explanatory power for mutual fund flows (Berk & van Binsbergen, 2016; Barber, Huang & Odean, 2016). Furthermore, as mutual fund investors treat all other factors than the market as alpha, I also estimate the CAPM alpha for each fund *i* over the same prior m months with a traditional one-factor market model using the OLS method:

$$(3)\ \ r_{i,\tau} - r_{f,\tau} = \alpha_{i,\tau}^{CAPM} + \beta_{i,t}\left(MKT_{\tau} - r_{f,\tau}\right) + \epsilon_{i,\tau},$$

where $\epsilon_{i,\tau}$ is the monthly noise term, the residual of each observation measured from the fitted regression model.

3.5 Fund flows

The net accumulation of funds is ultimately a function of three drivers. These are the fund inflows, fund outflows, and generated return (loss) on assets under management. Previous research has used a similar method (e.g., see Yang, 2020) in calculating monthly average flows per fund from quarterly data. The convention of quarterly data prevails since before 1992 most of the mutual funds have reported their AUM only quarterly. Thus, in this research, the average fund flows are primarily also quoted quarterly. Following the previous research and introduced intuitive logic above, the funds flows at time t are

$$(4)\quad Flow_{i,t} = AUM_{i,t} - \prod_{m=0}^{2}\left(1 + r_{i,t-\frac{m}{12}}\right) AUM_{i,t-\frac{1}{4}}$$

where $AUM_{i,t}$ is fund i's total AUM at time t.

4 Results

4.1 Fund flows and factor-related returns

Analysing the impact of FRRs on fund flows, I take a rolling-window approach and divide the mutual funds into fifteen different portfolios for each full calendar year. I start by dividing the mutual funds into five quintile portfolios based on their past 48 months risk-adjusted average monthly returns measured in FFC alphas (1). I then divide all mutual funds into three tercile portfolios based on the sample distribution of factor-related average monthly returns (2). Thus, in each top, middle, and bottom tercile portfolios, mutual funds are among the top, middle, or bottom third of all mutual funds, and not just within the same quintile portfolio. I conclude this procedure by winsorising the data from all extreme observations (below 1st and above 99th percentile) in quarterly fund flows and monthly factor-related returns. Next, I compare average quarterly fund flows of each fifteen fund portfolios over a given 48 months long regression period, showing the phenomenon of fund flows reacting to FRRs, controlling for the risk-adjusted returns. Table I reports the findings for all funds showing the time-series averages of fund flows and the time-series averages of FRRs.

Results suggest that mutual funds with higher FRRs appear to attract more funds than those with lower FRRs on average. The quintile portfolios with Top-Tercile mutual funds all have positive FRRs ranging between 2.8-3.5%. These funds attract more funds than Mid-Tercile and Bottom-Tercile portfolios within the same quintile, measuring average flows as a percentage of total average AUM at the start of the regression period. In Mid-Tercile section, the FRRs are near zero, around 0.3% each, being materially lower than those in Top-Tercile. Bottom-Tercile quintile fund portfolios, on the other hand, have all negative FRRs on average, ranging between -1.7% and -2.8%. As in the case of Top-Tercile portfolios trumping Middle-Tercile portfolios in fund flows, the Middle-Tercile quintiles exceed those Bottom-Tercile quintiles' corresponding figures.

Table I
The Response of Mutual Fund Flows to Factor-Related Average Returns: 1996-2019

For each calendar year of data, all mutual funds are sorted into five quintile portfolios based on their four-factor alpha (1) in prior 48 months. Each alpha-portfolio is then divided into three tercile portfolios based on their order in sample distribution of factor-related returns during the prior 48 months period. Thus, the top, middle, and bottom tercile portfolios represent a portfolio of mutual funds whose estimated factor-related average past 48-month returns are in the top, middle, and bottom third of all mutual funds. A_s and A_e (millions in U.S. dollars) are the time-series averages of cross-sectional arithmetic means of assets under management for a given fund portfolio at the start and the end of each 48-month estimation period. Flow (in millions) is the time-series averages of the cross-sectional mean of average quarterly flows over each same 48-month estimation periods. Δ and α^{CAPM} (in %) are the annualised time-series averages of the cross-sectional mean of the CAPM alphas and factor-related returns, respectively. t-stat is the t-statistic of a test of positive difference in average quarterly flows between the top and bottom tercile group within a given quintile. *, **, and *** denote 10%, 5%, and 1% statistical significance, respectively.

	A_s	A_e	Flow	Δ	α^{CAPM}	A_s	A_e	Flow	Δ	α^{CAPM}	A_s	A_e	Flow	Δ	α^{CAPM}	t -stat
	Top-Tercile Δ					Mid-Tercile Δ					Bottom-Tercile Δ					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
1 (L)	321	346	-5.3	3.4 %	-3.4 %	436	306	-9.8	0.3 %	-5.7 %	364	228	-6.4	-2.2 %	-9.1 %	2.05**
2	370	488	-3.8	2.9 %	0.1 %	474	504	-5.6	0.3 %	-2.3 %	496	423	-8.3	-1.8 %	-4.4 %	7.54***
3	562	934	1.0	2.8 %	1.5 %	648	944	-0.5	0.3 %	-0.7 %	668	745	-3.0	-1.7 %	-2.7 %	4.19***
4	482	1,045	7.5	2.9 %	3.1 %	795	1,390	2.7	0.3 %	0.8 %	797	1,015	-0.8	-1.8 %	-1.3 %	5.92***
5 (H)	329	938	8.3	3.5 %	8.2 %	540	1,140	12.3	0.3 %	4.1 %	496	835	5.5	-2.8 %	2.8 %	0.85

The last column is the t-statistic of a one-sided t-test comparing the Top-Tercile and Bottom-Tercile funds average fund flows within each quintile portfolio. Four out of five quintile portfolios have a t-statistic that indicates the presence of statistically significant evidence to conclude that the mutual funds with higher FRRs attract more funds than those funds with lower prior FRRs. Given also that each quintile portfolios fund flows appear to correlate with α^{CAPM}, the results further support previous findings of investors perceiving other factor exposures than the market as alpha. Thus, even with a broader inclusion of actively managed equity mutual funds in the sample data, mutual fund flows show responsiveness to factor-related returns. Thus, there is a strong case for concluding that mutual fund investors are unable to distinguish real managerial skill.

Table II is constructed identically to Table I, except for limiting the sample down to the observations between 2010 and 2019. This sub-sample is characterised by substantial industry-wide net outflows among actively managed funds, which is implicitly reported and easily observable from the sign and the magnitude of the cross-sectional time-series averages of the quarterly flows, as almost all fund portfolios have negative outflows during the past decade. Interestingly, with this sub-sample of relatively recent observations, a similar pattern emerges where higher tercile-assigned quintile portfolios have larger (less negative) fund flows than those of lower tercile correspondents. Looking at the t-statistics in comparing fund flows of Top-Tercile and Bottom-Tercile funds within each quintile portfolio, yet again four quintile portfolios out of five show statistically significant results, even at 1% significance level. Similarly, fund flows and α^{CAPM} continue to maintain their established relationship.

To summarise, these results show how higher past FRRs are associated with larger fund flows. Even during times of net outflows faced by the entire sector (i.e., decrease in the demand of the provided services), the established relationship of fund flows and FRRs prevail, indicating that investors confuse managerial skill to common FRRs. In the broad scheme of things, as fund flows reveal investors' beliefs about managerial skill, there is a fair reason to believe that mutual fund investors treat common FRRs attributable to size, value, and momentum as if they are signs of fund managers' alpha. The results argue convincingly about investors' incapability to distinguish real managerial skill.

Table II
The Response of Mutual Fund Flows to Factor-Related Average Returns: 2010-2019

For each calendar year of data, all mutual funds are sorted into five quintile portfolios based on their FFC alpha (1) in prior 48 months. Each alpha-portfolio is then divided into three tercile portfolios based on their order in sample distribution of factor-related returns during the same past 48 months period. Thus, the top, middle, and bottom tercile portfolios represent a portfolio of mutual funds whose estimated factor-related average past 48-month returns are in the top, middle, and bottom third of all mutual funds. A_s and A_e (millions in U.S. dollars) are the time-series averages of cross-sectional arithmetic means of assets under management for a given fund portfolio at the start and the end of each 48-months estimation period. Flow (in millions) is the time-series averages of the cross-sectional mean of average quarterly flows over each 48 months estimation period. Δ and α^{CAPM} (in %) are the annualised time-series averages of the cross-sectional mean of the CAPM alpha and factor-related monthly returns, respectively. t-stat is the t-statistic of a test of positive difference in average quarterly fund flows between the top and bottom group within a given quintile. *, ** and *** denote statistical significance at 10%, 5%, and 1% respectively.

	A_s	A_e	Flow	Δ	α^{CAPM}	A_s	A_e	Flow	Δ	α^{CAPM}	A_s	A_e	Flow	Δ	α^{CAPM}	t -stat
	Top-Tercile Δ					Mid-Tercile Δ					Bottom-Tercile Δ					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
1(L)	295	173	-8.3	2.1 %	-3.6 %	413	285	-10.2	0.3 %	-4.8 %	308	192	-6.9	-1.4 %	-8.0 %	-2.6
2	396	297	-11.0	1.9 %	-0.7 %	406	389	-7.4	0.3 %	-2.2 %	450	399	-8.9	-0.9 %	-3.6 %	1.7**
3	637	770	-5.4	1.9 %	0.5 %	562	694	-4.3	0.2 %	-1.0 %	832	864	-8.5	-0.9 %	-2.5 %	1.6*
4	351	462	-1.5	1.9 %	1.7 %	790	1121	-3.4	0.3 %	0.2 %	760	920	-8.1	-1.0 %	-1.3 %	2.9***
5(H)	332	536	1.2	2.0 %	4.6 %	676	1081	2.8	0.3 %	3.0 %	677	973	-1.4	-1.2 %	2.1 %	1.7**

4.2 Past factor-related returns and future investor alphas

In this section, I show that excessive fund flows lead to funds' future underperformance by showing that fund flows associated with positive factor-related returns are followed by expected negative net alphas for mutual fund investors on an aggregate level. In completely perfect and rational markets, investors can distinguish managerial skill from factor-related returns and profit from occasional mispricing, even if these factors were priced (Grinblatt & Titman, 1989; Pástor & Stambaugh, 2002a). However, as Berk & Green (2004) have hypothesised, further empirically supported by Chen, Harrison, Huang & Kubik (2004), Edelen, Evans & Kadlec (2013), Harvey & Liu (2017), Zhu (2018), and Yang (2020), the more assets an active fund manager accumulates, the worse is the fund's performance due to decreasing returns on scale. However, unlike previous research, this thesis aims to show how the investors' unsophistication to distinguish managerial skill is impacting directly in investor's expected net alphas.

I again take the rolling-window approach. For each calendar year, I divide mutual funds into five quintile portfolios based on their AUM at the start of the regression periods. I then split each AUM quintile portfolio into three tercile sub-portfolios depending on the sample distribution data of average monthly factor-related returns over the past 48-months. To capture the expected future return performance as Yang (2020) did, I compute monthly AUM-weighted expected return over the next 12 months for each fund portfolio. I continue to regress each fund portfolio's time-series average of monthly AUM-weighted net returns against the Fama-French-Carhart four-factor model (1). I finally present these results in Table III.

Some remarkable patterns are observable. Looking at each quintile portfolio, i.e., controlling for fund AUM, funds with higher prior FRRs are expected to perform materially worse in the future during the next 12 months ex-post the regression period. The expected future net alphas of Top-Tercile funds are 226bps to 341bps lower than those in Bottom-Tercile funds, considering a minimum statistical significance of 10%. These results are in line with findings made by Chen, Harrison, Huang & Kubik (2004), Edelen, Evans & Kadlec (2009), and Yang (2020).

Across five quintiles of AUM, funds with Top-Tercile prior FRRs have average expected net alphas between -212bps and -372bps (1% significance level). On the contrary, funds in the Bottom-Tercile have near-zero net alphas between -90bps and +32bps on average. The net alphas of Middle-Tercile funds are on average -131bps (1% statistical significance level), falling in between

Table III
Future annualised returns net of fees and managerial expenses: controlled for fund AUM, 1996-2019

For each calendar year, mutual funds are sorted in two dimensions. First, each mutual fund is sorted into five quintile portfolios based on their assets under management at the start of the 48 months long observation period. Each AUM quintile portfolio is then divided into three tercile portfolios based on the sample distribution of factor-related average returns (2) during the same 48 months-long period. Thus, the top, middle and bottom portfolios within each quantile comprise mutual funds whose estimated factor-related average returns during the past 48 months are among the top, middle, and bottom third of all mutual funds in that measure. I then compute the average AUM weighted monthly net returns of each fund portfolio in excess of risk-free rates and annualise it. I continue by regressing these monthly average returns in excess to risk-free rate against the FFC model (1) to obtain future benchmark-adjusted returns for each fund portfolio, as did Yang (2020) in his research. Both Ret and α_{FFC} are annualised figures in percentages, while *, **, and *** denote statistical significance at 10%, 5%, and 1% level, respectively.

	Panel A: Ret (%)				Panel B: α_{FFC} (%)			
	Top	Middle	Bottom	Diff	Top	Middle	Bottom	Diff
1(L)	3.27	4.91	5.52	2.25	-2.85*	-0.58	-0.90	1.95
					(-1.90)	(-0.45)	(-1.23)	(-1.14)
2	2.30	4.56	6.34	4.04	-3.72***	-1.41**	-0.31	3.41**
					(-3.51)	(-2.48)	(-0.42)	(-2.43)
3	3.97	4.84	7.14	3.17	-2.12**	-1.19**	0.32	2.40*
					(-2.32)	(-2.37)	-0.46	(-1.91)
4	3.54	4.41	6.52	2.98	-2.52***	1.34**	-0.21	2.31*
					(-2.72)	(-2.48)	(-0.32)	(-1.89)
5(H)	2.98	3.50	5.86	2.88	-2.77***	-2.04***	-0.52	2.26*
					(-2.76)	(-3.47)	(-0.73)	(-1.77)
All	3.23	4.38	6.33	3.10	-2.79***	-1.31***	-0.32	2.47***
					(-5.69)	(-3.85)	(-1.02)	(-3.96)

the averages of Top-Tercile and Bottom-Tercile correspondents. The main takeaway of these results is that controlling for fund AUM, mutual funds with the highest prior FRRs provide the lowest expected net return for the following calendar year of the regression period. Having previously shown that the fund flows react to FRRs, these findings are facilitating the possibility that mutual fund investors' inability to distinguish managerial skill impacts directly the expected underperformance of certain funds in the future. Interestingly, we are not able to detect a clear pattern between funds' AUM and future underperformance. These findings further support those conclusions made by Lou (2012) and Yang (2020), establishing an interesting starting point for the final analysis.

When performing a similar analysis with the 2010-2019 data, the patterns are even more striking. I report these findings in Table IV. There are two things to pay attention to in order to grasp the astonishing nature of the results. First thing to pay attention to is the Panel A and the higher net returns for all fund portfolios. Each fund portfolio has a materially higher average annualised monthly AUM weighted return net of fees and expenses compared to the full sample data. Between 1996-2019 the average AUM weighted net return of all Tercile-portfolios across quintiles was between 3.23-6.33%, while in 2010-2019 the corresponding figures are almost two to three times larger at 9.10-10.89%. Rather than managerial skill, the larger net returns in Panel A are a consequence of strong stimulus and loose monetary policy practised by Federal Reserve since the financial crisis in 2008, a well-documented phenomenon characterising the 2010's called Quantitative Easing.

The second thing to pay attention to is that despite higher net returns, each fund portfolio display signs of lower risk-adjusted net returns. All tercile-portfolios appear to have materially lower net investor alphas compared to the corresponding figures computed from the full sample data. In terms of investors' net alpha, the figures are 67-106bps smaller in 2010-2019 than in 1996-2019. The relative order of the magnitude between terciles remains similar. In Table IV, each quintile with top prior FRRs have an average negative net alpha between -339 bps and -442 bps (statistical significance of 1% and 5%). The average of all Top-Tercile quintile portfolios' net alpha is -372bps (1% significance level), which is materially lower than Middle-Tercile's averages, having a cross-quintile average net alpha of -237bps (1% significance level), being significantly lower than the Bottom-Tercile's corresponding figure of -97 bps (1% significance level). Furthermore, the results suggest that even some of the Bottom-Tercile fund portfolios begin to demonstrate statistically significant discrepancy from zero net alphas, serving as an explanation for the weakening of Diff column's statistical significance. The results imply that increasingly even the Bottom-Tercile fund portfolios cannot be ruled out to have equally low investors' net alphas as the Top-Tercile correspondents have.

These findings provide striking evidence for the unsophistication of investors driving the funds' expected future performance measured in investors' net alphas. Moreover, these findings are even

Table IV
Future annualised returns net of fees and managerial expenses: controlled for fund AUM, 2010-2019

For each calendar year, mutual funds are sorted in two dimensions. First, each mutual fund is sorted into five quintile portfolios based on their assets under management at the start of the 48 months long observation period. Each AUM quintile portfolio is then divided into tercile portfolios based on the sample distribution of factor-related average returns (2) during the same 48 months-long period. Thus, the top, middle and bottom portfolios within each quantile comprise mutual funds whose estimated factor-related average returns during the past 48 months are among the top, middle, and bottom third of all mutual funds in that measure. I then compute the average AUM weighted monthly net returns of each fund portfolio in excess of risk-free rates for the next calendar year and annualise it. I continue by regressing these monthly average returns in excess to risk-free rate against the FFC model (1) to obtain future benchmark-adjusted returns for each fund portfolio, as did Yang (2020) in his research. Both Ret and α_{FFC} are annualised figures in percentages, while *, **, and *** denote statistical significance at 10%, 5%, and 1% level, respectively.

	Panel A: Ret (%)				Panel B: α_{FFC} (%)			
	Top	Middle	Bottom	Diff	Top	Middle	Bottom	Diff
1(L)	8.28	9.34	10.43	2.15	-4.42**	-2.71**	-1.17	3.25
					(-2.54)	(-4.02)	(-1.47)	(-1.50)
2	8.57	9.92	10.36	1.80	-3.93**	-2.29***	-1.36*	2.57
					(-2.37)	(-3.78)	(-1.74)	(-1.24)
3	9.46	10.11	11.35	1.89	-3.39**	-2.10***	0.50	2.90
					(-2.47)	(-3.66)	(-0.70)	(-1.61)
4	9.42	9.92	11.39	1.97	-3.42**	-2.29**	-0.63	2.79
					(-2.22)	(-3.87)	(-0.96)	(-1.46)
5(H)	9.33	9.53	10.57	1.23	-3.44**	-2.48***	-1.19*	2.24
					(-2.33)	(-4.12)	(-1.69)	(-1.18)
All	9.10	9.78	10.89	1.79	-3.72***	-2.37***	-0.97***	2.75***
					(-5.40)	(-8.83)	(-3.00)	(-3.16)

more striking when considering that the results have been obtained from a sample that due to its nature controls automatically for several potential explanations, such as increase in prior FRRs, the demand of actively managed mutual funds' services, and funds' size. In terms of the demand of the services, Table I shows that net fund flows have been negative for nearly all fifteen fund portfolios, meaning that the increased demand is not driving the increase in fees for all funds on an industry-wide level (see Flows in Table I and II). Fund sizes, as for, are not any larger at the start of the regression periods during 2010-2019 than the full sample period (see A_s and A_e columns in Table I and II). Besides, according to Edelen, Evans & Kadlec (2013), as well as Busse, Chordia, Jiang & Tang (2017), the average trading costs for the U.S. actively managed equity mutual funds are approximately at 75-144 bps per annum of total net assets, including the indirect trading costs arising from price impact and the bid-ask spread. Also, they estimate these trading costs to be persistent over time. Hence, it is highly unlikely that the observed difference of 67-106 bps between the documented periods is explained alone by these components, as previous research has suggested.

Therefore, I conclude that these results are potentially indicative of two distinct insights. First, if fund managers' fees have increased, mutual fund investors are willing to pay more for returns that are not attributable to managerial skill. Second, if fund managers' fees have not increased, then investors fail so seriously in choosing the most skilled asset managers, that the prior FRRs are just a coincidence and investing in those managers with high prior FRRs leads to investing in less competent fund managers on average, ceteris paribus. Thus, the case is increasingly in favour for investors confusing higher net returns to be attributable to managerial skill. Investors indeed appear to pay for this ignorance on a risk-adjusted basis, which leads me to conclude that investors' inability to distinguish managerial skill impacts directly on investors' expected risk-adjusted returns in the future.

The findings of this section provide remarkable evidence on that investors' inability to recognise real managerial skill plays a significant role in the expected future performance of mutual funds in addition to the funds' transaction costs, higher fees due to the increased demand of provided services, and liquidity of the current positions. The results of this thesis show that those mutual funds with the highest prior FRRs continue to underperform in terms of expected investors' net alphas. The results even suggest that investors are completely unaware of fund managers' true skill, which becomes them costly, especially during times of high net returns that have little to do with the real managerial skill. These results are significant for the EMH in the context of the mutual fund industry, as discussed in the conclusions section.

5 Robustness of results

I perform several robustness checks to support the findings of this thesis. First, I conduct a similar analysis as above in Tables I-IV, but I change the method for tercile assignment. Instead of using the sample distribution of FRRs in assigning the terciles, I use the quintile distribution of FRRs in dividing each quintile into Top-Tercile, Middle-Tercile, and Bottom-Tercile sub-portfolios. Despite changing the assignment of tercile portfolios, the results remain similar. The results are available in the Appendix for Tables I and II (Tables V-VI). I also perform a similar analysis as used in Tables I-II with several different sub-samples of the full sample data between 1992-2019. I obtain similar results in all of the sub-sample analyses.

Finally, I perform two subsample analyses for the 2010-2019 subsample data. The first is conducted for a period of 2010-2014 and the second is for the latter half of 2015-2019. Both periods provide similar results. When it comes to Table II, the only difference is an indication of that the industry-wide net outflows are increasingly more rapid, hence less statistically significant difference between fund flows among lower quintile portfolios' when comparing the corresponding figures between Top-Tercile and Bottom-Tercile funds. In terms of Table IV, both halves of the original subsample provide similar results to the original 2010-2019 period. Thus, the results are robust in these respects.

6 Conclusions and discussion

The findings of this thesis are fascinating. They further shed light on investors' inability to choose their asset manager and thus support several of the previously published findings and theories, but they also reveal its true extent and direct implications to investors' annual net alphas. Overall, the results have two interesting implications.

6.1 Investors' unsophistication explains funds' expected future underperformance

As indicated by the extensive amount of previous research work on mutual fund flows, the results provide further evidence on mutual fund investors' inability to pick their asset managers – at least broadly speaking in actively managed equity mutual funds. As I showed in Table I and II, mutual fund flows respond positively to such performance that is simply a function of factor exposures, mixing it with the real alpha that the fund managers generate. However, the most striking pattern is observed in the change of investors' net alphas when comparing the results from full sample data and the sub-sample data of past decade. These findings suggest that financially unsophisticated money causes the expected fund underperformance. The previous research has widely ignored this perspective in expected future fund underperformance; hence, the results contribute materially to the existing understanding of mutual funds' performance drivers from an investors' perspective.

These findings present an interesting paradox. One motivation for investing in actively managed mutual funds is investors' lack of financial rigour to conduct the investing themselves. The paradox arises from the fact that if investors are neither able to manage investments directly nor to choose their asset managers successfully, there is no rationale for unsophisticated investors to become clients of actively managed mutual funds. Thus, there emerges a similar dynamic in market participation as there is in an IPO market with informed and uninformed investors. However, sophisticated investors should not either become clients, but rather they ought to conduct active investments themselves or invest passively due to the cost effectiveness. The findings of this thesis combined with the above discussion suggest that actively managed funds might be slowly heading at the end of their tale.

6.2 Implications for the Efficient Market Hypothesis in the context of mutual funds

The results presented in Tables III and IV cast doubts on the feasibility of certain assumptions in the EMH. The EMH assumes that investors are rational on an aggregate level, trying to maximise their profits by finding, interpreting, and enacting on new information continuously. Surely, the fact that investors do poorly in the above does not mean that the investors did not try their best, which is what the EMH assumes per se. However, if one unleashes a zoo in an antique store, she should not expect the animals to start buying china. Same would go with household investors and financial markets, even if it was just about reallocating capital between actively managed equity funds.

Surely, one would argue that the investors are paying for their ignorance, which aligns with the implications of the EMH. However, since Table IV shows even as low investors' net alphas as -442bps (1% significance level) on average, a strong case is built against the mutual fund investors ability to compose fund performance into managerial skill and factor exposures. The proponents of EMH are justified to question the believability of the theory from the perspective of rational investor behaviour on an aggregate level in the context of mutual fund investors over time.

6.3 Limitations and further research potential

Some limitations diminish the value of the results. First, I have not taken into account a phenomenon documented by Kamstra, Kramer, Levi & Wermers (2017). They find that flows into equity mutual funds from other fund categories, such as fixed-income funds or money market funds, occur more likely in spring. I do not account this seasonality in asset allocation.

In addition to the seasonality, I do not account for the National Bureau of Economic Research (NBER) recessions, nor use the alternative rolling-window approaches to confirm the findings. Also, I do not analyse the phenomenon using different asset pricing models, such as the seven-factor model used by Yang (2020). Furthermore, I do not combine those mutual funds with many share classes into single funds; thus, I end up over-weighting slightly more those mutual funds with more than one marketed share class. Finally, the results are robust neither against the CRSP-classified cap-based funds nor style-based funds, as they are in Yang's (2020) paper.

An interesting further research question is how much the transaction costs comprise the documented decrease in investors net alphas as net returns have risen. This is a very challenging empirical research question, as mutual funds do not report their transaction costs explicitly in their SEC filings. However, some previous papers have proposed different proxies for the transaction costs, which can be useful.

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8 Appendix

Table V
Response of Mutual Fund Flows to Factor-Related Average Returns: 1996-2019

For each calendar year of data, all mutual funds are sorted into five quintile portfolios based on their FFC alpha (1) in prior 48 months. Each alpha-portfolio is then divided into three tercile portfolios based on their order in sample distribution of factor-related returns during the same past 48 months period. Thus, the top, middle and bottom portfolios represent a portfolio of mutual funds whose estimated factor-related average past 48-month returns are in the top, middle, and bottom third of all mutual funds. A_s and A_e (millions in U.S. dollars) are the time-series averages of cross-sectional arithmetic means of assets under management for a given fund portfolio at the start and the end of each 48-months estimation period. Flow (in millions) is the time-series averages of the cross-sectional mean of average quarterly flows over each 48 months estimation period. Δ and α^{CAPM} (in %) are the annualised time-series averages of the cross-sectional mean of the CAPM alpha and factor-related monthly returns, respectively. t-stat is the t-statistic of a test of positive difference in average quarterly fund flows between the top and bottom group within a given quintile. *, ** and *** denote statistical significance at 10%, 5%, and 1% respectively.

	A_s	A_e	Flow	Δ	α_{CAPM}	A_s	A_e	Flow	Δ	α_{CAPM}	A_s	A_e	Flow	Δ	α_{CAPM}	t -stat
	Top-Tercile Δ					Mid- Tercile Δ					Bottom- Tercile Δ					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
1(L)	335	373	-5.3	3.7 %	-3.3 %	422	296	-9.5	0.4 %	-5.7 %	355	222	-6.2	-2.3 %	-9.2 %	2.8***
2	379	496	-3.7	2.8 %	-0.1 %	465	509	-4.9	0.2 %	-2.4 %	496	422	-8.3	-1.8 %	-4.4 %	6.3***
3	521	860	0.5	2.6 %	1.3 %	661	1025	1.2	0.2 %	-0.8 %	667	747	-2.9	-1.7 %	-2.6 %	2.8***
4	568	1,147	6.2	2.8 %	3.0 %	802	1,428	2.9	0.3 %	0.8 %	797	1,023	-0.7	-1.8 %	-1.3 %	5.7***
5(H)	323	886	7.2	3.9 %	8.9 %	519	1,160	12.2	0.5 %	4.3 %	497	837	5.5	-2.8 %	2.9 %	0.50

Table VI

Future Annualized Returns After Fees: Control for Fund AUM within each tercile

For each calendar year, mutual funds are sorted in two dimensions. First, each mutual fund is sorted into five quintile portfolios based on their assets under management at the start of the 48 months long observation period. Each AUM quintile portfolio is then divided into tercile portfolios based on the sample distribution of factor-related average returns (2) during the same 48 months-long period. Thus, the top, middle and bottom portfolios within each quantile comprise mutual funds whose estimated factor-related average returns during the past 48 months are among the top, middle, and bottom third of all mutual funds in that measure. I then compute the average AUM weighted monthly net returns of each fund portfolio in excess of risk-free rates for the next calendar year and annualise it. I continue by regressing these monthly average returns in excess to risk-free rate against the FFC model (1) to obtain future benchmark-adjusted returns for each fund portfolio, as did Yang (2020) in his research. Both Ret and α_{FFC} are annualised figures in percentages, while *, **, and *** denote statistical significance at 10%, 5%, and 1% level, respectively.

	Panel A: Ret (%)				Panel B: α_{FFC} (%)			
	Top	Middle	Bottom	Diff	Top	Middle	Bottom	Diff
1 (L)	3.36	4.89	5.54	2.18	-2.76**	-0.59	-0.89	1.87
					(-1.88)	(-0.47)	(-1.21)	(1.11)
2	2.29	4.55	6.33	4.04	-3.71***	-1.41**	-0.31	3.41**
					(-3.51)	(-2.47)	(-0.43)	(-2.43)
3	3.93	4.83	7.14	3.21	-2.15**	-1.19**	0.32	2.47*
					(-2.34)	(-2.37)	(0.46)	(-1.93)
4	3.55	4.37	6.52	2.97	-2.49***	-1.38**	-0.20	2.29*
					(-2.68)	(-2.55)	(-0.32)	(-1.87)
5 (H)	2.99	3.46	5.83	2.85	-2.76***	-2.11***	-0.54	2.22*
					(-2.72)	(-3.63)	(-0.77)	(-1.73)
All	3.24	4.35	6.33	3.09	-2.78***	-1.34***	-0.32	2.45***
					(-5.67)	(-3.96)	(-1.03)	(-3.94)