Mutual Fund Managerial Working Experience, Career Concern, New Fund Opening and Fund Performance

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To my grandmother

Acknowledgement

I herewith declare that I have produced this thesis without the prohibited assistance of third parties and without making use of aids other than those specified from other sources, and which have been identified as such. This thesis has not previously been presented in an identical or similar form to any other English or foreign examination board.

This thesis is the result of my research as a doctoral student at the Durham University Business School, Durham University between January 2014 and March 2018. During my research, I had the privilege of cooperating with a number of people who I would like to express my sincere gratitude and warmest thanks.

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Abstract

This thesis comprises three essays on mutual fund performance which provide new insights into different aspects of the mutual fund industry.

The first essay examines the relationship between the mutual fund manager's past experience and mutual fund performance. The skills and knowledge acquired from the prior working experience may be transferred to the current working context, thereby influencing the current job performance (Schmidt et al., 1986). Using data on U.S. mutual fund managers' work experience ranging from 1993 to 2012, we introduce a new method to evaluate mutual fund performance from the perspective of the manager's lifetime working experience. Specifically, the method involves using the Principal Component Analysis to construct a Managerial Experience Index (MEI) based on 3 professional experience factors from the past career history of each manager: (i) investment objectives of the funds that s/he has managed (Zambrana and Zapatero, 2017), (ii) fund companies that s/he has worked for and (iii) industries of stocks in which s/he has invested (Kacperczyk et al., 2005). The MEI would increase along with the experience accumulation for each mutual fund manager. We group the sample based on the MEI into 5 quintiles from the lowest MEI score (most concentrated experience) to the highest MEI score (most diversified experience). The findings suggest that managers with more specialised experience outperform managers with more diversified experience. In addition, the "Specialist" managers tend to exhibit stock-picking ability while the "Generalist" managers tend to exhibit market-timing ability.

The second essay analyzes the performance patterns of new funds during the early stage after their creation, and provides potential explanations for their short-lived outperformance. Using a sample of incubation-free mutual fund data from 1996 to 2015, we address the questions of (i)

whether new mutual funds outperform the market and (ii) if they do what may explain their superior performance. We find evidence of outperformance for the new funds during their emerging period defined here as the first 6 months of their existence, both before and after fund expenses are taken into account. This outperformance, however, only lasts for a short term and disappears soon after the emerging period. This short-lived outperformance can be explained by the small size effect and IPO stock allocation, but is only weakly associated with managerial characteristics such as team managers and prior experience in equity fund management. Our analysis also provides evidence on a flow-performance relationship. The results suggest that IPO allocation is an effective strategy that enhances investment flows during the emerging period of a new fund. In addition, we find that funds created by team managers attract more flows than funds created by individual managers.

The third essay examines if fund managers would take into account turnover risk from a tournament when adjusting the risk of portfolios under their management, where the tournament is defined as the competition in a group with the purpose of being rewarded on their relative performance Conyon et al. (2001). In addition to exploring a statistical correlation between a manager's discharge from a fund and the realized volatility of the fund that she had been managing, we use an instrumental variable (IV) approach to study whether one may infer causality from such a correlation. Using the instrumental variable (IV) measured as the peer flow pressure in the tournament following the "Rank-of-Ranks" approach in Kempf and Ruenzi (2008), we find that peer flow pressure is a highly statistically significant determinant of manager replacement. Further, the risk of replacement is significantly linked to the fund's realized idiosyncratic volatility. The finding is robust to the use of an alternative instrumental variable (*Segment Flow Rank*), an alternative measure of realized risk (*Carhart-adjusted Idiosyncratic Risk*), and finite distributed lag specifications that incorporate one-period lags of explanatory factors.

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List of Abbreviations

Abbreviation	Description
CAPM	Capital Asset Pricing Model
CEO	Chief Executive Officer
CPE	Conditional Performance Evaluation
CRSP	Center for Research in Security Prices
EMH	Efficient Market Hypothesis
ETF	Exchange-Traded Fund
ICI	Investment Company Institute
ISIN	International Securities Identification Number
IV	Instrumental Variable
MD	MorningStar Direct
MEI	Managerial Experience Index
MFLINKS	Mutual Fund Links
MP	MorningStar Principia
NASD	National Association Of Securities Dealers
OLS	Ordinary Least Squares
PCA	Principal Component Analysis
PCSE	Panel-Corrected Standard Errors
SDC	Securities Data Company
SEC	Securities and Exchange Commission
S&P	Standard & Poor's
TNA	Total Net Asset
WRDS	Wharton Research Data Services

Chapter 1

Introduction

1.1 Research Background

Globalization and the development of capital markets continue to fuel the growth of mutual fund management industry. A mutual fund is a type of investment instrument that pools money from investors, and invests their money in stocks, bonds, money-market instruments, other securities, or even cash. Different mutual funds may also be subject to different risks, fees and expenses.

By the end of year 2016, the total net asset (TNA) of U.S. mutual funds has reached $16.3 trillion, which constitutes an increment of $9.3 trillion from $7 trillion in year 2000. Figure 1.1 demonstrates the annual TNA of U.S. mutual funds from 1998 to 2016. The size of U.S. mutual fund industry has increased continually in the past two decades, apart from a small drop of $2.4 trillion in year 2008 which could be potentially caused by the global financial crisis.

Among the universe of U.S. mutual funds, 56% are equity funds as at the end of 2016, which mainly invest in equities. Within the equity funds, domestic funds which invest mainly in stock shares of U.S. corporations hold 42% of total assets[1]. The domestic equity funds remain as hot as ever. According to Thomson Reuters Lipper data, the average diversified U.S. equity fund registered a total return of 18.3% in 2017. In return, the positive performance of mutual funds helps to attract great flow into the industry, and therefore fuze the overall mutual fund marekt size.

The increasing importance of mutual funds, especially equity funds has stimulated a great number of researches among academics and practitioners. A large

[1]The relevant statistics are obtained from the 2017 Investment Fact Book published by the Investment Company Institute (ICI).

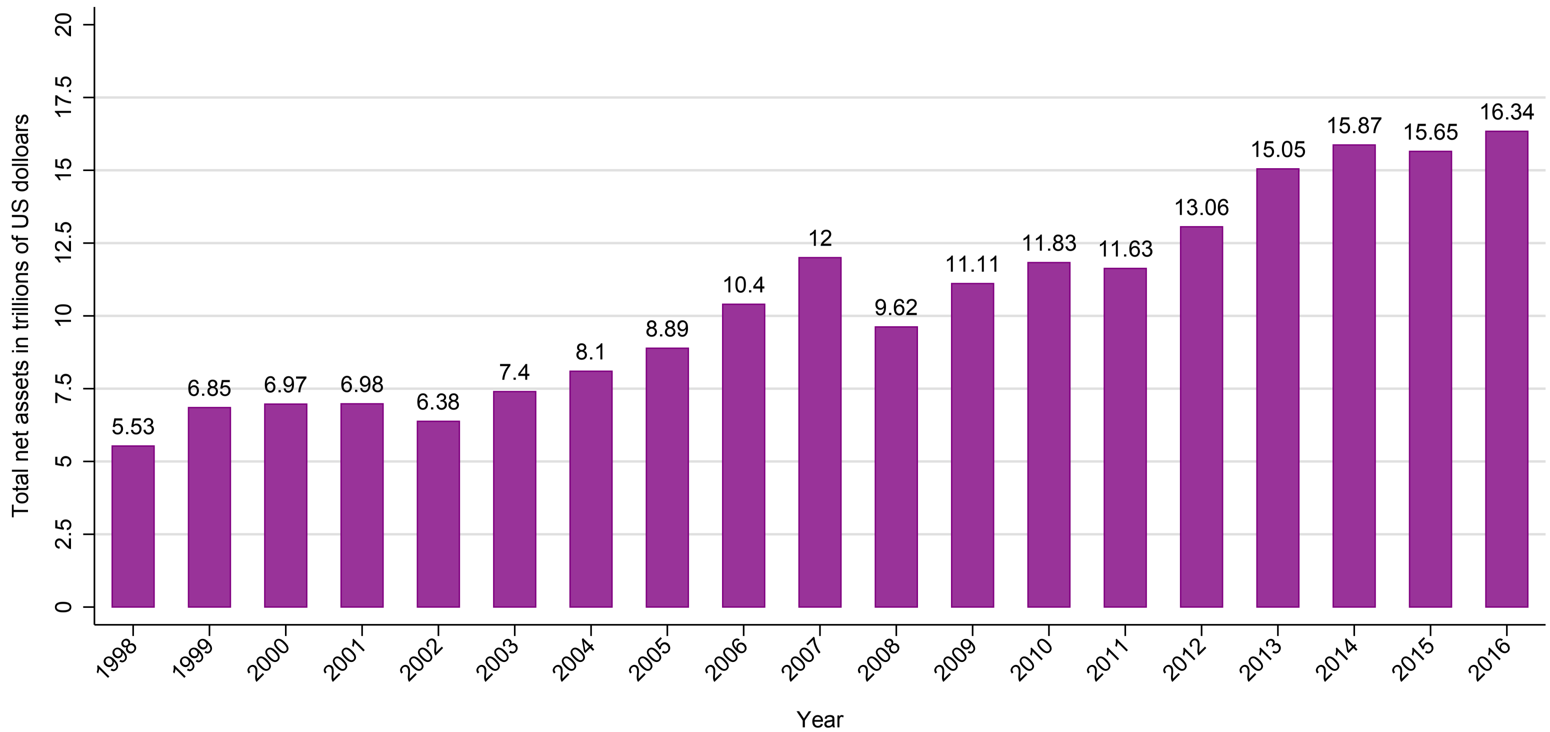

Figure 1.1: Total Net Assets of Mutual Funds in the United States from 1998 to 2016 (in trillion U.S. dollars)
The statistic presents the total net assets of mutual funds in the United States from 1998 to 2016. Sources: Investment Company Institute and Strategic Insight Simfund

strand of literature focuses on the mutual fund performance measurement and determinants of better performance. Specifically, building on Jensen (1968), a large number of studies have investigated (i) whether mutual funds perform better, on average, than a benchmark which is usually a passive market portfolio's performance (Daniel et al., 1997; Grinblatt and Titman, 1989; Huang et al., 2011; Jensen, 1968; Wermers, 2000), and (ii) potential determinants of the cross-sectional variance of performance across different mutual funds (Atkinson et al., 2003; Berk et al., 2004; Berk and Van Binsbergen, 2012; Simutin, 2014). The empirical evidence on whether the mutual fund manager could generate abnormal returns is mixed. On one hand, Carhart (1997) and Jensen (1968) find that the average equity mutual fund does not outperform the market. However, there are a few actively-managed funds perform better than a passive portfolio. On the other hand, the majority of individual investors tend to believe that some active portfolio managers have skills and could therefore "beat the market" (Wermers, 2004).

As a few funds are found to provide abnormal performance, there is a strand of the literature that focuses on certain fund or portfolio manager characteristics which are associated with superior performance. Several fund characteristics have been analyzed as potential determinants of future fund performance. For example, Chen et al. (2004) and Grinblatt and Titman (1989) empirically conclude that a large fund size would erode performance. Simutin (2014) reveals the positive relationship between the cash holding amount of a mutual fund and its performance. Most mutual funds are under the management of an individual or a group of portfolio managers who make investment decisions. Perhaps not surprisingly, an increasing number of studies have studied managerial traits and fund governance (Bär et al., 2011; Chevalier and Ellison, 1999b; Choi et al., 2016; Khorana, 1996; Qiu, 2003). For instance, Gottesman and Morey (2006) conclude a significant positive relationship between the education score of portfolio manager and the fund performance. Patel and Sarkissian (2017) analyze the fund management team structure, and find that team-managed funds outperform individual-managed funds across various performance metrics.

Building on the existing literature, the thesis tries to investigate the mutual fund performance, and seeks for potential explanations of mutual fund outperformance from various perspectives including managerial employment experience, managerial career concern and new fund initiation.

1.2 Research Objectives and Key Findings

There are three topics in mutual fund industry investigated in three independent empirical studies in the thesis. The three research topics include the fund manager's past working experience, new fund initiation and manager's career concern raised from peers. We discuss specific research objectives of three empirical studies in this section.

The first empirical study is presented in Chapter 3, following an overview of the literature in Chapter 2. This study examines the relationship between the mutual fund manager's past experience and the mutual fund's performance. The skills and knowledge acquired from prior working experience may be transferred to the current working context, thereby influencing the current job performance (Schmidt et al., 1986). Researchers have explored this topic from the perspectives of both applied psychology and empirical finance, where the latter particularly pertains to the CEO behavior analysis (Custódio et al., 2013). Building on this literature, we investigate the relationship between the mutual fund manager's past experience and mutual fund performance. Using data on U.S. mutual fund managers' work experience ranging from 1993 to 2012, this chapter introduces a new method to evaluate mutual fund performance from the perspective of the manager's lifetime working experience, by using the Principal Component Analysis to construct a Managerial Experience Index (MEI) based on 3 professional experience factors from the past career history of that manager: (i) investment objectives of the funds that s/he has managed (Zambrana and Zapatero, 2017), (ii) fund companies that s/he has worked for and (iii) industries of stocks in which s/he has invested (Kacperczyk et al., 2005). This chapter aims at addressing the following research questions:

- Is the fund's current performance affected by the manager's past working experience, including the number of investment objectives managed, the number of fund companies employed and the number of industries invested?

- How does the manager's past working experience influence the manager's investment ability, particularly the stock-picking and market-timing abilities?

The key findings of this chapter suggest that fund managers with more concentrated past working experience outperform those with more diversified experience. In addition, managers with more concentrated experience tend to exhibit stock-picking ability while those with more generalized experience tend to exhibit market-timing ability. The findings of this study are expected to be particularly useful for individual investors, since an observable managerial characteristic such as managerial past experience would allow them to more appropriately choose where to allocate their money for investment purposes.

Chapter 4 reports an analysis of the performance patterns of new mutual funds, and investigates the explanation for the short-lived outperformance. The increasing number of new funds has stimulated a debate among academics and practitioners about fund performance. Using U.S. mutual fund data from 1996 to 2015, we provide the first empirical evidence that new mutual funds can temporarily add value during its early stage, although this outperformance vanishes after a while. We restrict our sample to incubation-free funds like Evans (2010), by selecting funds with inception dates in the database close to the ticker creation date recorded in National Association Of Securities Dealers (NASD). This chapter aims at addressing the following research questions:

- Can the outperformance of newly-created fund be explained by the fund or managerial characteristics?
- Considering that fund creation is highly correlated with IPO volume, would the fund's access to IPO stocks become a valuable trading opportunity in creating new funds?

The first finding of this chapter is that new funds during their emerging period exhibit abnormal performance both before and after adjusting for fund expenses. The short-term outperformance during the emerging period is negatively related with the fund size, but not related to manager characteristics. We also find that IPO access is a significant explanation for the short-term outperformance and is associated with significant fund flow.

Chapter 5 investigates the idea that fund managers would take into account turnover risk that they face when adjusting the volatility of portfolios under their management. In addition to exploring a statistical correlation between a manager's discharge from a fund and the realized volatility of the fund that s/he had been managing, we use an instrumental variable (IV) approach to study whether one may infer causality from such a correlation. Our structural equation describes a fund's volatility as a function of whether its manager has been recently replaced, and we address the potential endogeneity of manager replacement using an IV that is motivated by the notion of a family tournament. The instrumental variable measures the peer flow pressure that a fund is facing in the tournament, and is based on the "Rank-of-Ranks" approach in Kempf and Ruenzi (2008). This chapter aims at addressing the following research questions:

- Is the peer flow pressure from the fund tournament a significant determinant of whether a mutual fund manager is replaced?
- Do fund managers adjust the risk of their funds based on the career risk that they are facing from the tournament?

We find an innovative explanation for the linkage of fund risk taking and the fund tournament. To be specific, fund managers are facing greater career concern if they perform badly in the tournament. Under the peer pressure, managers are more likely to hold more volatile portfolios so that to improve and secure their positions in the tournament.

1.3 Thesis Overview

This thesis comprises a total of six chapters. The current chapter is Chapter 1, and has presented a general introduction of the thesis, including the research background, motivations and research objectives. Chapter 2 provides an overview of the relevant literature, and also summarizes the theoretical framework, fund performance measurement and performance determinants that are applied in this thesis.

Chapters 3 to 5 present three original empirical studies. Specifically, the first empirical analysis (Chapter 3) examines the relation between the fund manager's past working experience and the performance of funds that s/he currently manages. Chapter 4 analyzes the performance patterns of new funds during their early stage. The third and final empirical study in Chapter 5 investigates the association between the fund's risk taking and the manager's replacement risk arising from within-family tournament to generate greater fund flow.

After presenting three empirical studies, the final chapter, Chapter 6, summarizes the conclusions of all three empirical analysis.

Chapter 2

Literature Review

This chapter provides a review of the literature on mutual funds, which relates to the research topics covered in the thesis. Specifically, this chapter includes the discussion in the research frameworks, estimation models used to evaluate fund performance and determinants widely applied in the literature in explaining fund out-performance.

2.1 Research Framework

According to the Efficient Market Hypothesis (EMH) (Fama, 1965, 1970), financial markets are "informationally efficient". If markets are efficient, then information gathering by mutual fund managers cannot produce abnormal returns consistently. However, testing this assertion is quite challenging because performance measures are imperfect.

Most of fund performance studies follow the methodology comparing a manager's performance with a benchmark index portfolio such as S&P 500 (Blume and Friend, 1973; Jensen, 1968; Jensen et al., 1972; Wermers, 2000). The major drawback of this method is the assumption of a consistent risk level of the portfolio without attention to the manager's stock selectivity skill (Lee and Rahman, 1990). Ferson and Qian (2004) suggests the Conditional Performance Evaluation (CPE) as a method to improve performance measurement by considering time-varying risk, and apply the new model to test U.S. equity mutual funds with conditional alphas. Malkiel (1995) and Carhart (1997) examine the performance using net returns data while Grinblatt and Titman (1983, 1992) and Wermers (2000) use the calculated return using portfolio stock holding information. Though they analyze fund performance using different data information, outcomes are similar which indicating that mutual funds have a slightly negative level of premium returns.

The empirical evidence on whether the mutual fund manager could generate abnormal returns is mixed. The average equity mutual fund does not outperform the market, but a few actively-managed funds perform better than a passive portfolio (Carhart, 1997; Jensen, 1968). Ferreira et al. (2013) find consistent empirical evidence that mutual funds underperform the market overall not only in U.S., but also in other 26 countries. It is commonly argued that actively managed mutual funds would not generate great returns because of management expenses that the fund managers charge. With small samples of mutual funds, Ferson and Schadt (1996) empirically show that the expense-adjusted performance is indeed negative under the traditional measurement model. However, the performance turns out to be neutral when one applies conditional measurement models (Ferson and Schadt, 1996). Ferson and Qian (2004) find that overall, the US equity mutual funds generate neutral risk-adjusted return, indicating those managers have the portfolio management ability only to cover the expenses. Moreover, several studies conclude that mutual fund performance is largely unpredictable, and suggest that the outperformance of some mutual funds is driven by luck instead of skills (Bollen and Busse, 2005; Carhart, 1997; Fama, 1970).

While some studies suggest that that overall, mutual funds underperform the market benchmark, others disagree. Moreover, the majority of individual investors tend to believe that some active portfolio managers could "beat the market" persistently for a long period (Wermers, 2004). Grinblatt and Titman (1989) show positive gross abnormal returns for both small funds and growth funds. Chevalier and Ellison (1999a) find that some managers would be expected to beat the market even after considering management fees. Wermers (2000) finds that the stocks mutual funds outperform broad market indices. The value of active fund management turns out to be significant: stocks held by fund managers outperform the characteristic-based benchmark by 1.3%, which suggests the existence of the stock-picking skill in active portfolio managers (Wermers, 2000). More recently, Kacperczyk et al. (2008) compare the actual performance of funds to the performance of the funds' beginning of quarter holdings and find that for the average fund, performance is indistinguishable, suggesting superior performance gross of fees and thus implying that the average manager adds value during the quarter after the beginning. Cremers and Petajisto (2009) show that the amount of portfolio holding of a fund that deviates from its benchmark is associated with better performance, and that this superior performance is persistent.

The empirical evidence on whether fund managers possess ability to generate abnormal performance is decidedly mixed. Some studies reveal that active portfolio managers fail to outperform the passive benchmark portfolios even before considering the expenses (Carhart, 1997; Gruber, 1996; Jensen, 1968; Malkiel, 1995). On the other hand, there are some studies find that active portfolio managers do exhibit securities picking ability by beating the benchmark (Daniel et al., 1997; Grinblatt and Titman, 1989).

2.2 Measurement of Mutual Fund Performance

As mentioned in Fan et al. (2017), turning the curse of dimensionality into blessing, the latent factors can be accurately extracted from the vast set of predictive variables and hence they can be reliably used to build models for response variables. For the same reason, factor-based models have been widely employed in portfolio management to examine the performance patterns of mutual funds.

There are a large number of studies that use factor-based models to estimate the mutual fund performance, such as Chen and Pennacchi (2009) and Kacperczyk et al. (2005). These models provide benchmarks against which the superior or inferior fund performance is assessed. As the main research objective of the thesis is to investigate mutual fund performance and reveal potential determinants for outperformance, we adopt factor-based asset-pricing models as the performance measurements following the existing literature.

The present section discusses these asset-pricing models including Fama-French 3 factor (Fama and French, 1993), Carhart 4 factor (Carhart, 1997), Ferson-Schadt conditional (Ferson and Schadt, 1996) and Fama-French 5 factor (Fama and French, 2015) models. Specifically, intercepts (Jensen's α) estimated from these models are often used as performance indicators.

2.2.1 Fama-French 3 Factor Model

The market beta from the single factor Capital Asset Pricing Model (CAPM) of Sharpe (1964) and Lintner (1965) is argued to be insufficient to explain the cross-asset variation (Harvey and Siddique, 2000). Therefore, Fama and French (1993) document the importance of two fundamental factors "Small Minus Big" (SMB) and "High Minus Low" (HML).

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,m}(R_{m,t} - R_{f,t}) + \beta_{i,smb}SMB_t + \beta_{i,hml}HML_t + \varepsilon_t^j \tag{2.2.1}$$

where we use i to donate the equity mutual fund, and t to donate the time unit. The dependent variable $R_{i,t} - R_{f,t}$ is the monthly return on portfolio in month minus the risk-free rate, and the independent variables are given by the returns of the four zero-investment factor portfolios. The expression $R_{m,t} - R_{f,t}$ measures the excess return of the market portfolio over the risk-free rate, which is also known as the "market premium" that equals the difference between the net return and the value-weighted aggregate proxy portfolio (Chen and Pennacchi, 2009); SMB_t is the return difference between small and large capitalization stocks; HML_t is the return difference between high and low book-to-market stocks. The last expression ε_t^j refers to the error item. One drawback of this model is that no theoretical argument exists justifying why these factors measure systematic risk in the economy. Fama and French (2010) recognize this limitation but argue that one can interpret the factors as simply alternative (passive) investment opportunities.

2.2.2 Carhart 4 Factor Model

One of the fund performance measures in this thesis is based on the Carhart (1997) four-factor model, which controls for risk and style factors. In the related literature, it is typically assumed that the riskiness of the manager's portfolio can be measured using factors identified by Fama and French (1995) and Carhart (1997). This model especially considers the momentum effect in stock returns (Jegadeesh and Titman, 1993). The regression that would be estimated is defined as:

$$\begin{aligned} R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,m}(R_{m,t} - R_{f,t}) + \beta_{i,smb}SMB_t + \beta_{i,hml}HML_t \\ + \beta_{i,mom}MOM_t + \varepsilon_t^j \end{aligned} \tag{2.2.2}$$

The dependent variable $R_{m,t} - R_{f,t}$ and explanatory variables $R_{m,t} - R_{f,t}$, SMB_t and HML_t are as previously defined in Section 2.2.1. The additional factor MOM_t is the return difference between stocks with high and low past returns. The Carhart four-factor measure is broadly used in measuring mutual fund performance (Chen and Pennacchi, 2009; Kacperczyk et al., 2005).

2.2.3 Ferson-Schadt Conditional Model

Traditional unconditional fund performance measures might be unreliable because of the common variation will be confounded with average performance (Ferson and Schadt, 1996; Kacperczyk et al., 2005). Therefore, Ferson and Schadt (1996) advocate the use predetermined instruments to capture time-varying loadings. In this thesis, the measurement model follows Wermers (2004) by introducing various macro-economic variables in addition to the Carhart (1997) 4 factor model. As a result, the model allows the interaction terms between various macro-economic factors and excess market return (Kacperczyk et al., 2005):

$$\begin{aligned} R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,m}(R_{m,t} - R_{f,t}) + \beta_{i,smb}SMB_t + \beta_{i,hml}HML_t \\ + \beta_{i,mom}MOM_t + \sum_{j=1}^{4} \beta_{i,j}[z_{j,t-1}(R_{m,t} - R_{f,t})] + \varepsilon_t^j \end{aligned} \tag{2.2.3}$$

Variables $R_{m,t} - R_{f,t}$, SMB_t, HML_t and MOM_t are as discussed in previous sections. The $z_{j,t-1}$ is the lagged value of macro-economic variable j. Four macro-economic factors include the 1-month Treasury bill yield, the dividend yield of the S&P 500 index, the Treasury bill spread (long- minus short-term bonds) and the quality spread in the corporate bond market (low- minus high-grade bonds).

2.2.4 Fama-French 5 Factor Model

Fama and French (2015) add the profitability (RMW) and investment (CMA) factors to the 3 factor model of Fama and French (1993). The Fama and French (2015) 5 factor model draws on evidence from Novy-Marx (2013) and Aharoni et al. (2013) suggesting that profitability and investment bear risk premia in the cross section. They use this evidence to support augmenting the Fama and French (1993) 3 factor model with the investment and profitability factors.

By adding the investment and profitability factors to the Fama and French (1993)

3 factor model, the model provides better power in explaining returns (Dittmar and Lundblad, 2017). The model is presented as follows:

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,m}(R_{m,t} - R_{f,t}) + \beta_{i,smb}SMB_t + \beta_{i,hml}HML_t$$
$$+\beta_{i,rmw}RMW_t + \beta_{i,cma}CMA_t + \varepsilon_t^j \tag{2.2.4}$$

As the model is based on the Fama and French (1993) 3 factor model, the dependent variable and some of the explanatory factors are defined as in Section 2.2.1. In addition, the profitability factor RMW_t is the return difference between stocks with robust and weak profitability and the investment factor CMA_t is the return difference between stocks with low and high investment firms.

2.3 Determinants of Mutual Fund Performance

As the mutual fund industry plays a dramatically increased role in financial markets in recent decades, investors are increasingly interested in mutual fund selection, demanding detailed mutual fund information and investment advice. Under this incentive, many authors have tried to explain the performance of mutual funds, which is a critical aspect in investor fund selection. In this section, we provide the literature review on the documented determinants of mutual fund performance from three aspects: fund characteristics, manager characteristics and managerial abilities.

2.3.1 Fund Characteristics

Several fund characteristics have been analyzed as potential determinants of future fund performance, including fund size, age, fees and expenses, loads, turnover, flows, and returns (Berk and Green, 2004; Chen et al., 2004; Edelen, 1999; Jensen, 1968; Jordan and Riley, 2015; Pollet and Wilson, 2008; Simutin, 2014; Wermers, 2004; Yan, 2006).

The fund size is defined as "the month-end net assets of the mutual fund" by MorningStar[2], and normally recorded in millions of dollars. Based on an analysis of a long term sample from 1962 to 1999, Chen et al. (2004) conclude that a large fund size would erode performance, which is consistent with the finding of Grinblatt

[2] Morningstar Inc. is an investment research and investment management firm headquartered in Chicago, U.S.. It also provides data and research insights on a wide range of investment offerings.

and Titman (1989) that fund returns decline with fund size. It is believed in some literature that large asset sizes would erode mutual fund performance due to higher trading costs associated with liquidity impact (Perold and Salomon Jr, 1991). Moreover, the negative relation between fund size and performance can be explained by the portfolio diversification. As mentioned in Pollet and Wilson (2008), a typical large fund held fewer than twice the number of stocks held by a fund less than 1% of its size. It is easier for a small mutual fund to put all assets into the best-performing portfolio than a large size fund (Chen et al., 2004).

Similarly, fund age is normally applied as the control variable in fund performance measurement. It is usually measured as the number of months since the fund started its first share class as mentioned in Jordan and Riley (2015). Fund age is normally highly correlated to fund size, as the TNA of a mutual fund typically grows over time. However, Jordan and Riley (2015) find a positive effect of fund age on the estimated alphas.

Sometimes it is argued that one may make abnormal returns by analyzing the cash flow information in small funds (Zheng, 1999). Fund flows would be greatly impacted by fund sizes and media attention since search costs could be affected by these characteristics (Sirri and Tufano, 1998). The significant positive relationship between fund flows and past performance does appear in the top 25% of past returns (Goetzmann and Peles, 1997). Berk and Van Binsbergen (2012) argue that money would flow to the most skilled manager until the manager could not deliver further abnormal returns. This evidence is rooted in diseconomies of scale in performance. In a similar vein, some literature tries to explain the observed convexity in the mutual fund flow-performance relationship with reference to the managers risk-taking (Berk et al., 2004; Lynch and Musto, 2003). Venkatesan (2014) finds the evidence that new money flows would follow skilled managers after controlling for past performance.

Cash holdings, as the largest non-equity asset class in the mutual fund, could generate dynamic differences in fund performance (Simutin, 2014). Yan (2006) argues that cash holdings are related to the fund size, fees and other characteristics. Simutin (2014) examines the relationship between the cash holding amount of a mutual fund and its performance. The result shows that funds managed with large abnormal cash holdings which exceed a predicted level would outperform those actively-managed funds with low cash holdings by more than 2% per annum due to the flexibility that the excess cash provides.

As expressed in the 2017 Investment Company Factbook, there are mainly two types of expenses and fees for mutual fund investors: ongoing expenses and sales loads. The ongoing expenses cover portfolio management, fund administration, distribution charges (known as 12b-1 fees) and other compliance costs (Malhotra and McLeod, 1997). Such expenses are included in the fund expense ratio, which is the annual charge expressed as a percentage of its total assets. The sales loads are paid at the time of share purchase (front-end loads), or at the time when shares are redeemed (back-end loads), or over time (level loads). The fund expense ratio tends to fall if the total assets of a fixed sample of funds rise over time. This is because some costs included in the expense ratio (such as accounting and auditing fees, transfer agency fees and director's fees) are mostly fixed in dollar terms. Another factor explaining a decline in the average expense ratio is the shift towards no-load share classes, particularly institutional no-load share classes that tend to have below-average expense ratios. Malhotra and McLeod (1997) argue that funds with higher expense ratio tend to take riskier investment decisions to achieve better returns so that these high expenses can be recouped. Further, Cashman et al. (2012) find the envidence that fund outflows increase with expense ratios which can be explained as the cost of staying in a fund for investors.

2.3.2 Manager Characteristics

In the 1990s, most studies on mutual fund performance ignored the essential role of fund managers, and mainly focused on fund characteristics. Kon et al. (1983) stress the importance of managerial characteristics on fund performance as it provides a better view in manager evaluation. Some literature has focused on the managerial level recently by studying the effects of manager characteristics and behavior including manager age (Taylor, 1975), gender (Atkinson et al., 2003) and education background (Chevalier and Ellison, 1999a; Gottesman and Morey, 2006) on fund performance.

One factor of fund management that relates closely to our studies is the size of the fund management team. Usually, researchers categorize funds into individual-managed and team-managed funds based on the number of managers. In the past decades, the number of mutual funds managed by a team has increased significantly from only 30% in 1992 to above 70% in 2010 (Patel and Sarkissian, 2017).

The current literature offers two competing hypotheses concerning individual-managed and team-managed funds. The group shift hypothesis (Hogg et al., 1990; Kerr, 1992) suggests that the opinion of team members shifts towards the opinion of the dominant person in a team. As that person typically holds very pronounced opinions, a team eventually gravitates towards extremes. Consequently, teams make more extreme decisions than individuals do. In contrast, the diversification of opinions hypothesis suggests that the team opinion is the average opinion of the team members. Because individual team members might have different opinions, the team decision will be a compromise (e.g., Sah and Stiglitz (1986, 1988)). Extreme opinions of members in a team are averaged out and teams eventually make less extreme decisions than individuals do.

The empirical evidence on the performance of individual and team management is rather mixed. For instance, most studies use the Center for Research in Security Prices (CRSP) or Morningstar Principia (MP) data and conclude there is no significant outperformance in teams over individually managed funds (Bär et al., 2011; Bliss et al., 2008; Chen et al., 2004; Massa et al., 2010). However, very recently, Patel and Sarkissian (2017) find that team-managed funds outperform individual-managed funds across various performance metrics using the relatively new Morningstar Direct (MD) mutual fund database.

Turning to the effects of education, a manager who attended a more selective SAT (Scholastic Aptitude Test) institution would have a better risk-adjusted return (Chevalier and Ellison, 1999a). With some improvement from the former article, Gottesman and Morey (2006) add more educational factors to pursue the study. A significant positive relationship between GMAT (Graduate Management Admission Test) score in MBA (Master of Business Administration) program and fund performance is proved.

Although the mutual fund industry is large in the U.S. financial market, the fraction of female fund managers is quite low, which has been singled out as a "trillion dollar question" by a recent New York Times article[3]. Niessen-Ruenzi and Ruenzi (2017) find no difference in fund performance between female and male managers. However, the fund flow attracted to funds managed by female managers is significantly more than male managers.

[3]This can be found in the New York Times article on 13/01/2017: A Trillion-Dollar Question: Why Don't More Women Run Mutual Funds?

Age is also one of characteristics that have received a lot of attention in the academic literature on fund performance. The effects of age and experience on the decision-making behavior are examined by Taylor (1975) by using data of 79 male line managers from factories. It is found that age matters more to decision making performance than experience (Taylor, 1975). In the literature investigating how the gender difference affects fund characteristics, Atkinson et al. (2003) show that there is no significant relationship between gender and fund performance. However, the net asset flow is comparatively low in female-managed fixed-income mutual funds than male-managed funds. Another interesting perspective is the geographic impact on the portfolio performance. It is observed that portfolio managers earn abnormal returns in assets invested in nearby areas because of the informational advantage (Coval and Moskowitz, 2001).

2.3.3 Managerial Abilities

Lee and Rahman (1990) document that fund managers obtain better performance due to obvious ability to "time" the financial market (market-timing) and/or the skill to forecast individual asset returns (stock-picking). Fama (1972) categorizes the portfolio manager's skills into two parts: micro forecasting of the price movement of individual asset (stock-picking), and macro forecasting of the price movement of the whole stock market (market-timing).

Stock selection skill allows the manager to forecast firm-specific events and therefore the prices of individual securities, while market timing ability is mainly concerned with predicting future realizations of the market portfolio (Kon et al., 1983). Lee and Rahman (1990) mention that a portfolio managers can be characterize as a stock-picker or/and market-timer based on the skill that revealed in the investment.

Further, Kacperczyk et al. (2014) investigate the interaction between two managerial skills and the business cycle by pointing out that managers exhibit more "stock-picking" skill in economic booms while greater "market-timing" ability in recessions. A skilled fund manager is likely to attract more fund inflows and also tend to set into the hedge fund industry in the future (Kacperczyk et al., 2014). And portfolio managers are approved to have the ability to effectively separate the stock-picking skill from the market-timing skill during the tenure (Treynor and Black, 1973).

According to Venkatesan (2014), on average mutual fund managers have the stock-picking skill and it is even more pronounced in smaller funds. Those skilled fund managers who turnover the portfolio more often would also charge more expenses, which might be used as a compensation for their skills (Venkatesan, 2014). Venkatesan (2014) concludes that the average of U.S. mutual fund managers has stock-picking skill and it is mainly driven by the ability to predict firms' inflows. This outperformance is persistent in the short term and cannot be explained by the momentum effect. However, Fama and French (2010) conclude that though top managers have the skill to beat the market, the average manager lacks the relevant skill. Additionally, Ding and Wermers (2004) find that the most experienced growth fund managers have substantially better stock selecting abilities than the less-experienced colleagues. Moreover, Ding and Wermers (2004) conclude that the managerial experience does matter for predicting future stock-picking successes of growth-oriented managers, but not that of income-oriented managers. This outcome supports the view that experience is positively related with the success in picking growth stocks.

The literature on the market timing ability of mutual fund managers mainly focuses on examining the managerial skill to time market return or volatility. Treynor and Mazuy (1966) develop a market timing measure but only find 1 out of 57 funds in the sample with significant timing ability. Likewise, Henriksson (1984) adopts the methodology in Henriksson and Merton (1981) to test the presence of market timing ability and concludes that only 3 out of 116 funds exhibit timing ability. Chang and Lewellen (1984) apply a joint test to examine the existence of stock picking and market timing ability of mutual fund managers, and conclude that neither type of skill exists. (Elton et al., 2009) find the evidence that the managerial timing ability lead to incorrect investment decisions and poor management performance.

Although most studies find virtually no evidence that fund managers exhibit timing ability, there is still some empirical evidence supporting the existence of timing ability. Fama (1972) proposes a model to test market timing ability. Later, Kon et al. (1983) follow the method by apply this method in an analysis of 37 mutual funds. Kon et al. (1983) conclude that the significant market-timing ability exist in individual portfolio managers. Bollen and Busse (2001) test the market timing ability of mutual fund managers using both daily and monthly data, and conclude that the use of daily returns makes it possible to detect timing ability. In line with this finding, Jiang et al. (2007) and Huang and Wang (2014) also show the existence of market timing ability by applying a holding-based approach.

Chapter 3

“Specialist” versus “Generalist”: Mutual Fund Performance and Manager Lifetime Work Experience

3.1 Introduction

This study extends the literature on mutual fund by analyzing novel data on the lifetime work experience of mutual fund managers to investigate whether a mutual fund’s performance varies with its fund manager’s managerial experience that the manager has accumulated over the course of her career.

This chapter is motivated by studies from applied psychology which suggest that individual behavior is partly shaped by past experiences (Nisbett and Ross, 1980; Taylor, 1975). Building on this literature, recent studies examine how past experiences affect investment decisions of individuals. Vissing-Jorgensen (2004) concludes that an individual’s current belief depends on her own prior investing experience, and this belief affects her portfolio shareholdings. Similarly, Kaustia and Knüpfer (2008) provide evidence on a positive linkage between past IPO investment returns and future subscriptions by individuals. Past experience affects not only the behavior of individual investors, but also that of mutual fund managers and CEOs. Using the mutual fund manager’s age as a proxy for her investment experience, Greenwood and Nagel (2009) find that younger, and hence less experienced according to their proxy, managers invested a larger amount of money into equities in the technology industry particularly at the peak of a bubble. Custódio et al. (2013) argue that CEOs with more general managerial skills, gained from the past working experience, are rewarded with a greater compensation relative to specialist CEOs. Overall, the existing empirical evidence agrees with the conclusion of Schmidt et al. (1986) that an individual's prior working experience is a valuable source of skills and knowledge which may be also applied to her current working context.

We investigate the relationship between the mutual fund manager's past experience and the mutual fund performance by exploiting data on the fund manager's career history, instead of using age as a proxy for the manager's experience. The main esearch questions examined in this chapter are listed as follows:

- Is the fund's current performance affected by the manager's past working experience, including the number of investment objectives managed, the number of fund companies employed and the number of industries invested?
- How does the manager's past working experience influence the manager's investment ability, particularly the stock-picking and market-timing abilities?

The mutual fund manager's past experience may encapsulate all the professional knowledge and skills acquired from the past career history. In this study, the fund manager's experience is captured by information on the numbers of (i) different fund types managed where different types are distinguished by different investment objectives, (ii) fund companies worked for and (iii) industries invested during the past career history. These three dimensions reflect the manager's investment styles, employment history and exposure to industry-specific information which may affect her current fund's performance via her skills and knowledge. For example, a more specialist manager, who has managed fewer fund types and invested in fewer industries in the past, may be expected to improve her fund's performance via better stock-picking and market-timing skills.

The existing literature on the determinants of mutual fund performance focuses either on the role of fund characteristics, such as fund flows (Berk and Green, 2004; Hu et al., 2011), turnover ratio (Pástor et al., 2015) and fund size (Chen et al., 2004; Pollet and Wilson, 2008), or that of managerial characteristics, such as the manager's education background (Chevalier and Ellison, 1999a; Gottesman and Morey, 2006), gender (Atkinson et al., 2003) and age (Taylor, 1975). This study extends the literature by investigating the impact of managerial professional experience acquired during the career of the manager. In addition, this study considers the channels through which such an impact may operate.

More specifically, this study proposes an index based on three managerial experience factors, which can represent the fund manager's past professional experience, and empirically investigates how the index is associated with the mutual fund performance. Based on the index rankings, the manager could be divided into "generalist" (with more diversified experience) or "specialist" (with more concentrated experience) based on the lifetime experience. The insights from applied psychology suggest that the past experience may affect the mutual fund manager's investment decisions via her lifetime accumulated experience and skills, thereby affecting fund performance. This study anticipates a potential relationship between the managerial experience and fund performance which would indicate that the past professional experience shaped the fund manager's decision making.

Moreover, this study provides evidence on the specific channels through which managerial experience acquired over the course of the manager's career may impact on the fund performance. Managers with more specific skills during their employment history might be more familiar with some individual stocks which could improve their stock-picking skill. Similarly, with more concentrated experience in certain industries, specialist fund managers are expected to possess better security-picking and market-timing ability due to more informational advantages obtained in certain industries than generalist managers.

The remainder of the study proceeds as follows. We present the literature review in Section 3.2. Next, we provide the data and methodology in the next section. The main empirical results and robustness tests are included in Section 3.4. Finally, we close the chapter with conclusion.

3.2 Prior Literature

This section presents the literature review on topics including individual's experience and job performance, mutual fund performance and managerial abilities.

The association between the individual's past experience and current decision making has long been examined in the literature. In the early 1970s, Slovic (1972) concludes that investor's prior investment decision making experience of a specific type had little effect on performance in subsequent decisions of the same type. Similarly, Taylor (1975) argues that the manager's age is a more influential determinant of the job performance in the decision making exercise than their prior decision making experience. Medoff and Abraham (1980) provide direct evidence on the relationship between experience and earnings, using data on managers and professional employees who do similar work in two major U.S. corporations. They conclude that there is a strong and positive linkage between manager experience and relative earnings, but there is no significant association between experience and relative job performance (Medoff and Abraham, 1980).

Another strand of the literature has found evidence that past experience has a significant influence on the current job performance. For instance, McDaniel et al. (1988) conduct a quantitative study in examining the relation between individual's job experience and job performance from a total sample of 16,058. Particularly, they find that length of experience and job complexity are the two key determinants for the job performance (McDaniel et al., 1988). This can be explained by argument that an individual's prior working experience is a valuable source of skills and knowledge which may be also applied to her current working context (Schmidt et al., 1986). Vissing-Jorgensen (2004) concludes that an individual's current belief depends on her own prior investing experience, and this belief affects her portfolio shareholdings. More recently, Custódio et al. (2013) argue that CEOs' managerial skills obtained from the past working experience are associated with their compensation. Specifically, CEOs with more general managerial skills are rewarded with a greater compensation relative to specialist CEOs based on 5 managerial experience factors (Custódio et al., 2013).

In the mutual fund industry, the fund abnormal return is normally considered as the measurement of the manager performance. The empirical evidence on whether the mutual fund manager could generate abnormal returns is mixed. On average, the equity mutual fund does not outperform the market, but a few actively-managed funds perform better than a passive portfolio (Carhart, 1997; Jensen, 1968). It is commonly argued that actively managed mutual funds would not generate great returns because of management expenses that the fund managers charge. While some studies suggest that that overall mutual funds underperform the market benchmark, others disagree. Moreover, the majority of individual investors tend to believe that some active portfolio managers could "beat the market" persistently for a long period (Wermers, 2004).

Prior literature suggests that stock selection and market timing abilities are potential channels through which a manager may affect fund performance (Fama, 1972; Lee and Rahman, 1990). Ding and Wermers (2004) and Chevalier and Ellison (1999a) find the evidence that the stock selecting ability exist in certain groups of fund managers. To be specific, Ding and Wermers (2004) reveal that experienced growth fund managers tend to show better skills in selecting stocks while Chevalier and Ellison (1999a) conclude that the manager with higher education grades would exhibit better stock-picking skill. More recently, Venkatesan (2014) shows a significantly positive relationship between managerial skill in stock-picking and the future performance, which suggests the fund manager could add value through their skills. Managers with more specific skills during their employment history might be more familiar with some individual stocks which could improve their stock-selecting skill (Lee and Rahman, 1990).

The main method of stock selectivity skill is to identify individual equities that are under- or overvalued with expected return significantly away from the security market line (Lee and Rahman, 1990). For the first managerial experience factor, with more concentrated investment objective styles, the manager has more expertise in managing certain type of mutual funds such as the Small-Cap and Health Sector funds. With the equipped superior experience in these fund styles, the specialist managers tend to have better skills in picking undervalued stocks in certain sectors. Secondly, the fund company normally has its own information advantages. Cohen et al. (2008) find that the private information flow would transfer from the top firm officer to portfolio managers through a network, and therefore affect the stock price and portfolio holdings. This information advantage could also be obtained through social or/and educational networking (Cohen et al., 2008). The manager with more company-employment history is more likely to be familiar with the superior information from inside the company of picking under-valued stocks. Finally, managers with certain industry expertise or information advantage on certain industries, i.e. specialist fund managers, are expected to exhibit better stock-picking ability. To be specific, a specialist with more concentrated professional experience in fewer industries would have the informational expertise to invest in better-performing stocks. On the contrary, a generalist manager who is equipped with more diversified managing experience are more likely to chase the market portfolio, and diversify more to reduce unsystematic volatility. Moreover, Kacperczyk et al. (2005) find that more industry-concentrated funds would outperform well-diversified portfolios. Mutual fund managers would prefer concentrating the fund holding if they believe they have superior information in selecting profitable stocks.

Market timing refers to dynamic capital allocation among a wide range of investments, commonly restricted to stocks and short-term government bonds (Bollen and Busse, 2001). To be specific, a fund manager with better timing ability would increase the portfolio weight on stocks prior to a rise in the market and/or decrease the weight before the market starts to fall. According to Henriksson and Merton (1981), the market timing ability is a macro-forecasting skill that aims at forecasting the price movements of the general market. A fund manager with more concentrated experience would have better skill in timing the market than a manager with broader experiences, since a specialist manager is more familiar with the price movement with the more focused past professional experience.

To be specific, the manager with more focused investment objectives is more experienced in certain types of stocks such as the Value stock or Natural Resource Sector equities. Having concentrated more on certain types of equities makes them familiar with the price movement along with the business cycle therefore they could exhibit better timing ability compared to managers with more diversified experiences. According to Jiang et al. (2007), mutual fund managers apply non-public information to time the market and predict market returns, which the manager could obtain from the fund company. Avramov and Wermers (2006) prove that long-only strategy outperform the Fama-French and Momentum benchmark by 2% - 4% per year by timing industries over the business cycle. Moreover, Kacperczyk et al. (2005) measure the industry-adjusted fund performance with the industry concentration index, and conclude that the more concentrated fund exhibits better ability in timing industries. This conclusion also indicates that the market timing funds tend to be industry concentrated (Jiang et al., 2007).

Normally, firms would hire workers based on the working experience since they believe workers would have obtained relevant skills, and knowledge to improve their current working performance (Rynes et al., 1997). The prior employment history would affect the future working performance (Dokko et al., 2009; Rynes et al., 1997). In fund companies, mutual fund managers often manage a smaller sector of funds as their career starts, and will be promoted to higher positions that will enable them to manage greater income funds afterwards (Chevalier and Ellison, 1999a). They also argue that mutual fund managers in different career stages behave differently and fund performance is determined by comprehensive managerial characteristics of mutual fund managers. Chevalier and Ellison (1999a) test whether some managerial characteristics including ability, knowledge or effort could affect fund performance using a sample of mutual funds over a short time period. Later, Ding and Wermers (2004) also raise the hypothesis of considering the performance at the manager level rather than the fund level. They find that the manager's experience matters, but only for growth-oriented fund managers.

According to Becker (1962), general human capital improves working productivity across all firms while firm-specific capital only works in the current firm. Apart from these managerial traits, the past working experience of a fund manager could also be considered as one of the essential components of his/her background. However, there is little empirical evidence on its impact on fund performance. Only a small number of studies analyzed fund performance by applying the past working experience information of mutual fund managers.

Our study mainly focuses on the professional fund managing experience of the fund manager, which could be acquired from the investment decision experience in the mutual fund industry. There are three managerial experience factors that may capture the past professional mutual fund management experience, specifically investment objectives (Brown and Goetzmann, 1997), employment history (Dokko et al., 2009) and industry concentration (Kacperczyk et al., 2005) information. These are experiences and skills which have been previously found to affect fund performance. Specifically, Dokko et al. (2009) argue that individuals are able to transfer the knowledge and skill acquired from prior related work experience and improve the current job performance. Kacperczyk et al. (2005) find the empirical evidence that funds with more concentrated stock holdings tend to outperform more diversified portfolio. This can be explained by the management team's expertise in concentrated industries and therefore they are more likely to pick profitable stocks.

3.3 Data and Methodology

This section explains the data sources and describes the main characteristics of mutual funds included in the study sample. The main methodology in constructing the Managerial Experience Index and in measuring managerial abilities are included in this section.

3.3.1 Sample Selection

The primary data source for most of mutual fund characteristics used in this study is the CRSP U.S. Survivorship-Bias-Free Mutual Fund Database. The CRSP database covers the U.S. open-end mutual fund and provide fund characteristics information like TNA (total net asset), fund returns, fund management structures, investment objectives, holdings, turnover rates and fund manager' identity (Niessen-Ruenzi and Ruenzi, 2017). Next, we merge the CRSP mutual fund database with the Thomson Reuters Mutual Fund Holdings Databases (formerly known as the Thomson Financial CDA/Spectrum Holdings Database) using the MFLINKS file (see Simutin (2014); Wermers (2004)) obtained from the Wharton Research Data based on (Wermers, 2000). The Thomson Financial database provides long positions in domestic common stock holdings of mutual funds and the data are collected both from submitted reports of mutual funds to SEC (U.S. Securities and Exchange Commission) and from volunteer reports generated by some mutual funds (Huang et al., 2011)[4].

Since our study captures the managerial experience from the manager level, we restrict our dataset to funds managed by individual managers, as opposed to teams (Zambrana and Zapatero, 2017). We manually correct manager names with different spellings and assign each manager a unique identifier[5].

Like previous studies (Glode, 2011; Kacperczyk et al., 2008, 2014; Simutin, 2014), we mainly focus on actively managed diversified domestic equity mutual funds in U.S., and exclude international, balanced, sector, bond, money market, and index funds[6]. This allows us to work with holdings data which are mostly complete and

[4]The Security and Exchange Commission (SEC) requires mandatory disclosure frequency from quarterly to every 6 months. In 2004, SEC increased the disclosure frequency back to quarterly.

[5]In some cases the same manager is reported with or without the middle name, or using abbreviated first name.

[6]First, we select funds with the following Lipper objectives: CA, CG, CS, EI, FS, G, GI, H, ID, LCCE, LCGE, LCVE, MC, MCCE, MCGE, MCVE, MLCE, MLGE, MLVE, MR, NR, S, SCCE, SCGE, SCVE, SG, SP, TK, TL, UT. If a fund does not have any of the above objectives, we select funds with the following Strategic Insights objectives: AGG, ENV, FIN, GMC, GRI, GRO, HLT, ING, NTR, SCG, SEC, TEC, UTI, GLD, and RLE. If a fund has neither the Lipper nor the SI objective, then we use the Wiesenberger Fund Type Code to select funds with the following objectives: G, G-I, G-S, GCI, IEQ, ENR, FIN, GRI, HLT, LTG, MCG, SCG, TCH, UTL, and GPM. Since the reported objectives are not always accurate in characterizing a fund, funds without a CS policy (holding less than 80% asset allocation in equity market) would also be excluded. Index funds are identified based on their names.

reliable. As Busse et al. (2015) find, smaller funds tend to outperform larger funds primarily when small-cap stocks outperform large-cap stocks; we therefore exclude funds that managed less than $5 million assets in the previous month, and exclude funds that did not disclose their holdings in the previous 36 months (Huang et al., 2011). Additionally, we exclude funds for which the observation date precedes the inception date, to avoid incubation bias (Evans, 2010; Zambrana and Zapatero, 2017).

Our final sample includes 5,406 U.S. open-end domestic equity funds. The sample spans the period from 1993 to 2012[7], and includes 1,106 management companies and 3,122 portfolio managers.

3.3.2 Specialist and Generalist

One goal of this study is to test if a specialist fund manager could over-perform the generalist manager where "specialist" and "generalist" are defined in relation to working experience. To fulfill this purpose, the index of the fund manager's past working experience in equity funds (Managerial Experience Index) prior to the current position would be created. This index captures the working experience of equity fund managers that can be transferred across mutual funds and management companies. We consider three proxies to capture the managerial working experience.

3.3.2.1 Managerial Experience Factors

Managerial experience factors that we use in this study are obtained at the manager's level. To analyze if the managerial experience affects fund performance, we focus on 3 factors which are representative of the manager's life-time experience: (1) number of fund objective styles the manager has managed, (2) number of fund companies the manager has worked for, and (3) number of industries the manager has invested in. These 3 factors capture different aspects of the manager's past working experience, and are defined as follows:

1. Number of Fund Styles (X1): This variable measures the total number of different mutual fund types a manager has managed e.g. Mid-Cap funds or Growth

[7] The sample ends at year 2012 is because of we only have the database access to an older version of MFLINKS, which ends at March 2012 rather than the latest version.

and Income Funds[8]. A fund manager who managed fewer types of mutual funds may be considered more specialized in the investment objective(s).

2. Number of Fund Companies (X2): This is the total number of companies that a mutual fund manager has worked for. A fund manager who worked for multiple companies may be equipped with more diversified managing skills, instead of company-specific skills.

3. Number of Invested Industries (X3): This variable captures the total industries which the stocks the manager has invested in. A manager with stock holdings in fewer industries may be considered as having more specific experience and expertise in those industries than a manager with broader industry investment experiences. This proxy will be calculated with accumulated number of holding industries using the Fama-French 48 industrial classification code.

We calculate each type of managerial experience factor using historical data on manager-level information. For example, we sort the data by the manager ID, date and investment objective code and calculate the number of fund styles for each manager which is accumulated over time. We do similar measurement to factor X2 (Number of Fund Companies) and factor X3 (Number of Invested Industries) for each manager over time.

3.3.2.2 Managerial Experience Index

The Principal Component Analysis (PCA) will be applied to extract common components and combine the three experience factors into a single index. PCA is helpful in reducing the dimensionality of data, while keeping as much variation as possible (Custódio et al., 2013). We are aware that using an index composed from individual factors by PCA has certain limitations. Some information included in factors may be missing in the index due to the PCA methodology. However, using a single index instead of 3 separate factors makes the method easier to apply and interpret[9].

The correlation coefficients among three managerial experience factors are below 0.4 as shown in Panel A of Table 3.1. In addition, it shows high correlations between

[8] CRSP U.S. Survivor-Bias-Free Mutual Funds database includes style and objective codes from three different sources over the life of the database. The CRSP Style Code builds continuity within the database by using three codes: Wiesenberger Objective codes, Strategic Insight Objective codes and Lipper Objective codes as its base and provides consistency with those codes provided.

[9] The result using three individual managerial factors instead of the MEI index remains unchanged.

Table 3.1: Managerial Experience Index: Principal Component Analysis

Panel A: Correlation Structure				
	MEI	Objective (X1)	Company (X2)	Industry (X3)
MEI	1			
Objective Number (X1)	0.7784***	1		
Company Number (X2)	0.6164***	0.2397***	1	
Industry Number (X3)	0.7601***	0.3828***	0.2115***	1

Panel B: Principal Component Analysis			
	Objective (X1)	Company (X2)	Industry (X3)
Loadings	0.778	0.616	0.76
Scores	0.623	0.493	0.608
Proportion Explained		0.521	
Eigenvalue		1.56	

Panel A presents the correlation coefficient matrix of the Managerial Experience Index, the Style Number (X1), the Company number (X2) and the Industry number (X3). Panel B summarize the Principal Component Analysis estimation based on three managerial factors. The factor loadings and correlation scores are given in the first two rows, followed by the proportion explained by the component and the eigenvalue. The significance levels are abbreviated with asterisks: *, ** and *** donate significance at the 10%, 5% and 1% levels, respectively.

MEI and experience factors which ranges from 0.62 to 0.78. Panel B of Table 3.1 presents the outcome of principle component analysis for the Managerial Experience Index. We obtain a component with an eigenvalue greater than 1 (eigenvalue = 1.56 in this study), which indicates that the extracted component has better explanatory power than any one of the original experience factors. The proportion explained by this component is 52.1% which represents over half of all observed variations. Also, all positive factor loadings of PCA indicate a positive correlation between this component and all initial factors. Therefore, a higher value of this index could reflect more diversified past experience of managers.

The Managerial Experience Index of fund manager i in month t is calculated by applying scores in Table 3.1 for each managerial experience factors as reported. According to the score coefficients, the index gives close to equal weights to X1 (Style Number) and X3 (Industry Number) and slightly less to X2 (Company Number). The index has been standardized to have the mean of zero and the standard deviation of one.

$$MEI_{i,t} = 0.62X_{1i,t} + 0.49X_{2i,t} + 0.61X_{3i,t} \tag{3.3.1}$$

In Table 3.2 we document summary statistics for the Managerial Experience Index and other managerial and fund characteristics. The MEI index ranges from

Table 3.2: Summary Statistics

Variable	Mean	Std. Dev.	Min	Max
Panel A: Managerial Characters				
Managerial Experience Index (MEI)	0	1.25	-2.22	6.6
Number of Managed Fund Style	1.42	0.75	1	6
Number of Employed Management Company	1.49	0.86	1	8
Number of Invested Stock Industry	32.09	11.91	1	48
Number of Equity Funds managed	2.84	2.55	1	24
Manager Tenure (in years)	2.8	2.69	0.08	18.5
Panel B: Fund Characters				
Total Net Assets (TNA) (in Millions)	745.79	3229.12	5	109,796
Fund Age (in Years)	10.45	9.39	0.08	52.08
Expense Ratio (%)	1.36	0.59	-0.26	14.05
Turnover Ratio (%)	95.77	169.03	0	9150
Fund Load (%)	1.67	1.67	0	9
Raw Return (%)	0.65	5.79	-46.2	59.62
Total Number of Funds	5,406			
Total Number of Managers	3,122			
Total Number of Management Companies	1,106			
Total Number of Observations	102,287			

This table summarize the descriptive information of managerial and fund characters. Panel A presents the summary statistics of the MEI and other managerial factors. The MEI is extracted using the Principal Component Analysis based on 3 managerial experience factors: X1 (the style number), X2 (the company number) and X3 (the industry number). Panel B reports the fund characteristics of the actively managed domestic equity mutual funds included in this study.

-2.2 to 6.6 with the mean of zero, which demonstrates a significant variation across individuals. The average manager tenure is 2.8 years and the average number of funds managed by each manager is 2.84. Apparently, on average, individual managers included in the sample have a relatively short tenure and manage multiple funds. Funds managed by managers with more specialized experiences may differ substantially from funds managed by generalist managers in several characteristics, such as fund age, size, management fees and turnover ratio. The average age of funds in our sample is 10.45 years. The 95.77% turnover ratio indicates that funds included in the sample tend to be actively managed. The average monthly return is 0.65% but returns are distributed with large variation.

3.3.3 Timer and Picker

There are two potential managerial skills to be considered in our study, namely stock-picking and market-timing ability. The hypothesis is that the fund manager would exhibit either of these two portfolio management skills, and the skill would be reflected in fund performance.

Existing market timing measures, such as those of Henriksson and Merton (1981) and Treynor and Mazuy (1966), are based on nonlinear regressions of realized fund returns against contemporaneous market returns. As the literature shows, however, the return-based timing measures using monthly fund returns tend to underestimate timing ability. Most of recent studies use portfolio holdings to determine timing and selection ability (Jiang, 2003; Kacperczyk et al., 2014). However, given the shortcomings of the existing databases, the holding-based measurement of timing and picking abilities does not fulfill our requirements[10]. Based on the market-timing model of Treynor and Mazuy (1966), we estimate the following model with multi-risk factors to identify the managerial skill:

$$
\begin{aligned}
R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,m}(R_{m,t} - R_{f,t}) + \gamma_{i,m}(R_{m,t} - R_{f,t})^2 \\
+\beta_{i,smb}SMB_t + \beta_{i,hml}HML_t + \beta_{i,mom}MOM_t + \varepsilon_t^j
\end{aligned}
\tag{3.3.2}
$$

where $R_{i,t} - R_{f,t}$ refers to the mutual fund's before-expense return in month t minus the risk-free rate; $R_{m,t} - R_{f,t}$ is the market excess return; SMB_t , HML_t and MOM_t are the monthly size, book-to-market and momentum factors as defined in the Carhart (1997) 4 factor model.

Next, we obtain the timer and picker ability for each fund using coefficients α_i and $\gamma_{i,m}$. We classify a fund is being managed by a manager with stock-picking ability if α_i is significantly positive and with market-timing ability if $\gamma_{i,m}$ is significantly positive. We are aware that the timer indicator $\gamma_{i,m}$ measures the market-timing effect other than the momemtum factor MOM_t, which already serves as a market-timing index. For each fund, we estimate all factor coefficients using data covering previous 36 months, and test each coefficient's significance at the 10% significance level.

Our estimates suggest that while most fund managers tend to exhibit either stock-picking or market-timing ability, a small number of managers, which consists of 4.3% of the sample, have both or none of these abilities. However, we eliminate managers who are equipped with both or none of the two abilities to facilitate the comparison of the pure effect between two skills.

[10]The database commonly used to obtain the portfolio holding information is the Thomson Reuters Mutual Funds Holding S12 database. However, the S12 database reports portfolio holdings infrequently as SEC requires mutual fund disclose holding semiannually before 2002 and quarterly afterwards.

3.3.4 Performance Measures

In this study, fund performance is evaluated using factor-based measures from the 4 factor model of Carhart (1997), the conditional model of Ferson and Schadt (1996), and the 5 factor model of Fama and French (2015). The estimated intercept (Jensen's α_i) is the parameter that measures fund performance. Section 2.2 above summarizes each of these models in detail. However, the key equations are outlined here for the purpose of completion.

The Carhart (1997) 4 factor model is as follow:

$$\begin{aligned} R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,m}(R_{m,t} - R_{f,t}) + \beta_{i,smb} SMB_t + \beta_{i,hml} HML_t \\ + \beta_{i,mom} MOM_t + \varepsilon_t^j \end{aligned} \tag{3.3.3}$$

We also use the following Ferson and Schadt (1996) conditional measure by adding four macro-economic variables in addition to the Carhart (1997) 4 factor model:

$$\begin{aligned} R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,m}(R_{m,t} - R_{f,t}) + \beta_{i,smb} SMB_t + \beta_{i,hml} HML_t \\ + \beta_{i,mom} MOM_t + \sum_{j=1}^{4} \beta_{i,j}[z_{j,t-1}(R_{m,t} - R_{f,t})] + \varepsilon_t^j \end{aligned} \tag{3.3.4}$$

Finally, we estimate the fund performance following the Fama and French (2015) 5 factor model, which adds the profitability (RMW) and investment (CMA) factors to the three-factor model of Fama and French (1993):

$$\begin{aligned} R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,m}(R_{m,t} - R_{f,t}) + \beta_{i,smb} SMB_t + \beta_{i,hml} HML_t \\ + \beta_{i,rmw} RMW_t + \beta_{i,cma} CMA_t + \varepsilon_t^j \end{aligned} \tag{3.3.5}$$

We examine factor-adjusted returns before and after netting out expenses. According to Berk and Green (2004) and Kacperczyk et al. (2005), looking at the before-expense returns enables us to better evaluate the investment ability of mutual fund managers since managers with better skills normally charge higher expenses to extract rents. On the other hand, understanding the after-expense fund performance would be beneficial for mutual fund investors.

The monthly fund returns reported in CRSP are net from any expense or fees.

However, as mentioned in Amihud and Goyenko (2013), fund gross return measures fund managers' skill before accounting for expenses. Therefore, we measure the fund performance using fund returns before and after adjusting for expenses. The fund gross return are calculated by adding the monthly expenses (annual expenses divided by 12) back to the net fund return.

3.4 Empirical Results

This section reports our empirical results, starting from the quinitle portfolio analysis using fund gross and net returns. Next, we present the multi-variate regression using difference fund performance measures. For robustness check, we also include sub-periods multivariate analysis in this section. Finally, we provide the analysis of stock-picking ability and market-timing ability.

3.4.1 Evidence from Univariate Analysis

We start off with the univariate analysis comparing the performance of mutual funds managed by generalists with that of mutual funds managed by specialists. To this end, we group the mutual funds into 5 quintile portfolios based on the ranking of MEI, where Rank 1 captures portfolios managed by the most specialized managers while Rank 5 captures portfolios managed by the most generalist or least specialized managers. All mutual fund performance will be examined both before and after adjusting for expenses.

Table 3.3 summarizes the portfolio performance estimated using the 4 factor model of Carhart (1997), the conditional model of Ferson and Schadt (1996), and the 5 factor model of Fama and French (2015), before and after adjusting for expenses. For statistical inferences, we compute and use panel-corrected standard errors (PCSE) which are robust to heteroskedasticity and within-fund serial correlation in idiosyncratic errors (Beck and Katz, 1995). Our sample is an unbalanced panel since most mutual funds do not exist for the whole sample period.

Firstly, the average fund performance is significantly positive before adjusting for fund expenses. However, most of the outperformance disappears after considering expenses and fees, as the average abnormal returns for each factor becomes significantly negative in Panel B of Table 3.3. This finding is consistent with most

Table 3.3: Quintile Portfolio Performance Measures

	Abnormal Return (% per month)			Factor Loadings (Carhart Model)			
MEI	Carhart	Ferson-Schadt	Fama-French	Market	Size	Value	Momentum
Panel A: Before Expenses							
All Funds	0.087***	0.081***	0.086***	0.977***	0.183***	0.094***	-0.005**
	(0.012)	(0.012)	(0.013)	(0.003)	(0.003)	(0.004)	(0.002)
Quintile 1	0.157***	0.176***	0.217***	0.965***	0.236***	0.116***	-0.022
	(0.038)	(0.039)	(0.044)	(0.015)	(0.021)	(0.031)	(0.013)
Quintile 2	0.086***	0.091***	0.061**	0.980***	0.178***	0.085***	-0.018*
	(0.026)	(0.027)	(0.03)	(0.01)	(0.018)	(0.018)	(0.01)
Quintile 3	0.035	0.02	0.008	0.982***	0.181***	0.109***	-0.006
	(0.022)	(0.024)	(0.027)	(0.01)	(0.018)	(0.019)	(0.008)
Quintile 4	0.085***	0.065***	0.051**	0.969***	0.156***	0.088***	0.01
	(0.021)	(0.022)	(0.024)	(0.011)	(0.018)	(0.019)	(0.008)
Quintile 5	0.076***	0.065***	0.079***	0.988***	0.166***	0.079***	0.006
	(0.022)	(0.023)	(0.025)	(0.012)	(0.017)	(0.017)	(0.008)
2nd half -	-0.033	-0.054**	-0.064***	0.005	-0.362**	-0.011	0.017*
1st half	(0.024)	(0.024)	(0.027)	(0.01)	(0.16)	(0.019)	(0.009)
5th quintile -	-0.080*	-0.111***	-0.139***	0.024	-0.07***	-.036	0.028*
1st quintile	(0.045)	(0.046)	(0.051)	(0.019)	(0.027)	(0.346)	(0.015)
Panel B: After Expenses							
All Funds	-0.023**	-0.027**	-0.02	0.978***	0.184***	0.089***	-0.003
	(0.012)	(0.012)	(0.013)	(0.006)	(0.009)	(0.01)	(0.004)
Quintile 1	0.057	0.082***	0.131***	0.971***	0.238***	0.092***	-0.015
	(0.037)	(0.038)	(0.042)	(0.014)	(0.020)	(0.030)	(0.013)
Quintile 2	-0.033	-0.029	-0.055*	0.979***	0.182***	0.083***	-0.015
	(0.025)	(0.027)	(0.03)	(0.010)	(0.018)	(0.018)	(0.010)
Quintile 3	-0.077***	-0.093***	-0.057***	0.983***	0.174***	0.111***	-0.007
	(0.022)	(0.024)	(0.026)	(0.010)	(0.018)	(0.019)	(0.008)
Quintile 4	-0.02	-0.043*	-0.057***	0.969***	0.158***	0.089***	0.009
	(0.021)	(0.022)	(0.024)	(0.010)	(0.017)	(0.019)	(0.008)
Quintile 5	-0.033	-0.043*	-0.029	0.990***	0.163***	0.079***	0.006
	(0.022)	(0.023)	(0.025)	(0.012)	(0.017)	(0.017)	(0.007)
2nd half -	-0.032	-0.055**	-0.07***	0.01	-0.04***	-0.00	0.013
1st half	(0.023)	(0.024)	(0.027)	(0.46)	(0.016)	(0.019)	(0.009)
5th quintile -	-0.09**	-0.125***	-0.16***	0.019	-0.075***	-0.013	0.0211
1st quintile	(0.044)	(0.045)	(0.049)	(0.018)	(0.026)	(0.034)	(0.000)

This table summarizes abnormal returns and the factor loadings using the Carhart (1997) 4 factor model for different portfolios of mutual funds for the period of 1993 to 2012 using fund return after adjusting for expenses. The second and third columns show the conditional Ferson and Schadt (1996) conditional and Fama and French (2015) 5 factor model estimated abnormal return before expenses. The last four columns summarize the factor loadings for the model using return before expenses. We divide the sample into 5 quintiles based on Managerial Experience Index constructed on 3 factors X1 (the style number), X2 (the company number) and X3 (the industry number) calculated based on the past working experience information of individual equity fund managers. The table includes the differences in the abnormal return between the top and the bottom quintiles, and the top and the bottom halves of the mutual funds. The returns are expressed at the monthly frequency and the portfolios are re-balanced monthly. Panel-corrected standard errors are given in parentheses. The significance levels are abbreviated with asterisks: *, ** and *** donate significance at the 10%, 5% and 1% levels, respectively.

studies on mutual fund performance, which suggest that the outperformance on the market would vanish when taking into account the fund expenses (Bollen and Busse, 2005; Carhart, 1997; Fama, 1970; Wermers, 2004). The primary explanation for this finding is that better-performing funds normally charge higher management fees and therefore the outperformance could decrease by subtracting the fund fees in the fund return calculation.

The abnormal performance estimates are similar across 3 measures – the greatest outperformance concentrates in quintile 1 portfolios. The first 3 quintiles exhibit a decreasing trend in fund performance as the MEI increases. However, fund performance bounces back at quintile 4 and quintile 5, which outperform quintile 3. The difference between the 1st and 2nd halves of the portfolios (i.e. between portfolios below and above the median MEI) and the difference between the 5th quintile and the 1st quintile are mostly negative and significant, which indicate that more specialized portfolios (i.e. those with smaller MEI) tend to outperform less specialized portfolios.

3.4.2 Evidence from Multivariate Regression

The univariate analysis above has two limitations: 1) the subgroup portfolio analysis in the univariate approach does not control for mutual fund characteristics that may affect fund performance and 2) the univariate analysis assumes that factor loadings remain constant over time. In this section, the empirical study will be extended to the multivariate approach, which involves a statistical analysis of more than one outcome variable at a time. The multivariate regression analysis could help us to investigate the relationship between the managerial experience factors and subsequent fund performance. The multivariate analysis allows us to control for other potential fund characteristics that are likely to affect the fund performance.

The primary purpose of the multivariate analysis is to test whether fund performance is significantly related to how specialized the manager's experience has been. The significance of MEI in the multivariate regression would indicate the existence of the relationship between managerial experience factors and fund performance.

3.4.2.1 Multivariate Regression Model

We first use 3 years of past monthly fund returns to estimate the coefficients of all three measurement models. Then, we use each model's fitted values to compute expected returns and subtract the expected returns from realized returns to obtain model-adjusted returns, which can be interpreted as abnormal returns. One limitation of this methodology is that young funds which do not have a sufficiently long history would be excluded. In the next stage, we regress the model-adjusted abnormal return on the MEI and other fund characteristics. We include a series of control variables when we evaluate fund performances including expense ratio, turnover ratio, fund age, size and past return. The general form of multivariate regression model can be specified as below:

$$PERF_{i,t} = \alpha_i + \sigma_i MEI_{i,t-1} + \beta_1 EXP_{i,t-1} + \beta_2 TU_{i,t-1} + \beta_3 LAGE_{i,t-1} \\ + \beta_4 LTNA_{i,t-1} + \beta_5 PastReturn_{i,t-1} + \varepsilon_t^j \tag{3.4.1}$$

The dependent variable in each regression model is one of four performance measures of an individual mutual fund $PERF_{i,t}$ within a particular month t, using the rolling window procedure with 36 lagged monthly return. The shortcoming of the rolling window method is that we lose the fund performance in the first 3 years. However, the rolling performance can offer better insight into a fund's more comprehensive return history, which is not skewed by the most recent data. The four performance measures include: (1) the raw fund return $R_{i,t}$; (2) the Carhart (1997) 4 factor model adjusted return; (3) the Ferson and Schadt (1996) conditional model adjusted return; and (4) the Fama and French (2015) 5 factor model adjusted return.

Control variables in this study include the expense ratio of the fund EXP, the turnover ratio TU, the age of the fund $LAGE$ defined as the logarithm of $(1+AGE)$, the natural logarithm of total net assets under management of the fund $LTNA$, and the average prior year return $PastReturn$ as defined in Huang et al. (2011). As suggested in Huang et al. (2011), mutual funds with bad prior performance are likely to continue to perform poorly because of the inferior ability. Therefore we include the past performance as a control variable. The expense ratio measures the cost of the investment management while the turnover ratio refers to the percentage of a mutual fund's holdings that has been replaced with other holdings in a given year. The fund age indicates the time duration since the inception of the fund, and finally the total net assets measure the size and value of the mutual fund (Kacperczyk and Seru, 2012). All control variables are lagged at least by one month in this study.

The first column of Table 3.4 shows the coefficients from the panel regression that uses the monthly fund return before expenses as the dependent variable. The sign and magnitude of the coefficient on MEI are consistent with the univariate analysis above. Specifically, the increment on the MEI is negatively correlated with the fund return. The adjusted returns based on the Carhart (1997) 4 factor model, the Ferson and Schadt (1996) conditional model and the Fama and French (2015) 5 factor model yield similar results, with the coefficient estimates of -2.6%, -2.3% and

Table 3.4: Multivariate Analysis

	Fund Performance Measure			
	Raw	Carhart	Ferson-Schadt	Fama-French
MEI	-0.051***	-0.026***	-0.023***	-0.037***
	(0.017)	(0.005)	(0.005)	(0.006)
EXP (%)	17.5***	5.188***	6.809***	10.484***
	(4.216)	(1.659)	(1.743)	(1.99)
TU (%)	-0.019	-0.002	-0.002	0.01
	(0.015)	(0.005)	(0.006)	(0.007)
LAGE	-0.13***	-0.07***	-0.076***	-0.078***
	(0.031)	(0.112)	(0.110)	(0.014)
LTNA	0.123***	0.046***	0.036***	0.057***
	(0.013)	(0.004)	(0.004)	(0.005)
Lag_Return	6.3***	4.08***	3.79***	4.58***
	(1.354)	(0.43)	(0.581)	(0.675)
Number of Observations	95,135	83,541	83,541	83,541

This table presents the output of the multivariate regressions using four different fund performance measurements. The dependent variable, $PERF_{i,t}$ measures the monthly abnormal return using the Carhart (1997) 4 factor model, the Ferson and Schadt (1996) conditional model and the Fama and French (2015) 5 factor model based on 36 months of lagged data. The independent variables are the expense ratio of the fund EXP, the turnover ratio TU, the logarithm of monthly total net asset of the fund $LTNA$, the age of the fund defined as the logarithm of the fund life length $(1+AGE)$ and the lagged return $PastReturn$ which refers to the prior year average return. The numbers of observations used in each regression is reported in the bottom of the table. The significance levels are abbreviated with asterisks: *, ** and *** donate significance at the 10%, 5% and 1% levels, respectively. Clustered standard errors are in parentheses.

-3.7%, respectively. This effect is economically and statistically significant. Fund expenses, TNA and prior year returns have statistically significant positive effects on the fund performance. The fund age is negatively related to the fund performance, which is consistent with the finding in Busse et al. (2015). But the turnover ratio has no significant impact on any fund performance measure, which is not favored by the finding in Pástor et al. (2015) that the fund's next month's gross return is positively related to turnover ratio.

To conclude, the multivariate regression results agree with the preceding results from the univariate analysis. MEI has a negative relationship with mutual fund performance, which could be interpreted as evidence that the more concentrated the manager's experience has been, the better performance the manager could achieve consistently.

3.4.2.2 Sub-Period Performance

Our whole sample spans 20 years from 1993 to 2013. Many fund characteristics may change over time during 20 years. For example, the average TNA per fund increases substantially during the later time periods since more capital has been invested in the fund market as time passes. To mitigate the effects of possible structural breaks, we follow the method in Kacperczyk et al. (2005) to examine the relationship between the manager experience concentration and fund performance for three sub-sample periods: 1993 – 1998, 1999 – 2006 and 2007 – 2012.

In Table 3.5, we report the results from estimating the multivariate regression model 3.4.1 for each sub-period. The dependent variable, $PERF$ is measured as the monthly abnormal return using the Carhart (1997) 4 factor model, the Ferson and Schadt (1996) conditional model or the Fama and French (2015) 5 factor model based on 36 months of lagged data. The results show a negative relationship between the MEI and fund performance in all 3 time periods.

In this analysis, the estimated coefficients on MEI are significantly negative across all sub-periods, providing robust evidence on the negative linkage between fund performance and MEI. The coefficients on MEI based on the Carhart (1997) 4 factor model and the Ferson and Schadt (1996) conditional model are around -0.04 with no apparent trend across time periods. However, the coefficients on MEI using the Fama and French (2015) 5 factor model varies somewhat from -0.07 to -0.04, indicating the association between MEI and Fama and French (2015) 5 factor model adjusted return becomes less negative overtime.

3.4.3 MEI and Managerial Ability

There are two basic abilities of portfolio managers examined in the literature based on the theory of market efficiency with costly information: stock selectivity and market timing (Ferson and Mo, 2016; Jiang, 2003; Kacperczyk et al., 2014). The hypothesis is that the fund manager would exhibit either of these two portfolio management skills, and the skill would be reflected in fund performance. We measure the stock-selecting and market-timing ability at the fund level on the 36 month rolling window basis, following the estimation model 3.3.2. Zambrana and Zapatero (2017) classify the portfolio manager as a stock picker if α_i for this particular fund is greater than 0 and statistically significant, and as a market timer is γ_i is greater than 0 and statistically significant. We follow this approach and use the α_i and γ_i as indicators for the stock selecting and market timing ability.

Table 3.5: Multivariate Analysis: Sub–Periods

	1993-1998			1999-2006			2007-2012		
	Carhart	Ferson-Schadt	Fama-French	Carhart	Ferson-Schadt	Fama-French	Carhart	Ferson-Schadt	Fama-French
MEI	-0.04***	-0.046***	-0.067***	-0.041***	-0.042***	-0.049***	-0.037***	-0.041***	-0.041***
	(0.011)	(0.012)	(0.016)	(0.007)	(0.006)	(0.007)	(0.009)	(0.008)	(0.009)
EXP (%)	1.806	3.254	8.035	5.336***	7.336***	10.71***	10.23***	9.872***	13.297***
	(3.315)	(2.967)	(5.22)	(1.862)	(2.012)	(1.92)	(2.917)	(2.648)	(3.266)
TU (%)	-0.047***	-0.027*	0.014	-0.012	0.017	0.015	0.003	0.002	0.003
	(0.019)	(0.015)	(0.015)	(0.012)	(0.015)	(0.012)	(0.004)	(0.004)	(0.006)
LAGE	-0.037**	-0.041***	-0.065***	-0.128***	-0.135***	-0.144***	-0.04*	-0.046	-0.033
	(0.017)	(0.021)	(0.027)	(0.015)	(0.02)	(0.018)	(0.021)	(0.029)	(0.024)
LTNA	0.044***	0.037***	0 .065***	0.064***	0.062***	0.072***	0.037***	0.038***	0.043***
	(0.006)	(0.007)	(0.009)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)
Lag_Return	12.12***	10.82***	10.3**	5.544***	6.482***	5.356***	1.93***	2.37***	3.67***
	(0.52)	(0.872)	(5.0)	(0.434)	(0.639)	(0.503)	(0.356)	(0.412)	(0.376)
Observations	17,142	17,142	17,142	43,044	43,044	43,044	23,355	23,355	23,355

The table reports the coefficient of monthly panel multivariate regression. The sample includes actively managed domestic equity funds and spans the period of 1993 to 1998 (left panel), 1999 to 2006 (middle panel) and 2007 to 2012 (right panel). The dependent variable, $PERF_{i,t}$ measures the monthly abnormal return using the Carhart (1997) 4 factor model, the Ferson and Schadt (1996) conditional model and the Fama and French (2015) 5 factor model based on 36 months of lagged data. The independent variables are the expense ratio of the fund EXP, the turnover ratio TU, the logarithm of monthly total net asset of the fund $LTNA$, the age of the fund defined as the logarithm of the fund life length $(1 + AGE)$ and the lagged return $PastReturn$ which refers to the prior year average return. The numbers of observations used in each regression is reported in the bottom of the table. The significance levels are abbreviated with asterisks: *, ** and *** donate significance at the 10%, 5% and 1% levels, respectively. Clustered standard errors are in parentheses.

Table 3.6: Stock-Picking and Market-Timing Ability

MEI	Stock-Picking Estimator	Market-Timing Estimator
Quintile 1 (More Specialised)	0.536***	-18.121**
	(0.026)	(1.353)
Quintile 2	0.252***	-5.728***
	(0.013)	(0.641)
Quintile 3	0.107***	0.713
	(0.010)	(0.451)
Quintile 4	0.117***	0.84*
	(0.009)	(0.444)
Quintile 5 (More Generalised)	0.07***	1.034***
	(0.008)	(0.365)
Quintile 5 - 1	-0.466***	19.255***
	(0.027)	(1.401)

The table reports the stock-picking and market-timing indicators in 5 MEI quintiles. The stock-picking and market-timing abilities are calculated based on the regression $R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,m}(R_{m,t} - R_{f,t}) + \gamma_{i,m}(R_{m,t} - R_{f,t})^2 + \beta_{i,smb}SMB_t + \beta_{i,hml}HML_t + \beta_{i,mom}MOM_t + \varepsilon_t^j$, using the 36-month rolling window procedure. The α_i captures the stock selecting skill while the γ_i represents the market timing ability. We sort the sample into 5 quintiles based on MEI constructed based on 3 factors – X1 (the style number), X2 (the company number) and X3 (the industry number) calculated based on the past working experience information of individual equity fund managers. The coefficients are the mean of estimators α_i or γ_i in MEI quintiles. The significance levels are abbreviated with asterisks: *, ** and *** donate significance at the 10%, 5% and 1% levels, respectively. Standard errors are in parentheses.

Specifically, we run the regression of model 3.3.2 for each fund-month observation to obtain the α_i and γ_i estimators. As we use the rolling window of prior 36 month returns, the stock-picking and market-timing indicators starts from the 37th month for each fund. Next, we sort the sample based on the MEI we constructed in the previous analysis into 5 quintiles. For each MEI quintile, we calculate the mean of the stock-picking and market-timing estimator, and test each coefficient's significance at the 10% significance level.

Table 3.6 presents the mean of stock-picking and market-timing estimators for 5 MEI quintiles. As mentioned before, Quintile 1 captures funds managed by the most specialized managers while Quintile 5 captures mutual funds managed by the most generalist or least specialized managers. The average stock-selecting ability decreases from 0.536 to 0.07 from MEI quintile 1 to 5. On the other hand, the mean of market-timing skill from Quintile 1 to 5 increases from -18.121 to 1.034. Most of the mean coefficients are statistically significant, indicating they are different from 0. The difference between coefficients of MEI quintile 5 and 1 are presented in the bottom of Table 3.6. To conclude, the average stock-picking ability is more prevalent in funds that are managed by managers with more concentrated working experience. Funds managed by managers with more diversified experience exhibit more market-timing ability.

We also present the relation between the MEI and two types managerial skills in Figure 3.1. We sort the sample into 15 ranks containing an even number of observations based on the MEI distribution instead using 5 quintiles, so that the trend can be more clearly presented. The average stock-picking and market-timing ability indicators are presented in line graph in two panels. The bars are average raw fund returns of the 15 MEI groups. The picking and timing abilities are displayed in two separate panels.

First of all, we present the average monthly gross return of mutual funds in bars, which decreases along with the manager's accumulated experience. Panel A displays a negative link between market-timing ability and MEI – the market-timing ability increases as the manager's experience becomes more generalized. Panel B shows the positive relationship between stock-picking ability with MEI – managers with more concentrated experience exhibits greater stock-picking ability.

3.5 Summary

This chapter considers an individual's past working experience as an essential determinant of their current career performance and provides a new method to evaluate the mutual fund performance from the perspective of manager's lifetime working experience. An individual's past working experience may be considered as an essential determinant that shapes their current career performance. The skills and knowledge acquired from the prior working experience may be transferred to the current working context, thereby influencing the current job performance (Schmidt et al., 1986). Researchers have explored this topic from the perspectives of both applied psychology and empirical finance, where the latter particularly pertains to the CEO behavior analysis (Custódio et al., 2013). Building on this literature, we investigate the relationship between the mutual fund manager's past experience and mutual fund performance.

Using U.S. mutual fund managers' work experience data spanning year 1993 to year 2012, we extend the mutual fund performance literature by investigating whether mutual fund performance relates to accumulated experience that the fund manager has acquired during his or her career. To measure the experience generality of each manager, we use the Principal Component Analysis to construct a

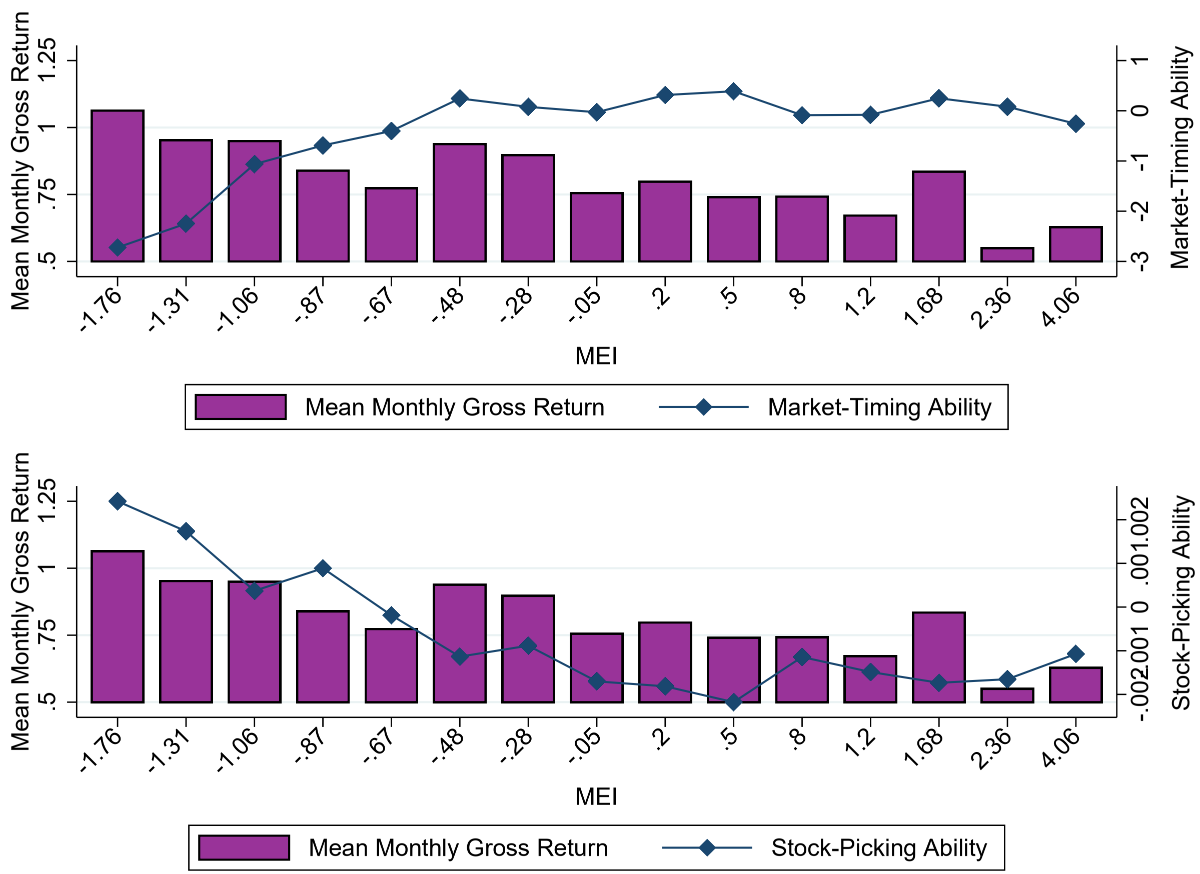

Figure 3.1: Market-Timing, Stock-Picking Ability and Managerial Experience Index

The figure illustrates the relationship between the Managerial Experience Index (MEI) and managerial skills. Sample is sorted into 15 ranks with even observations based on MEI. The stock picking and market timing ability for each MEI group are calculated as the mean of the stock-picking estimator (α_i) and market-timing estimator (γ_i) captured by model 3.3.2.

Managerial Experience Index (MEI) based on 3 professional experience factors from the past career history of that manager: (i) investment objectives of the funds that s/he has managed (Zambrana and Zapatero, 2017), (ii) fund companies that s/he has worked for and (iii) industries of stocks in which s/he has invested (Kacperczyk et al., 2005). The resulting MEI increases as the manager accumulates more experience in the three underlying factors.

We firstly group the sample into 5 quintiles from the lowest MEI score (most concentrated experience) to the highest MEI score (most diversified experience). Therefore, the "Specialist" refers to portfolio managers with a more concentrated professional history while the "Generalist" refers to those with more diversified experience in mutual fund management. We use the Carhart (1997) and Ferson and Schadt (1996) models to adjust fund returns, and find that the mutual fund managed by a "Specialist" manager who has more concentrated experience tends to outperform the mutual fund managed by a "Generalist" manager.

This finding is robust to the multivariate analysis controlling for the expense ratio of the fund EXP, the turnover ratio TU, the age of the fund $LAGE$ defined as the logarithm of $(1+AGE)$, the natural logarithm of total net assets under management of the fund LTNA and the averaged prior year return $PastReturn$ as proposed by Huang et al. (2011). The conclusion stills holds in a sub-period analysis where we perform the multivariate analysis separately for three time periods to mitigate the effects of possible structural breaks following Kacperczyk et al. (2005).

We also examine the stock picking ability and market timing ability of fund managers with different career histories. The results indicate that a "Specialist" manager tends to exhibit significant stock-picking ability while a "Generalist" manager tends to exhibit market-timing ability. This empirical study provides useful implications for individual investors, since an observable managerial characteristic such as managerial past experience would allow them to more appropriately choose where to allocate their money for investment purposes. In addition, fund family could also benefit from the findings in the portfolio manager recruitment process.

Chapter 4

New Mutual Fund Opening and Performance

4.1 Introduction

The mutual fund is considered as one of the largest asset classes in the financial market, and the total net asset (TNA) of U.S. mutual funds has reached \$16.3 trillion by the end of 2016. The capital size of the industry has increased about 40% in the past 15 years, along with the large growth of the number of mutual funds opening by 49.59% from 16,738 to 25,038. One interesting fact is that the number of fund families drops slightly from 8,155 to 8,116 in the corresponding period. It appears that fund families have strong incentive to create new funds to attract new investors and money inflows. This growth, however, has varied from period to period – some periods have bursts of new funds while other periods have much lower new fund activity.

We present the volume of new funds opening in years from 1990 to 2012 in Figure 4.1. The new fund creation seems to be highly correlated with the market performance. For instance, during the hot market period 1998 - 2000, 1,337 new funds opened, whereas only 138 opened during the financial crisis period 2008 - 2010. Also, we realized that the new fund activity is related to the initial public offerings (IPOs), which also follows the market performance. In the corresponding period, there were 1,139 IPOs initiated in 1998 - 2000 while only 153 during 2008 - 2010.

The increasing number of introduced new funds facilitated a debate among aca-

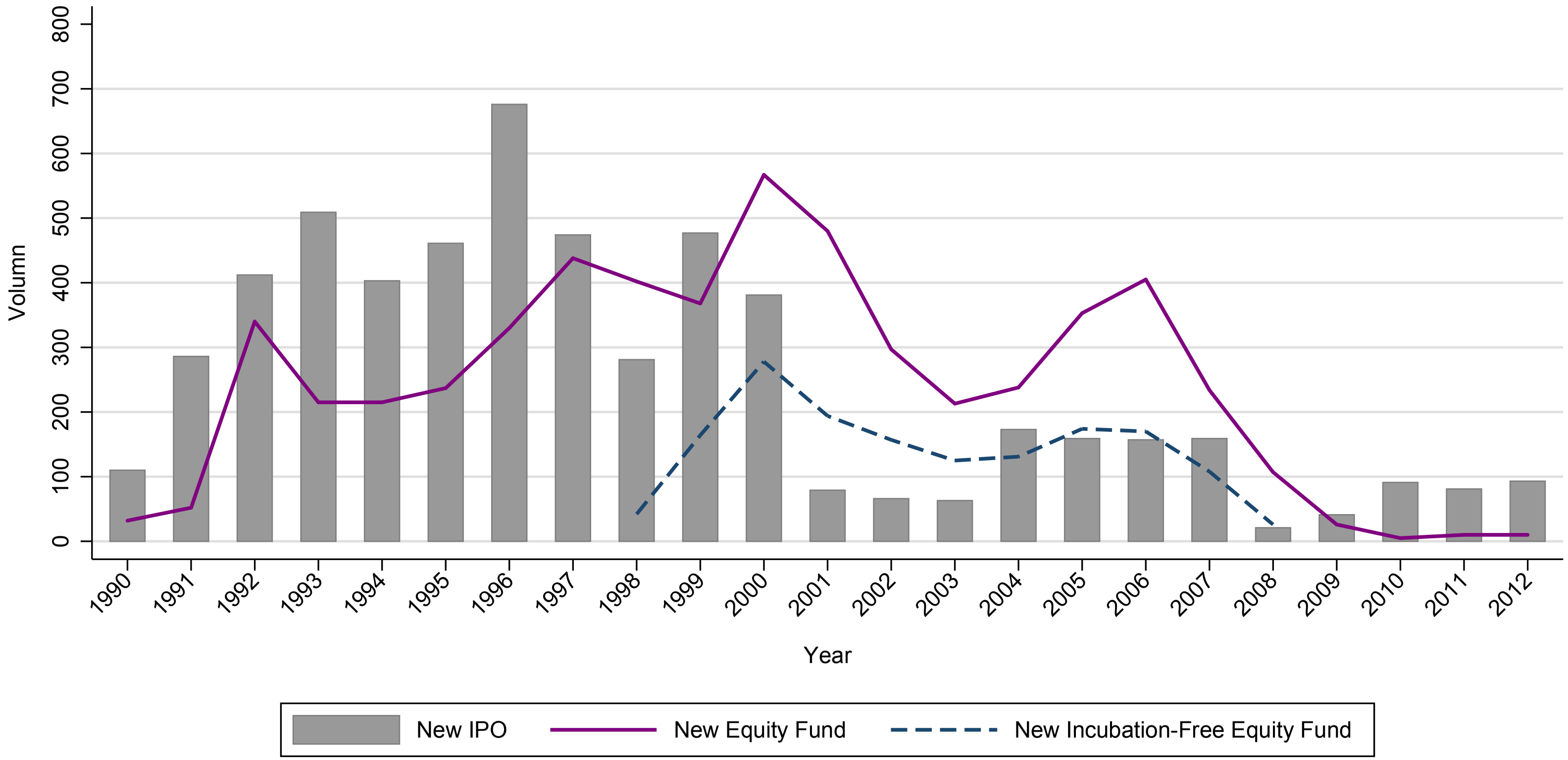

Figure 4.1: Number of Initial Public Offerings and New Funds Opening in Years, 1990-2012
Source: IPO volume is obtained from the IPO Data published by Jay R. Ritter, University of Florida. Only operating company IPOs with an offer price of at least $5 per share are included. Banks and S&Ls, natural resource limited partnerships, and ADRs are also not counted. Numbers of mutual funds opening in years are obtained from CRSP U.S. Survivorship-Bias-Free Mutual Fund Database. The incubation-free equity funds are identified using the method in Evans (2010). The number of IPOs are presented in bars whereas number of new funds are shown in lines.

demics and practitioners about fund performance. There is a sizable literature which finds that a typical actively managed equity fund in the U.S. earns a negative after-fee risk-adjusted alpha, which is estimated from asset pricing models (Brown and Goetzmann, 1995; Carhart et al., 2002; Daniel et al., 1997; Elton et al., 1993; Ferson and Schadt, 1996; Grinblatt and Titman, 1989; Kacperczyk et al., 2005). Although some funds can generate superior performance, it is explained as an outcome of luck instead of skill since fund performance is largely unpredictable (Bollen and Busse, 2005; Carhart, 1997; Gruber, 1996; Zheng, 1999).

Do newly-created funds add value in the emerging period? If so, how long would the outperformance last, and could the outperformance be explained by size effect or managerial characteristics? Moreover, given that extant literature shows that mutual funds have preferential access to IPOs (Aggarwal et al., 2002; Reuter, 2006), and that the typical IPO is substantially underpriced (Ritter and Welch, 2002), another interesting question we may investigate is whether fund families would take IPOs as investment opportunities in creating new funds. Specifically, this chapter aims at addressing the following research questions:

- Can the outperformance of newly-created fund be explained by the fund or managerial characteristics?

- Considering that fund creation is highly correlated with IPO volume, would the fund's access to IPO stocks become a valuable trading opportunity in creating new funds?

Instead of focusing on the whole life of funds, this chapter concentrates on the emerging period of mutual funds, defined as the first 6 months after creation of new funds. Most of previous studies use fund age as the factor explaining performance using cross-sectional regressions in calendar time. These studies are concerned with the performance pattern of newly-created funds. Instead, we examine fund performance using the event time approach, where the event is the time when the fund is initiated. The event time approach is powerful as it is able to capture the outperformance concentrated among new funds, while the performance analysis by calendar time will miss it. For instance, Karoui and Meier (2009) provide evidence that new U.S. equity mutual funds outperform their peers by 0.15% per month over the first 3 years. However, the event time used in our study is measured in months since a short horizon provides a more precise method to identify outperformance when it is short-lived (Bollen and Busse, 2005). We also eliminates the incubation bias by by applying an incubation period filter following Evans (2010). Funds in incubation outperform non-incubated funds by 3.5% on the basis of risk-adjusted returns, and attract higher flows after becoming public than non-incubated funds, which will bias our analysis.

Using U.S. mutual fund data from 1996 to 2015, we provide the empirical evidence that new mutual fund can temporarily add value in its early stage although the outperformance vanishes after a while. Reasons for the short-lived outperformance include the competitive nature of the mutual fund industry (Berk and Green, 2004; Chevalier and Ellison, 1999a). The emerging fund short-term outperformance is negatively related with the fund size. Also, we find that funds created by individual managers do not outperform funds created by multiple managers in the emerging period, and the experience of fund managers does not make significant difference. Karoui and Meier (2009) find that funds start off with investing more actively in small-cap stocks and holding more industry-concentrated portfolios, and gradually increase their exposure to market risk and reduce unsystematic risk relative to total risk. Therefore we also look into the stock holding of newly-created funds, and find that the short-term outperformance is more likely to be determined by the access to IPO stocks. This result indicates that newly created mutual funds, especially new funds with IPO allocations contain great investment opportunity especially in first 6 months of their lives. We find that opportunities for trade such as IPO allocations, whose usefulness can fade away over time, could also induce a short-lived performance effect.

Our study focuses on the emerging period of mutual funds, defined as first 6 months of existence. The main reason for focusing on fund creation is to understand why and how managers start a new fund. We examine the relation between emerging funds performance and fund size at creation to understand if the total net asset at the creation month will influence fund performance in the emerging period. Moreover, we attempt to analyze the fund performance in the emerging period from the perspective of a portfolio manager. Fund managers have strong incentives to make optimal investment decisions since their compensation is directly related to the fund performance, which is the outcome of their decision. Existing portfolio managers are motivated to outperform to preserve or improve their reputation and to attract more inflows for both existing and newly established funds, while new-entry managers have strong incentives to prove their ability in the beginning of their careers[11].

The remainder of the chapter proceeds as follows. Firstly we review the prior literature related to the topic of mutual fund creation, then we describe the data and methodology in the next section. Next, we report main results with robustness tests. We close the chapter with some conclusions.

4.2 Prior Literature

The well-documented evidence indicates that a typical actively managed equity fund in the U.S. earns a negative after-fee risk-adjusted alpha estimated from asset pricing models (Carhart et al., 2002; Fama and French, 2010; Gruber, 1996). Grinblatt and Titman (1989) show positive gross alphas for both small funds and growth funds. Chevalier and Ellison (1999a) find the evidence of outperformance of some fund managers and explain it by behavioral difference and selection biases. Cremers and Petajisto (2009) show that the amount a fund deviates from its benchmark is associated with better performance, and that this superior performance is persistent.

4.2.1 Fund Size

Creation of new funds may be attractive for a number of reasons. One argument closely linked with the new fund creation is the size. The definition of fund size is given as "the month-end net assets of the mutual fund" by MorningStar, and normally recorded in millions of dollars. Mutual funds normally start from a relatively small size when being created, and attract investment flow gradually. The evidence investigating the relation between fund size and performance in the mutual fund industry is mixed. It is believed in some literature that large asset size would erode mutual fund performance due to higher trading cost associated with liquidity impact (Perold and Salomon Jr, 1991). Meanwhile, small funds could be easily managed by putting all assets into the best portfolio, while this strategy is difficult to apply in large funds (Chen et al., 2004). However, the negative relationship between size and performance contradicts the finding in Grinblatt and Titman (1989) and Wermers (2000) that there is no significant difference across net performance of small and

[11] Aggarwal and Jorion (2010) argue that new managers tend to put more effort in improving portfolio performance rather than marketing to new investors.

large funds. In a related empirical study, Chen et al. (2004) find that smaller funds tend to outperform larger funds due to diseconomies of scale.

4.2.2 Managerial Characteristics

Another set of arguments for emerging funds is related to the manager effect. Money managers have strong incentive to make optimal investment decisions because their salary is based on the fund performance directly. Kacperczyk et al. (2005) argue that mutual fund managers might still differ substantially in their investment abilities although strong evidence shows that actively managed funds underperform passive benchmarks on average. In the mutual fund industry, Massa and Patgiri (2009) compare the usual fixed management fee setup with arrangements where this fee decreases as a function of asset size. This concave function provides a negative incentive effect, which is found to be associated with worse performance, as predicted.

Managerial experience can be influential in the new fund creation. Although they both have incentives to outperform, the investment outcome may vary because of informational advantage or lack of experience. For existing portfolio managers, they are motivated to outperform for the reputational reason and to attract more inflows for both existing and newly established funds (Aggarwal and Jorion, 2010). For emerging managers, they have strong incentives to prove their ability at the beginning of their career. However, Aggarwal and Jorion (2010) argue that new managers tend to put more effort in improving portfolio performance rather than marketing to new investors to attract new flow. Also, in terms of marginal utility, non-experienced managers have stronger incentive to outperform than existing managers because their initial wealth is smaller (Aggarwal and Jorion, 2010).

Some studies attribute the superior performance to the specialized knowledge and information held by portfolio managers. Coval and Moskowitz (1999) find that geography is important – funds that invest a greater proportion of their assets locally tend to do better. Kacperczyk et al. (2005) conclude that funds that concentrate on a few industries do better than funds that do not. Shumway et al. (2009) produce evidence that superior performance is associated with beliefs that more closely predict future performance. Cohen et al. (2008) provide evidence that portfolio managers place larger bets on firms they are connected to through their social network, and perform significantly better on these holdings relative to their non-connected holdings.

4.2.3 IPO Allocation

Our study also relates to the literature on IPO allocations and fund performance. It is well accepted that underwriters have a considerable latitude in how to allocate IPO stocks. In this vein, Aggarwal et al. (2002) find that underwriters allocate to institutional investors IPO stocks in excess of that explained by bookbuilding alone. Reuter (2006) looks within institutional investors and finds that allocations of underpriced IPOs are positively associated with the level of brokerage business directed to lead underwriters. We extend the existing literature by linking IPO allocations to new fund performance. Thus, access to IPO allocations could be a motive for creating new funds. Other motives include whether the new fund helps the family to generate additional fee income and economies of scale within fund families (Khorana and Servaes, 1999).

4.3 Data and Methodology

This section includes the data description on actively-managed domestic equity funds in the U.S., managerial information, their portfolio holdings and returns. We also describe the method in incubation fund identification and event time approach.

4.3.1 Sample Selection

The sample used in this study is built from several databases. Firstly, we start with the CRSP U.S. Survivorship-Bias-Free Mutual Fund Database, which includes fund returns and comprehensive fund characteristics such as total net asset (TNA), fund returns, fund management structures, investment objectives, turnover ratios and fund manager' identity (Kacperczyk et al., 2005). We mainly focus on the actively managed diversified domestic equity mutual fund in U.S. by excluding international, balanced, sector, bond, money market, and index funds. To ensure the sample consists of funds that mainly invest in equities, we only include funds that have an average of 80% or greater of assets held in common stock (CRSP variable *per_com*).

Further, we exclude all non-U.S. funds using investment objective codes[12].

Next, we merge this database with a list of mutual fund tickers and their creation date from the NASD[13]. This list covers the period from January 1999 to August 2008. Therefore, all the new funds created prior to 1st January, 1999 or after 31st August, 2008 are excluded. The NASD ticker creation date is the actual date that the NASD assigned a ticker to a particular fund. To address the possibility of incubation bias, we measure the difference between the ticker creation date and the date of the first reported monthly return for the fund in CRSP. Finally, we drop funds with fewer than 12 months of performance.

4.3.2 Identification of Fund Incubation

Evans (2007) mentions the substantial incubation bias existing in mutual funds. The fund incubation refers the creation and management of a mutual fund before opening it to the public, and is a strategy that fund families use to develop new fund offerings. During incubation, families open multiple new funds (normally with limited amount of internally-raised funds) and choose to have IPO's or to shut down funds at the end of an evaluation period. Evans (2007, 2010) show evidence that the return of incubated funds can be unusually high during the incubation period. The incubation bias arise when the fund family incubate several new funds and only keep the tracking record of the surviving incubated funds, not the terminated funds.

There are various ways to exclude incubation funds. For instance, Kacperczyk et al. (2014) exclude observations for which observation year is prior to the initial information reporting year in the CRSP database. Kacperczyk et al. (2014) also exclude funds that have TNA less than $5 million or fewer than 10 stocks in the latest reporting month, as incubation funds are likely to be small in size and have fewer stock in the portfolio holding. However, non-incubated funds can be meanwhile excluded if they have less capital to start with. Therefore, we adopt the method in Evans (2010) to address the possibility of incubation bias.

Specifically, the fund family or sponsor would apply for a ticker symbol when the fund is to be sold to the public. The NASD would keep the record of the date that

[12] We remove those observations where the CRSP variables *icdi_obj*, *sp_style_cd*, and *policy* are equal to C&I, GE, IE, AGF, DSC, EAP, EAX, ECH, EEU, EGA, EIA, EJP, ELA, ESC, SCI, SGL.

[13] These data and instructions is provided in Evans (2010), and can be found in the Supplements & Datasets section of the Journal of Finance website: http://afajof.org/page/Supplements.

Table 4.1: Summary Statistics

Variable	Mean	Std. Dev.	Min	Max
Total Net Assets (TNA) (in Millions)	483.5	2,879	0.1	143,043
Fund Age (in Years)	10.72	3.65	0.08	17
Expense Ratio (%)	1.27	0.62	-0.03	14.71
Turnover Ratio (%)	85.66	147.61	0	5,466
Fund Load (%)	0.18	0.63	0	6.01
Raw Return (%)	0.51	5.51	-41.6	48.87
Fund Flow (%)	14.61	880	-131	185,492
Total Number of Funds	1,569			
Total Number of Observations	166,556			
Total Number of Recognizable Managers	957			
Total Number of Fund Families	584			

This table presents the summary statistics of the actively-managed equity mutual funds. Funds included in the sample are non-incubated. The Mean, Standard deviation, Minimum and Maximum are reported for the total net assets of the fund ($M), fund age in years, expense ratio (%), turnover ratio (%), fund load (%), return after expenses (%) and fund flow (%). The table also reports the number of funds, individual fund managers and fund families.

the ticker symbol is issued to the fund. This NASD ticker issue date is considered as the end of incubation date for incubated funds. While for non-incubated funds, the NASD ticker issue date is the date of new fund creation. Next, we examine the difference between the NASD ticker issue date and the CRSP first return reporting date for each fund. On one hand, a more negative difference represents either an error in the ticker creation date data or an error in the ticker match. Therefore, we remove funds with a negative difference greater than 3 months following Evans (2010) which consists 4.26% of the sample. On the other hand, a positive difference indicates a delay between the authorization of a ticker for the fund and the start of the fund, which is likely to be related to the strategy of fund incubation. In the prior literature, there are different selection criteria applied – Evans (2010) sets a cut-off point of 12 month difference while Aggarwal and Jorion (2010) set a cut-off of 6 month. We set the stricter cutoff of 12 months in this study following Evans (2010). In other words, if the difference between the NASD ticker date and the CRSP first report date is greater than 12 months, the fund would be classified as the incubated fund.

4.3.3 Summary Statistics

Our final sample spans the time period between January 1998 and December 2015 because of the data availability. Overall, we have 1,569 incubation-free equity funds included in the sample, with 166,556 fund-month observations. There are 957 individual portfolio managers that can be identified in the sample, coming from 584 fund families. The summary statistics are presented in Table 4.1.

The average of total net asset (TNA) ranges across funds is \$483.5 million, ranging from \$0.1 to \$143 billion. The CRSP reported TNA as 0.1 indicates the size of fund is less than 1 million. We do not apply any filter on fund TNA because we are interested in every fund's emerging period performance regardless of their sizes. The average fund age is 10.7 years, with the longest existing funds survives for 17 years. The average expense ratio is 1.27% per year, whereas the average fund load stands at 0.18%. The average turnover is 85.6% which indicates funds' holding position is regularly changed. The mean of fund flow is 14.6%, indicating mutual fund on average attracts positive inflow even the variation is huge with the minimum flow is negative at -131%. On average, funds included in our sample attract positive inflows.

4.3.4 Performance Measurement

We implement the main performance analysis using an event time approach. Specifically, we consider the first reported month of fund performance as month zero. During the sample period, we have 204 months in total event time. Starting from month 1 we have 1,569 funds and this number falls due to fund attrition. Overall, with this approach the largest number of funds is in month 1, and declines smoothly in event time.

To examine the performance pattern of new mutual funds, we use the factor-based performance measures, namely the Carhart (1997) 4 factor and Ferson and Schadt (1996) conditional model. We use Jensen's Alpha as the indicator of portfolio performance.

Most studies in the literature implicitly assumes that the riskiness of the manager's portfolio can be measured using the risk and style factors identified by Carhart (1997). This Carhart (1997) 4 factor model especially considers the momentum effect in stock returns (Jegadeesh and Titman, 1993) besides Fama and French (1995) factors. However, traditional unconditional fund performance measures might be unreliable because of the common variation will be confounded with average performance (Ferson and Schadt, 1996; Kacperczyk et al., 2005). Therefore, we adopt the

Ferson and Schadt (1996) conditional model for the purpose of robustness check. Ferson and Schadt (1996) advocate the use of predetermined instruments to capture time-varying loadings. The detail of model discussion is presented in Section 2.2. However, we list the key equations here for the purpose of completion.

The Carhart (1997) 4 factor model is as follow:

$$\begin{aligned} R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,m}(R_{m,t} - R_{f,t}) + \beta_{i,smb} SMB_t + \beta_{i,hml} HML_t \\ + \beta_{i,mom} MOM_t + \varepsilon_t^j \end{aligned} \tag{4.3.1}$$

We also use the following Ferson and Schadt (1996) conditional measure by adding four macro-economic variables in addition to the Carhart (1997) 4 factor model:

$$\begin{aligned} R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,m}(R_{m,t} - R_{f,t}) + \beta_{i,smb} SMB_t + \beta_{i,hml} HML_t \\ + \beta_{i,mom} MOM_t + \sum_{j=1}^{4} \beta_{i,j}[z_{j,t-1}(R_{m,t} - R_{f,t})] + \varepsilon_t^j \end{aligned} \tag{4.3.2}$$

Similarly as in the previous chapter, we examine factor-adjusted returns before and after netting out expenses. The monthly fund returns reported in CRSP are net from any expense or fees. The fund gross return are calculated by adding the monthly expenses (annual expenses divided by 12) back to the net fund return.

4.4 Empirical Result

We report and discuss empirical evidences in this section, including the portfolio performance in event times and the size effect. The multivariate estimation in different model specifications are also included.

4.4.1 Short-Term Outperformance of New Funds

We first present estimation results for alphas and liquidity factor loadings based on Carhart (1997) and Ferson and Schadt (1996) models in event time, in order to examine the performance pattern of new funds. Table 4.2 and 4.3 demonstrate the same set of results using fund returns before and after expenses, respectively. As we are interested in the emerging period of newly established funds, we only report the

Table 4.2: Mutual Fund Monthly Performance after Inception in Event Time (Before Expenses)

Fund Age	Abnormal Performance (%)		Factor Loadings on Carhart Model			
(month)	Carhart	Ferson-Schadt	Market	Size	Value	Momentum
1	0.446***	0.42***	1.021***	0.207***	-0.001	0.042
	(0.108)	(0.119)	(0.033)	(0.043)	(0.04)	(0.028)
2	0.537***	0.561***	0.993***	0.26***	-0.079*	0.094***
	(0.103)	(0.108)	(0.031)	(0.053)	(0.041)	(0.024)
3	0.315***	0.35***	1.031***	0.242***	-0.075	0.098***
	(0.096)	(0.102)	(0.032)	(0.042)	(0.046)	(0.026)
4	0.175*	0.173	1.033***	0.229***	-0.045	0.094***
	(0.101)	(0.11)	(0.033)	(0.048)	(0.04)	(0.026)
5	0.231**	0.273**	1.082***	0.217***	-0.048	0.082***
	(0.107)	(0.118)	(0.036)	(0.045)	(0.048)	(0.025)
6	0.264***	0.262**	1.086***	0.147***	-0.078	0.076***
	(0.1)	(0.106)	(0.032)	(0.044)	(0.048)	(0.028)
7	0.04	0.114	1.054***	0.258***	0.017	0.074***
	(0.09)	(0.104)	(0.029)	(0.044)	(.038)	(0.024)
8	-0.014	-0.038	1.076***	0.179***	-0.114***	0.044*
	(.094)	(0.102)	(0.031)	(0.052)	(0.043)	(0.025)
9	0.071	0.054	1.101***	0.17***	-0.074	0.039
	(0.105)	(0.116)	(0.031)	(0.045)	(0.048)	(0.028)
10	-0.119	0-.155	1.06***	0.25***	0.011	-0.009
	(0.09)	(0.096)	(0.025)	(0.04)	(0.04)	(0.024)
11	0.003	-0.043	1.101***	0.147***	-0.074*	0.019
	(0.092)	(0.099)	(0.028)	(0.047)	(0.04)	(0.029)
12	0.065	0.035	1.088***	0.065*	-0.041	0.03
	(0.092)	(0.106)	(0.03)	(0.039)	(0.04)	(0.025)
1 - 6	0.323***	0.335***	1.039***	0.22***	-0.055**	0.079***
	(0.048)	(0.05)	(0.048)	(0.25)	(0.026)	(0.14)

This table presents estimated abnormal returns and factor loadings performance of portfolios aligned by fund age within 1 year of fund inception. Funds included in the sample are non-incubated. Fund gross return is used in calculating excess return. Carhart (1997) and Ferson and Schadt (1996) adjusted alphas are presented in the first two columns. Factor loadings of Carhart 4 factor are reported. Pooled regression estimation of subsample with fund age less and greater than 6 months are also reported in the bottom rows. The significance levels are abbreviated with asterisks: *, ** and *** donate significance at the 10%, 5% and 1% levels, respectively. Clustered standard errors are in parentheses.

estimated coefficients within the first year after inception. Overall, we observe the short-term outperformance of mutual fund, which lasts for the first 6 months after fund creation.

First two columns in Table 4.2 reports estimated abnormal alphas before excluding expenses in event time. First of all, we can observe the statistically significant outperformance in first 6 months after fund inception from both Carhart and Ferson-Schadt measures. The outperform peaks in month 2 at 0.537% from Carhart measure and 0.561% from Ferson-Schadt measure, respectively. It starts to drop from month 3 at 0.21% to the 6th month at 0.10% remaining positive. Estimated performance becomes statistically insignificant and even negative from the month

7. As the Ferson-Schadt measure gives very similar estimated coefficients compared to the Carhart measure, we mainly report estimation results for the Carhart (1997) measure.

In the bottom of Table 4.2, we also report the pooled OLS regressions of fund-month observations that are within 6 month existence, and those that are older than 6 months. The pooled regression results are consistent with our finding in event time analysis. The Jensen's Alpha of new fund observations (fund-month that are younger than 6 months) is 0.323% in Carhart measure while 0.335% in Ferson-Schadt estimation. The outperformance vanishes for fund observations that are more than 6-month old, standing at 0.008% and 0.024% for Carhart and Ferson-Schadt measures, respectively.

The right section of Table 4.2 presents the Carhart factor loadings in every estimation. The market and size factors are significantly positive in all estimations. Apart from month 2, other market estimates are well above 1, suggesting that funds are generally taking greater risk than the market portfolio. The positive size estimators suggest that the small size effect exists in each pooled regression. The value factor shows mostly negative estimates, but the significance is not consistent. Finally, we have the momentum factor which is mostly positive, and statistically significant from month 2 to 8.

The outperformance period is shortened to 3 months when we apply the same set of analysis using fund returns after adjusting for expenses as reported in Table 4.3. In contrast with other studies which report a negative after-fee alpha, we still observe significantly positive alphas in the first 3 months after fund inception. The peak performance appears in month 2 at 0.537% and 0.561% for two different measures. Estimated performance becomes significantly negative from month 4.

We also report the pooled OLS regressions that from month 1-6 in the bottom row. Consistently we have significantly positive alphas for new fund observations which are above 0.2%. The Carhart factor loadings are very similar to what we reported in the previous table.

Overall, we find short-term outperformance for newly created funds using the incubation-free equity fund sample. The outperformance lasts for 6 months after fund inception using fund gross return, whereas for 3 months using net returns. We also present the results in graphs as shown in Figure 4.2. It plots estimated alphas based on Carhart (1997) and Ferson and Schadt (1996) measures over the 12 months

Table 4.3: Mutual Fund Monthly Performance after Inception in Event Time (After Expenses)

Fund Age	Abnormal Performance (%)		Factor Loadings on Carhart Model			
(month)	Carhart	Ferson-Schadt	Market	Size	Value	Momentum
1	0.333***	0.306**	1.021***	0.207***	-0.002	0.042
	(0.108)	(0.119)	(0.033)	(0.043)	(0.04)	(0.028)
2	0.426***	0.449***	0.994***	0.259***	-0.08**	0.095***
	(0.103)	(0.108)	(0.031)	(0.053)	(0.041)	(0.024)
3	0.203**	0.238**	1.031***	0.241***	-0.077*	0.097***
	(0.096)	(0.102)	(0.032)	(0.042)	(0.046)	(0.026)
4	0.061	0.06	1.034***	0.228***	-0.046	0.096***
	(0.101)	(0.109)	(0.033)	(0.048)	(0.04)	(0.026)
5	0.121	0.163	1.081***	0.216***	-0.051	0.082***
	(0.107)	(0.118)	(0.036)	(0.045)	(0.048)	(0.025)
6	0.153	0.149	1.087***	0.145***	-0.079*	0.076***
	(0.1)	(0.106)	(0.032)	(0.044)	(0.048)	(0.028)
7	-0.073	0.002	1.054***	0.257***	0.017	0.075***
	(0.09)	(0.104)	(0.029)	(0.044)	(0.038)	(0.024)
8	-0.126	-0.149	1.075***	0.178***	-0.116***	0.044*
	(0.094)	(0.102)	(0.031)	(0.052)	(0.043)	(0.025)
9	-0.04	-0.056	1.101***	0.168***	-0.075	0.039
	(0.105)	(0.116)	(0.031)	(0.045)	(0.048)	(0.028)
10	-0.231**	-0.268***	1.059***	0.251***	0.01	-0.009
	(0.09)	(0.096)	(0.025)	(0.04)	(0.04)	(0.024)
11	-0.109	-0.154	1.101***	0.145***	-0.076*	0.02
	(0.092)	(0.099)	(0.028)	(0.047)	(0.04)	(0.029)
12	-0.048	-0.08	1.089***	0.065*	-0.041	0.03
	(0.092)	(0.106)	(0.03)	(0.039)	(0.04)	(0.025)
1 - 6	0.211***	0.222***	1.039***	0.219***	-0.056**	0.08***
	(0.048)	(0.05)	(0.013)	(0.025)	(0.027)	(0.014)

This table presents estimated abnormal returns and factor loadings performance of portfolios aligned by fund age within 1 year of fund inception. Funds included in the sample are non-incubated. Fund net return is used in calculating excess return. Carhart (1997) and Ferson and Schadt (1996) adjusted alphas are presented in the first two columns. Factor loadings of Carhart 4 factor are reported. Pooled regression estimation of subsample with fund age less and greater than 6 months are also reported in the bottom rows. The significance levels are abbreviated with asterisks: *, ** and *** donate significance at the 10%, 5% and 1% levels, respectively. Clustered standard errors are in parentheses.

after fund inception. Panel which uses fund return before and after adjusting for expenses are presented in the top and bottom, respectively. We also include monthly means returns to compare the estimated performance and actual fund returns.

Figure 4.2 shows that the average monthly return of mutual funds is usually between -0.1% and 1.1% before excluding expenses, -0.1% and 1.0% after expenses. We can observe the decreasing trend in estimated alphas (both Carhart and Ferson-Schadt alphas) as well as the average fund monthly returns as the fund age increases. Interestingly, the alphas and mean return in month 12 have a jump back. Nevertheless, Figure 1 suggests the estimated fund performance is different from the actual realized returns, and is decreasing in first 12 months after creation.

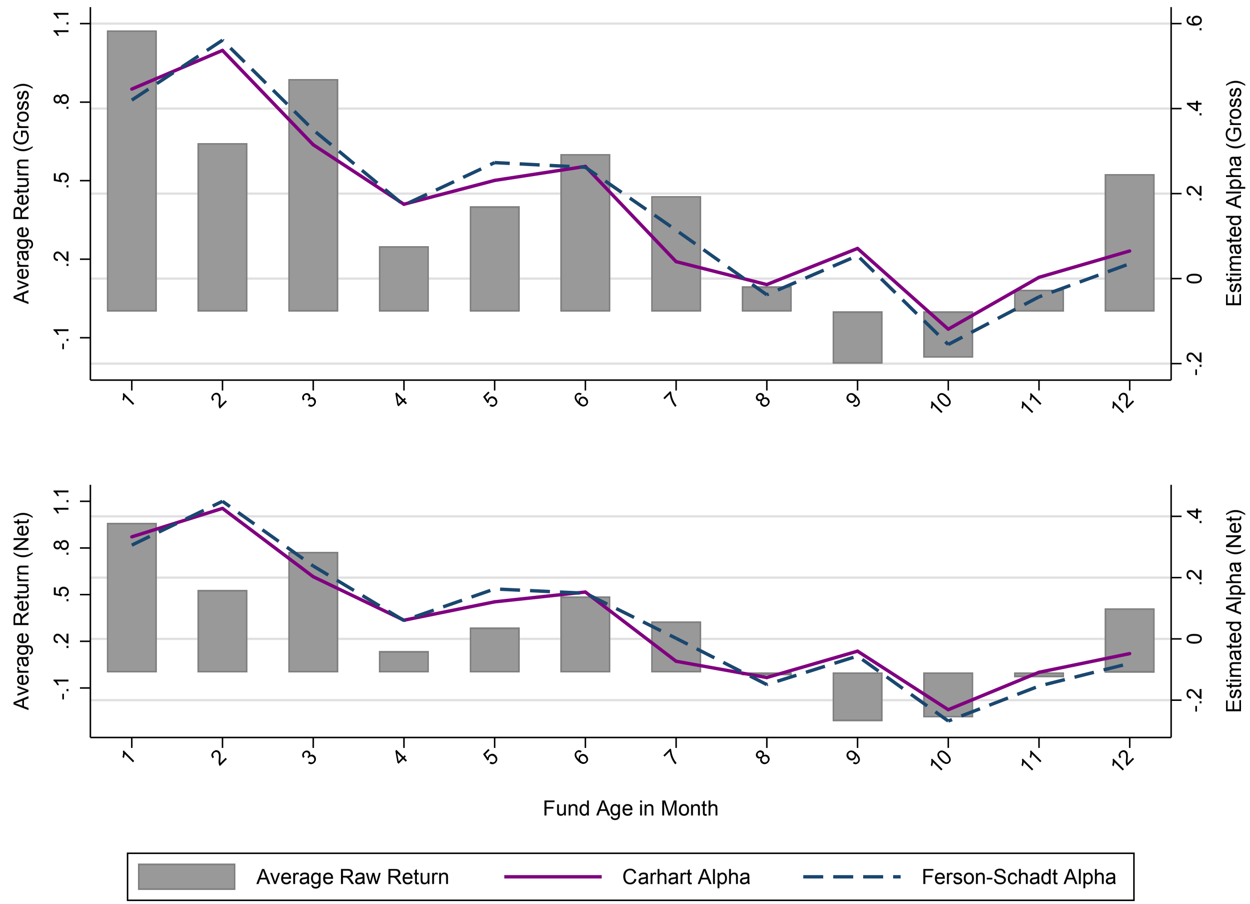

Figure 4.2: Fund Performance Over First 12 Months After Inception
This graph presents the performance of portfolios aligned by months within the first year after fund creation. Estimated alphas are measured by Carhart (1997) and Ferson and Schadt (1996) models. The bar graph shows the average fund return in the corresponding month. Performance before and after adjusting for fund expenses are presented in separate sections.

4.4.2 Controlling for Size

One potential explanation for the short-term outperformance is the small-size effect. In prior studies, Chen et al. (2004) report some evidence of a negative relationship between fund returns and size, but this is exclusively confined to funds that invest in small stocks, which tend to be illiquid. The finding is confirmed by Allen (2007), who reports no difference across size for institutional investors except for the small cap category, which is capacity-constrained and for which small funds perform better. To test the hypothesis if the short-term superior performance is related with the size, we firstly group funds into different size groups based on the fund size at the time of inception. Next, we compare the portfolio performance in each size group during different time period.

We track the fund performance in different size groups in different stages. Based on the fund size at the inception time (TNA reported in the first month), we categorize funds into *Minor* (TNA<1 million), *Small* (1<TNA≤15 million), *Medium* (15<TNA≤50 million) and *Large* (TNA>50 million) groups. As most new funds starts with limited capitalization, over 65% of mutual funds start with the TNA less than $15 million.

Next, we perform the pooled regression analysis in different age period, keeping each fund in the same size group without re-balancing. In other words, funds may increase or decrease in the TNA, but their assigned groups remain unchanged since it is based on the size at inception. This analysis could be viewed as choosing funds based on their sizes when they start. Therefore, this could answer the question of whether funds that are small initially outperform or not. One limitation of this method is that it does not ensure a continuously balanced allocation to size groups. To be consistent with the finding reported in Table 4.2 and Table 4.3, we enlarge the time horizon into fund age within month 1-6, 7-12, 13-18, 19-24 and 24 onwards. The result is presented in Table 4.4, with portfolio alphas estimated based on the Carhart 4-factor model. Table 4.4 includes 2 panels where panel A reports estimations using fund gross returns and panel B presents results using net returns.

The first column in Panel A presents portfolio performance in the first 6 months after fund inception before adjusting expenses for 4 different size portfolios. *Minor*, *Small* and *Medium* funds all outperform the market with significantly positive alphas, while *Large* funds have no significant return. *Small* funds have the largest es-

Table 4.4: Mutual Fund Portfolio Performance by Fund Age in Different Size Groups

	Fund Age (month)				
Fund Size ($ million)	≤ 6	7-12	13-18	19-24	> 24
Panel A: Before Expenses					
Minor (TNA ≤ 1)	0.227***	-0.046	0.056	0.08	0.023**
	(0.077)	(0.061)	(0.050)	(0.059)	(0.012)
Small ($1 <$ TNA ≤ 15)	0.5***	0.119*	0.096	0.121*	0.002
	(0.092)	(0.069)	(0.070)	(0.063)	(0.013)
Medium($15 <$ TNA ≤ 50)	0.324***	-0.034	0.029	0.11*	-0.012
	(0.105)	(0.086)	(0.070)	(0.063)	(0.012)
Large(TNA > 50)	0.173	-0.094	0.103	-0.182**	-0.025**
	(0.134)	(0.108)	(0.081)	(0.083)	(0.011)
Panel B: After Expenses					
Minor (TNA ≤ 1)	0.102	-0.171***	-0.069	-0.045	-0.095***
	(0.077)	(0.061)	(0.049)	(0.058)	(0.012)
Small ($1 <$ TNA ≤ 15)	0.384***	0.004	-0.02	0.004	-0.106***
	(0.092)	(0.069)	(0.070)	(0.063)	(0.013)
Medium($15 <$ TNA ≤ 50)	0.221**	-0.138	-0.074	0.006	-0.109***
	(0.105)	(0.086)	(0.070)	(0.064)	(0.012)
Large(TNA > 50)	0.082	-0.183*	0.013	-0.273***	-0.107***
	(0.134)	(0.108)	(0.081)	(0.083)	(0.011)

This table presents the portfolio performance of different size groups in different stages. Estimated Alphas are measured by Carhart (1997) 4-factor model using fund return before and after excluding expenses, and presented in percentage. Funds are categorized into *Minor* (TNA<1 million), *Small* (1<TNA≤15 million), *Medium* (15<TNA≤50 million) and *Large* (TNA>50 million) groups based on the fund size at the inception time. The fund ages are divided into 5 stages as month 1-6, 7-12, 13-18, 19-24 and month 24 onwards. The significance levels are abbreviated with asterisks: *, ** and *** donate significance at the 10%, 5% and 1% levels, respectively. Clustered standard errors are in parentheses.

timated abnormal return of 0.5%. After the first 6 months after fund inception, only the *Small* fund group still shows some statistically significant outperformance. We also notice that 2 years after new fund establishment, *Minor* funds still continue to provide a significantly abnormal return around 0.023%, which cannot be observed in other groups. One hypothesis is that the size of *Minor* funds still remains relatively small capitalization after being created for 2 yeas.

Panel B shows that *Minor* and *Large* funds do not provide evidence in generating abnormal performance in emerging period using fund net returns. The reason for the vanishing outperformancec of *Minor* funds might be the high expense ratio on minor fund operation. But *Small* and *Medium* funds still provide significant positive alphas even after excluding expenses at 0.384% and 0.221%, respectively. This contradicts the evidence provided in Grinblatt and Titman (1989) and Wermers (2000) that there is no significant difference across the net performance of small and large funds.

Table 4.5: Fund Portfolio Performance by Access to IPO Stocks

Fund Age	Carhart Alpha Before Expenses (%)		Carhart Alpha After Expenses (%)	
(month)	IPO Fund	Non-IPO Fund	IPO Fund	Non-IPO Fund
1	0.942***	0.026	0.822***	-0.082
	(0.192)	(0.116)	(0.192)	(0.116)
2	0.832***	0.172*	0.715***	0.065
	(0.196)	(0.093)	(0.195)	(0.093)
3	0.732***	-0.031	0.615***	-0.14
	(0.17)	(0.098)	(0.17)	(0.098)
4	0.431**	-0.076	0.311*	-0.185*
	(0.176)	(0.102)	(0.176)	(0.102)
5	0.418**	0.074	0.303	-0.031
	(0.192)	(0.098)	(0.192)	(0.098)
6	0.414**	0.145	0.298	0.036
	(0.182)	(.097)	(0.182)	(0.097)
7	0.04	-0.031	-0.079	-0.14
	(0.156)	(0.097)	(0.157)	(0.096)
8	0.019	-0.107	-0.098	-0.213**
	(0.171)	(0.086)	(0.171)	(0.086)
9	0.176	-0.12	0.059	-0.228**
	(0.192)	(0.109)	(0.192)	(0.109)
10	-0.152	-0.086	-0.27*	-0.194**
	(0.164)	(0.091)	(0.164)	(0.091)
11	0.031	-0.028	-0.086	-0.135
	(0.167)	(0.095)	(0.167)	(0.095)
12	-0.014	0.091	-0.134	-0.018
	(0.177)	(0.093)	(0.177)	(0.093)
1 - 6	0.62***	0.053	0.501***	-0.055
	(0.088)	(0.043)	(0.088)	(0.043)

This table presents estimated abnormal returns and factor loadings performance of portfolios aligned by fund age within 1 year of fund inception. Funds included in the sample are non-incubated equity funds, and are catergorised into IPO funds which hold IPO(s) during the first 6 months after inception, and Non-IPO funds which are funds have no IPO allocation. Carhart-adjusted alphas are presented using both gross and net fund return. Pooled regression estimation of subsample with fund age less and greater than 6 months are also reported in the bottom rows. The significance levels are abbreviated with asterisks: *, ** and *** donate significance at the 10%, 5% and 1% levels, respectively. Clustered standard errors are in parentheses.

In general, our finding suggests that variation across size groups is as important as variations across fund age stages. In other words, picking a fund by its age is as essential as by its size. To the extent that there are significant patterns due to size effect in the first 6 months after fund inception, *Small* and *Medium* funds seem to perform better than *Minor* and *Large* funds, even after controlling for fund expenses.

4.4.3 IPO Allocation and Fund Creation

In this section, we analyze the effect of IPOs on new fund performance. Previous studies on IPOs find evidence that the typical IPO provides substantial first-day returns, a phenomenon known as underpricing (Ritter and Welch, 2002). In addition, mutual funds seem to have preferential treatment in IPOs. Reuter (2006), for instance, finds a positive relation between underpriced IPO allocations to mutual fund families and brokerage commissions that families paid the underwriters in the months surrounding the IPO. Similarly, Aggarwal et al. (2002) argue that underwriters may favor institutional investors by allocating them more shares in hot issues. Therefore, access to IPOs could be a potential explanation about new mutual fund outperformance. We test this hypothesis by investigating whether the new fund short term outperformance concentrated among funds that hold IPO stocks in the 6-month emerging period.

We separate the incubation equity fund sample into two categories – those have IPO stock allocation during the emerging period and those do not. We use the Securities Data Companys (SDC) New Issues database to identify IPOs issued in North America during the period 1998-2008. For each of these IPOs, SDC provides the ISIN (International Securities Identification Number) of the issuing firm. Because IPO allocations are not publicly available, we construct a proxy for IPO allocations by matching the IPO information with the mutual fund holdings using all the reports with the reporting period starting within the 6-month after the inception. If a new fund holds at least one IPO stock holding, then we classify the fund as an IPO new fund, alternatively as a non-IPO new fund. Among our 1,569 new funds, 698 funds (or 44.49% of the sample) are identified as IPO funds, while 871 funds (or 55.51% of the sample) are non-IPO funds. This shows that access to IPO allocations is popular among new mutual funds.

We present the event time portfolio performance estimation results for IPO and Non-IPO funds in Table 4.5. Our main interest is the portfolio alphas therefore we abbreviate factor loadings. Also, we abbreviate Ferson-Schadt alphas because they are very similar to Carhart measures. Table 5.4 reports Carhart alphas using fund returns before and after adjusting for expenses. We can observe the statistically significant outperformance of IPO funds in first 6 months while mostly no significant abnormal performance for Non-IPO funds. The risk-adjusted performance for new funds which have access to IPO allocation peaks at 0.942% in month 1, and decreasing gradually until month 6. The outpeformance still holds for IPO funds even after subtracting expense in fund return, though the outperforming period reduces to 4 months instead of 6 months. Funds which have no IPO allocation in the emerging period have no significantly positive alpha in the first 12 month after inception. The pooled OLS regression estimates in the bottom two rows suggest the consistent finding, that funds have access to IPO stocks in the emerging period generate significant outperformance relative to those who have no IPO access.

4.4.4 Fund Manager and Fund Creation

Apart from the size effect and IPO stock allocation, the managerial characteristics can used to explain the short-term outperformance of newly established funds. Bär et al. (2011) examined investment decisions of single fund managers and management teams. They conclude that team-managed funds present less extreme performance, less extreme investment objectives and less industry concentration in stock holdings than individual-managed funds. This might also be explained as that individual team members have different opinions, thus the team decision will be a compromise (Sah and Stiglitz, 1986, 1988). Therefore, we investigate if the superior performance of new funds is driven by individual managers rather than management teams in this section[14].

We firstly identify the managerial information for each fund at the inception month. At the creation month, if the fund is reported as under the management of a single manager, it is defined as the fund created by *Individual Manager*[15]; if the fund is reported as under the management of multiple managers or a management team, it is defined as a fund created by *Multiple Manager*. Next, we separate the sample into two groups based on the number of portfolio managers in the management team at the inception month. In our sample, out of the 1,569 new funds, 862 (or 54.94%) are managed by teams, while 707 (or 45.06%) are managed by individual managers. Using each of these sub-samples, we re-estimate the Jensens Alpha for the event time portfolios.

The result is presented in Table 4.6, which includes estimated event time portfolio performance using both fund returns before and after adjusting for expense. Gen-

[14]The manager information is not fully disclosed in the CRSP since the manager information is not required to disclose by the SEC prior to 1988. Even after 1988, funds are not required to disclose detailed information of each manager in the team by the SEC. Until February 2006, funds are required to disclose information about each manager in a team (up to at least four of the members) by the SEC. Therefore, we group our sample into 2 categories: mutual funds created by an individual manager and by multiple managers.

[15]We assign each recognizable individual manager with a unique ID as described in Appendix A.

Table 4.6: Fund Portfolio Performance by Manager Types

Fund Age	Before Expenses (%)		After Expenses (%)	
(month)	Individual Manager	Multiple Manager	Individual Manager	Multiple Manager
1	0.545***	0.39***	0.431**	0.278**
	(0.17)	(0.137)	(0.17)	(0.137)
2	0.638***	0.446***	0.525***	0.335**
	(0.161)	(0.136)	(0.161)	(0.136)
3	0.481***	0.177	0.367**	0.067
	(0.147)	(0.126)	(0.147)	(0.126)
4	0.307*	0.07	0.192	-0.042
	(0.164)	(0.126)	(0.163)	(0.126)
5	0.265	0.227	0.153	0.118
	(0.165)	(0.142)	(0.165)	(0.142)
6	0.273*	0.272**	0.159	0.162
	(0.149)	(0.135)	(0.149)	(0.135)
7	0.208	-0.105	0.093	-0.216*
	(0.143)	(0.116)	(0.143)	(0.117)
8	0.02	-0.003	-0.092	-0.113
	(0.158)	(0.116)	(0.158)	(0.116)
9	0.15	-0.008	0.037	-0.118
	(0.176)	(0.129)	(0.176)	(0.129)
10	-0.071	-0.159	-0.186	-0.27**
	(0.143)	(0.115)	(0.143)	(0.115)
11	0.109	-0.078	-0.005	-0.188
	(0.145)	(0.119)	(0.145)	(0.119)
12	-0.05	0.156	-0.165	0.044
	(0.146)	(0.117)	(0.146)	(0.117)
1 - 6	0.409***	0.258**	0.294***	0.148**
	(0.075)	(0.062)	(0.075)	(0.062)

This table presents estimated abnormal returns and factor loadings performance of portfolios aligned by fund age within 1 year of fund inception. Funds included in the sample are non-incubated equity funds, and are categorized into funds created by individual managers, and funds created by multiple managers. Carhart-adjusted alphas are presented using both gross and net fund return. Pooled regression estimation of subsample with fund age less and greater than 6 months are also reported in the bottom rows. The significance levels are abbreviated with asterisks: *, ** and *** donate significance at the 10%, 5% and 1% levels, respectively. Clustered standard errors are in parentheses.

erally, the results indicate that the Alphas for both funds created by an individual manager or a team are positive and statistically significant in the pooled portfolio regression. The estimated alphas in the emerging period are 0.409 and 0.258 for individual and team manager created funds, respectively. However, the result is slightly different in the event time portfolios. Individual manager outperform the market in 5 out of 6 months in the emerging period, while only outperform in only 3 months for multiple manager funds. Also, the magnitude of alphas is greater for individual managers than multiple managers. The result still holds while applying fund net returns as shown in the right section of Table 4.6. Overall, the management team does not make a significant difference in explaining the short-lived outperformance of new funds in the first 6 months after inception.

Further, we attempt to investigate the new fund outperformance in relation to managerial characteristics by taking a deeper look at individual managers. Existing and newly emerging portfolio managers all have incentives to generate superior returns for various reasons. We can test if experience in managing mutual funds matters in outperforming the market for newly-created funds. For funds managed by individual managers, we again categorize them into experienced and non-experienced managers, by examining if this fund is the first mutual fund managed in his/her career. We sort the sample by the manager name, time and fund identification number. If the fund is identified as the first funds under management of the manager, then we flag the manager as *Non-Experienced Manager*. Otherwise, if other funds are managed by the manager before the new fund creation date, we flag the manager as *Experienced Manager*. However, the identification method is not optimal given the nature of database. The manager information disclosure is not required by the SEC. It is possible that our identified *Non-Experienced Manager* actually has experience but the corresponding information is not disclosed and trackable.

The event time portfolios of *Experienced Manager* and *Non-Experienced Manager* are reported in Table 4.7, applying both fund return before and after adjusting for expenses. Firstly, *Experienced Manager* and *Non-Experienced Manager* both have some statistically significant outperformance within the first 6 months after being created. Specifically, funds created by *Experienced Manager* have significant performance from month 1-4, peaking at 0.628% in month 2. Funds initiated by *Non-Experienced Manager* provide outperformance at month 1, 3 and 6 above 4%. Secondly, the pooled regression presented in the bottom raws indicates that managerial experience does not make a difference in generating outperformance within 6 month of the emerging period (p-value 0.13). Finally, the result is confirmed by applying fund net returns. In short, managerial experience is not a powerful determinant in explaining the short-term outperformance for new funds.

Generally, we aim at comparing performance of new funds in emerging period (first 6 months after inception) among different groups. Firstly, we examine performance of funds created by *Individual Manager* and *Multiple Managers*. Next, we compare the performance of funds created by *Experienced Manager* and *Non-Experienced Manager*. Overall, we find out funds created by individual managers exhibit slightly better performance than funds managed by multiple managers during the new fund emerging period, defined as 6 months after fund creation. This

Table 4.7: Fund Portfolio Performance by Individual Manager Experience

Fund Age	Before Expenses (%)		After Expenses (%)	
(month)	Experience Mgr	No Experience Mgr	Experience Mgr	No Experience Mgr
1	0.535**	0.578**	0.416**	0.472*
	(0.211)	(0.264)	(0.211)	(0.263)
2	0.628***	0.324	0.509**	0.218
	(0.199)	(0.249)	(0.199)	(0.249)
3	0.448**	0.485**	0.331*	0.378
	(0.182)	(0.236)	(0.182)	(0.236)
4	0.395*	0.323	0.275	0.216
	(0.206)	(0.239)	(0.205)	(0.238)
5	0.251	0.171	0.133	0.072
	(0.207)	(0.225)	(0.207)	(0.225)
6	0.178	0.4*	0.058	0.296
	(0.193)	(0.214)	(0.193)	(0.214)
7	0.241	0.181	0.121	0.078
	(0.189)	(0.182)	(0.188)	(0.182)
8	0.19	-0.207	0.073	-0.31*
	(0.214)	(0.186)	(0.214)	(0.186)
9	0.23	0.082	0.112	-0.02
	(0.21)	(0.249)	(0.21)	(0.249)
10	-0.061	-0.117	-0.179	-0.224
	(0.18)	(0.207)	(0.181)	(0.207)
11	0.27	-0.198	0.152	-0.303
	(0.183)	(0.215)	(0.183)	(0.215)
12	-0.153	0.199	-0.273	0.095
	(0.182)	(0.2)	(0.183)	(0.199)
1 - 6	0.398***	0.356**	0.279***	0.251***
	(0.098)	(0.086)	(0.098)	(0.085)

This table presents estimated abnormal returns and factor loadings performance of portfolios aligned by fund age within 1 year of fund inception. Funds included in the sample are non-incubated equity funds that are created by individual managers. The sub-sample is further categorized into funds created by experienced individual managers, and funds created by inexperienced managers. Carhart-adjusted alphas are presented using both gross and net fund return. Pooled regression estimation of subsample with fund age less and greater than 6 months are also reported in the bottom rows. The significance levels are abbreviated with asterisks: *, ** and *** donate significance at the 10%, 5% and 1% levels, respectively. Clustered standard errors are in parentheses.

evidence supports the finding in Bär et al. (2011) that management teams are less likely to achieve extreme performance. One explanation is the hypothesis of diversification of opinions (Sah and Stiglitz, 1986, 1988), which indicates that team decisions are averaged and compromised from individual members' ideas. Another hypothesis is that information advantage known by individuals is easier to realize if he/she manage the fund alone than in a management team. However, the managerial experience does not provide evidence in explaining the short-term outpeformance, as both *Experienced Manager* and *Non-Experienced Manager* presents significant positive risk-adjusted returns in event time analysis and pooled regression. This is because that both new-entry and existing managers have strong incentive to generate abnormal performance.

4.4.5 Flow-Performance Analysis

From the previous analysis, it seems that new funds outperform during the 6-month period after inception. We also investigate several mechanism that can explain the short-lived outperformance, including IPO stock allocation and managerial characteristics. It is concluded in the prior literature that abnormal performance is the key in attracting investment flow. Therefore, in this section, we further extend our analysis using multivariate regressions to examine flow-performance relation of different types of new funds. The multivariate analysis differs from the portfolio analysis applied in previous sections by simultaneously controlling for other mutual fund characteristics that are related to fund performance.

Given that outperformance is relatively short-term, investors may not give credence to these returns, and thus provide no additional investment flow. However, flow is highly sensitive to past performance because investors chase returns (Kostovetsky and Warner, 2015). Therefore we are interested in investigating if new fund attract significant flow in the emerging period.

To do this, we firstly build the indicator *New Fund* which equals 1 if the fund-month observation is within the emerging period, and equals 0 otherwise. To be consistent with the previous analysis, we split the *New Fund* into two groups: funds created by *Individual Manager* and funds created by *Multiple Manager*. Finally, we split the *Individual Manager* into two groups again: funds created by *Experienced Manager* and funds created by *Non-Experienced Manager*. Specific multivariate models are listed in following equations:

$$Flow_t^j = \alpha_0 + \alpha_1^j NewFund_t^j + \alpha_2 \mathbf{X}_t^j + \varepsilon_t^j \tag{4.4.1}$$

$$Flow_t^j = \alpha_0 + \alpha_1^j IPOFund_t^j + \alpha_2^j NonIPOFund_t^j + \alpha_3 \mathbf{X}_t^j + \varepsilon_t^j \tag{4.4.2}$$

$$Flow_t^j = \alpha_0 + \alpha_1^j IndManager_t^j + \alpha_2^j MultiManager_t^j + \alpha_3 \mathbf{X}_t^j + \varepsilon_t^j \tag{4.4.3}$$

$$\begin{aligned} Flow_t^j = \alpha_0 &+ \alpha_1^j ExpManager_t^j + \alpha_2^j NonExpManager_t^j + \alpha_3^j MultiManager_t^j \\ &+ \alpha_4 \mathbf{X}_t^j + \varepsilon_t^j \end{aligned} \tag{4.4.4}$$

The dependent variable $Flow_t^j$ is the monthly net dollar flow into the fund calculated as $\frac{TNA_t^j - TNA_{t-1}^j(1+R_t^j)}{TNA_{t-1}^j}$, starting from month 2, ranked by year and month. The reason why we use the fractional rank of net dollar flow instead of the commonly used percentage measure is because that news funds exhibit substantial variation in the total net assets and the fractional rank controls for such outlier effects (Evans, 2010). In addition, there is substantial variation in the net dollar flow across different market states. Thus, ranking flows within year and month also controls for this variation. We also use the fractional rank methodology in calculating some of the control variables for the same purpose.

$\boldsymbol{X}$ is a vector of fund-specific control variables, including the fund size factor *Log(TNA)* measured as the natural logarithm of funds monthly total net assets, the fund family size factor *Log(Family TNA)* computed as the natural logarithm of fund familys monthly total net asset, *Fund Age* measured as the difference between the current calendar year and fund's initiation year, *Expense Ratio Rank* calculated as the demeaned monthly fractional rank of funds expense ratio, *Turnover Rank* calculated as the demeaned monthly fractional rank of funds turnover ratio, *Fund Load Rank* calculated as the demeaned monthly fractional rank of funds load, *Lag Fund Flow Rank* computed as the demeaned monthly fractional rank of funds one month lag of fund flow, and *Cumulative Total Return* measured as the funds cumulative net return since inception[16].

We estimate the regressions with panel-corrected standard errors (PCSE) which adjust for not only the contemporaneous correlation and heteroskedasticity among fund returns, but the autocorrelation within each funds returns (Beck and Katz, 1995). We analyze the unbalanced panel, since most mutual funds do not exist over the whole sample period. Table 4.8 and 4.9 reports the multivariate regression estimations. The number of observations, adjusted R-squared and number of cluster for each model specification are also reported in the bottom of tables.

Table 4.8 reports the flow-performance estimation result of new funds, and funds with/out IPO stock allocation. Model specification (1)-(3) focus on the *New Fund* indicator variable, aim at examining whether the 6-month outperformance leads to greater investment flows, while specification (4) and (5) further split the *New Fund* into the *IPO Fund* and the *Non-IPO Fund*.

The results of model (1) show that new funds in the emerging period attracts investment flow, as the coefficient is 0.101 and statistically significant, including only

[16]Kacperczyk et al. (2005) and Huang et al. (2011) use alternative fund performance measures which is the model adjusted alpha based using rolling window calculation. The window ranges from 12-36 months. We do not consider such method for the reason that any rolling window procedure would waste first 12-36 months observations, which makes it impossible for us to examine the performance in new fund emerging period.

Table 4.8: Multivariate Analysis: New Funds and IPO Allocation

	(1)	(2)	(3)	(4)	(5)
New Fund	0.101***	0.027***	0.011***		
	(0.006)	(0.007)	(0.003)		
IPO Fund				0.045***	0.019***
				(0.009)	(0.005)
Non-IPO Fund				0.008	0.001
				(0.008)	(0.004)
Difference (IPO vs. Non-IPO)				0.037***	0.018***
				(0.011)	(0.006)
Log(Family TNA)		0.005***	0.003***	0.005***	0.003***
		(0.001)	(0.001)	(0.001)	(0.001)
Log(TNA)		0.006***	-0.000	0.006***	-0.000
		(0.001)	(0.001)	(0.001)	(0.001)
Fund Age		-0.026***	-0.013***	-0.026***	-0.013***
		(0.001)	(0.001)	(0.001)	(0.001)
Expense Ratio Rank		-0.073***	-0.042***	-0.073***	-0.042***
		(0.011)	(0.005)	(0.011)	(0.005)
Turnover Rank		-0.056***	-0.023***	-0.056***	-0.023***
		(0.009)	(0.004)	(0.009)	(0.004)
Fund Load Rank		-0.006	-0.001	-0.006	-0.001
		(0.011)	(0.005)	(0.011)	(0.005)
Lag Fund Flow Rank			0.550***		0.549***
			(0.008)		(0.008)
Cumulative Total Return			0.041***		0.041***
			(0.005)		(0.005)
Constant	0.399	0.480***	0.206***	0.481***	0.208***
	(0.354)	(0.0759)	(0.0703)	(0.079)	(0.072)
Observations	164,962	133,014	131,881	133,014	131,881
Adjusted R2 (%)	0.483	5.98	34.9	5.99	34.9
Number of Cluster	1,568	1,510	1,510	1,510	1,510

This table presents the coefficients from regressions of funds investor flows on performance and new fund characters. The dependent variable is the monthly net dollar flow to the fund, starting from month 2, ranked by year and month. Indicator variable *New Fund* equals 1 if the fund-month observation is within the emerging period, and 0 otherwise. IPO equals 1 if the fund holds IPO stock(s) within the 6 months after fund inception, and 0 otherwise. Similarly, indicator variable Non-IPO equals 1 if the fund does not hold any IPO stock within the 6 months after fund inception, and 0 otherwise. Control variables include fund size, measured the natural log of funds total net assets (*Log TNA*), log of fund familys total net asset (*Log Family TNA*), fund age in year (*Fund Age*), the demeaned monthly fractional rank (between 0 and 1) of funds expense ratio (*Expense Ratio Rank*), turnover ratio (*Turnover Rank*) and load (*Fund Load Rank*), one month lag of fund flow rank (*Lag Fund Flow Rank*) and funds cumulative net return since inception (*Cumulative Total Return*). The differences between indicator variables and Non-IPO dummy are reported. Monthly fixed effect are included in regressions and clustered standard errors are in parentheses. The significance levels are abbreviated with asterisks: *, ** and *** donate significance at the 10%, 5% and 1% levels, respectively.

month fixed effects to control for time trends on flows. In specification (2) and (3), we consider control variables which lead to some loss of observations due to the missing data. Largely, the coefficient estimates of the control variables are consistent with the prior literature. Specifically, fund size and family size have a positive impact on investment flows, while fund age, expense ratio and turnover affect negatively on flows. Most importantly, however, the inclusion of control variables does not affect our previous findings. The results consistently show that the new fund is associated with significant net dollar flow rank within 6 month after inception. One thing to note is that with the lagged dependent variable (*Lag Fund Flow Rank*) and funds cumulative net return since inception (*Cumulative Total Return*) included in model (3), the indicator variable coefficient decreases slightly from 0.027 to 0.011 but with any change in the significance level.

We split the *New Fund* into two dummy variables *IPO Fund* and *Non-IPO Fund*, based on if the fund holds IPO stock in the emerging period or not. Model (4) and (5) indicate that IPO fund have positive net dollar flow ranks, with statistically significant coefficients. These results support the view that investors recognize the short-lived nature of new fund outperformance, especially that of a fund which has access to IPO stock(s). Moreover, the market provide additional investment flow to IPO funds relative to non-IPO funds, as the differences are tested to be statistically significant.

Next, we examine whether the portfolio manager characteristics has any impact on investment flows and results are presented in Table 4.9. To do so, we perform a simple regression as specification (1), with two indicator variables *Individual Manager* which equals 1 if the fund is created by an individual portfolio manager and within the 6 months after fund inception, and 0 otherwise, and *Multiple Managers* equals 1 if the fund is initiated by a team and within the 6 months after fund inception and 0 otherwise. We find that both individual-created and team-created funds are linked with significant flow rank in the first 6 month after inception. The difference between individual and multiple manager created funds is estimated as -0.027 and is statistically significant ($p<0.01$), as shown at the bottom of Table 4.9. In other words, new funds attract flows regardless of the number of managers at the time of inception, but team managers outperform individuals slightly.

We are also interested in the managerial experience in attracting fund flow into new funds. Therefore, we identify funds created by individual managers into two subgroups – *Experienced Individual Manager* and *Non-Experienced Individual Manager* which depends on if the manager has experience in managing other funds prior to the fund creation date. We run the regression without control variables in model (2), and gradually add control factor in (3) and (4). In specification (3), we find that all types of managers are associated with positive flows, but it is the inexperienced

Table 4.9: Multivariate Analysis: Managerial Characteristics

	(1)	(2)	(3)	(4)
Individual Manager	0.073***			
	(0.008)			
Multiple Manager	0.100***	0.100***	0.026***	0.011**
	(0.007)	(0.007)	(0.008)	(0.004)
Experienced Individual Manager		0.089***	0.003	-0.007
		(0.013)	(0.014)	(0.008)
Non-Experienced Individual Manager		0.066***	-0.001	-0.005
		(0.01)	(0.011)	(0.006)
Log(Family TNA)			0.009***	0.004***
			(0.001)	(0.001)
Log(TNA)			0.002	-0.002***
			(0.002)	(0.001)
Fund Age			-0.013***	-0.0071***
			(0.001)	(0.001)
Expense Ratio Rank			-0.078***	-0.043***
			(0.012)	(0.005)
Turnover Rank			-0.064***	-0.026***
			(0.01)	(0.004)
Fund Load Rank			-0.017	-0.006
			(0.011)	(0.005)
Lag Fund Flow Rank				0.559***
				(0.008)
Cumulative Total Return				0.033***
				(0.004)
Difference	-0.027***			
(Individual vs. Multiple)	(0.01)			
Difference		-0.011	-0.023	-0.018**
(Experienced Ind vs. Multiple)		(0 .014)	(0.015)	(0.008)
Difference		-0.035***	-0.026**	-0.015**
(Non-Experienced Ind vs. Multiple)		(0.012)	(0.013)	(0.007)
Constant	0.496***	0.496***	0.567***	0.262***
	(0.003)	(0.003)	(0.011)	(0.006)
Observations	164,962	164,962	133,014	131,881
Adjusted R2 (%)	0.491	0.492	4.14	34.5
Number of Cluster	1,568	1,568	1,510	1,510

This table presents the coefficients from regressions of funds investor flows on performance and new fund characters. The dependent variable is the monthly net dollar flow to the fund, starting from month 2, ranked by year and month. Indicator variable *Individual Manager* equals 1 if the fund is created by an individual portfolio manager and the observation is within the 6 months after fund inception, and 0 otherwise. Similarly, indicator variable *Multiple Managers* equals 1 if the fund is initiated by a team and within the 6 months after fund inception and 0 otherwise. We further split the *Individual Manager* subsample into individual managers with experience in managing equity fund before *Experienced Individual Manager* and those who do not have experience *Non-Experienced Individual Manager*. Control variables include fund size, measured the natural log of funds total net assets (*Log TNA*), log of fund familys total net asset (*Log Family TNA*), fund age in year (*Fund Age*), the demeaned monthly fractional rank (between 0 and 1) of funds expense ratio (*Expense Ratio Rank*), turnover ratio (*Turnover Rank*) and load (*Fund Load Rank*), one month lag of fund flow rank (*Lag Fund Flow Rank*) and funds cumulative net return since inception (*Cumulative Total Return*). The differences between indicator variables are reported. Monthly fixed effect are included in regressions and clustered standard errors are in parentheses. The significance levels are abbreviated with asterisks: *, ** and *** donate significance at the 10%, 5% and 1% levels, respectively.

individual managers who significantly underperform team managers. In specification (4), we include the fractional rank variable of one-month lag fund flow (*Lag Fund Flow Rank*) and the funds cumulative return since inception (*Cumulative Total Return*) as additional control variables. Essentially, this specification addresses concerns about a potential dynamic endogeneity impact on investment flows. The results show that lagged fund flows and cumulative return have a positive impact on the net dollar flow ranks. In addition, the inclusion of additional control variables makes the difference in flows between experienced individual managers and team managers – the difference between these two becomes statistically significant ($p<0.05$).

Overall, these results are consistent with the view that investors differentiate among new funds created by multiple managers, and reward them with additional flow during the 6-month period after inception. Recall the previous finding that the event time portfolio performance of individual-created and team-created funds do not differ. This phenomenon can be explained by that investors have confidence in team management as they are a safer choice.

4.5 Summary

With a large growth in the number of new funds offered to the market, understanding the performance of new funds during the first few months following their creation is becoming an increasingly relevant issue. Several recent studies have analyzed various aspects of mutual fund performance, but very little about the issue of the early stage performance of mutual funds when they may be considered as "new". Our study provides the analysis of the performance patterns of new mutual funds, and investigate the explanation for the short-lived outperformance. Using U.S. mutual fund data from 1996 to 2015, we address the questions of whether new mutual funds outperform the market and if they do, what may explain their superior performance. Our analysis and main findings may be summarized as follows.

First, we examine how the performance of mutual funds evolves over time following their inception using the event time approach. This approach allows us to develop deeper insight into the relationship between fund performance and fund age than the common practice of treating fund age merely as a control variable. We find evidence of new funds outperformance during their emerging period, which is defined as the first 6 months of their existence, both before and after fund expenses are taken into account. This outperformance, however, only lasts for a short term and disappears soon after the emerging period.

Second, our findings suggest that performance variations across fund age stages are as important as more well-known variations across size groups. The size effects seem to become relevant as early as during the first 6 months after fund inception: *Minor*, *Small* and *Medium* funds seem to perform better than *Large* funds especially during the first 6 months.

Thirdly, we link the new fund outperformance with IPO allocation and find that funds have access to IPO stocks in the emerging period largely outperform those have no IPO access. Therefore, IPO allocation seems to be an effective strategy to start a new funds. This finding is also consistent with the prior literature which finds a positive relation between under-priced IPO allocations to mutual fund families and brokerage commissions that families paid the underwriters in the months surrounding the IPO (Reuter, 2006).

Finally, we find that funds created by individual managers slightly outperform team-created funds during the 6-month emerging period. This is consistent with the findings of Bär et al. (2011) which show that management teams are less likely to achieve extreme performance. We also find that the managerial experience in managing mutual funds does not improve the performance of newly created funds, which indicates that the short-term ourperformance is due to information advantage rather than managerial experience.

We also contribute to the literature on fund flows for new funds. Existing literature largely focuses on the relationship between investment flows with past performance (Chevalier and Ellison, 1997; Sirri and Tufano, 1998), fund ratings (Del Guercio and Tkac, 2008), incubation bias (Evans, 2010), media coverage (Solomon et al., 2014), and trendy mutual funds (Greene and Stark, 2016). We show that IPO allocations is an effective strategy that enhances investment flows during their early months after the inception of a new fund. Also, funds created by team managers are likely to be awarded with more flows than individual managers. The findings have implications for both portfolio managers and fund families, since we show that IPO allocation is an effective strategy in enhancing investment flows during the emerging period of a new fund.

Chapter 5

Fund Manager Replacement and Risk Taking

"…While past performance is not indicative of future results, it's even less relevant when the management team changes hands. …You start over to some extent. We punish funds for a manager change, even though that change could be good or bad, but it adds unknowns and that's a risk people should be aware of. …"

— Jonathan Burton at marketwatch.com

5.1 Introduction

The previous empirical study focuses on the new mutual fund opening, and finds out that new funds opened by individual managers, especially inexperienced individual managers generate slightly better performance than funds opened by multiple managers. The finding is consistent with Aggarwal and Jorion (2010) which argue that newly-entry managers have strong incentives to prove their ability in the beginning of their careers by putting more effort in enhancing portfolio performance rather than marketing those funds to new investors. Therefore, we investigate further in the topic of fund manager career concern in this chapter.

This chapter investigates the idea that fund managers would take into account turnover risk that they face when adjusting the volatility of portfolios under their management. In addition to exploring a statistical correlation between a manager's discharge from a fund and the realized volatility of the fund that she is managing, we use an instrumental variable (IV) approach to study whether one may infer causality from such a correlation. Specifically, our structural equation describes a fund's volatility as a function of whether its manager has been recently replaced, and we address the potential endogeneity of manager replacement using an IV that is motivated by the notion of a family tournament.

The basic structure of the family tournament that we postulate is as follows. Each fund manager observes the position of her funds relative to other funds in the same family (family rank) on a continuous basis. Based on this family rank, fund managers decide on the amount of risk to take accordingly. Thus, it may be reasonable to assume that a fund manager's primary goal is to reach a top position by the end of a calendar year based on the performance within that year. We perform the analysis on a yearly basis since most fund managers are compensated in relation to their performance during a calendar year. Although investment decisions by some fund investors and decisions by families to advertise or promote managers might depend on longer period horizons, the one-year horizon is the most natural choice (Kempf and Ruenzi, 2008). Moreover, according to Sirri and Tufano (1998), a manager's performance in the prior year is the most important determinant of investment decisions by fund investors. Thus, trying to reach a top position by the end of the year based on the performance within this year is arguably a natural goal for fund managers to pursue.

Previous work shows that manager risk-shifting behavior is affected by compensation and employment incentives. Empirical studies indicate that fund managers would try to secure their position in the family tournament so as to avoid dismissal risk and achieve better compensation. For example, Hu et al. (2011) find that the managers compensation and employment risk incentives would lead to a nonmonotonic (U-shaped) relation between the risk choices relative to peers and prior relative performance from the pooled OLS regressions.

However, the omitted variable bias may exist since manager replacement factor could be correlated with the error term in the risk choice model. Our focus is to examine the casual effect of manager turnover risk on the riskiness of a manager's investment portfolio. To test the casual relation, we adopt an instrumental variable (IV) estimator. The IV estimator can be computed in two stages where the first stage regression models the replacement risk of fund managers, and the second stage regression uses the predicted replacement risk from the first stage to explain the riskiness of an investment portfolio. We employ this approach, but we are also mindful of the fact that several fund and manager characteristics associated with the manager turnover are also arguably directly related to the portfolio's riskiness. Our task, therefore, is to identify factors providing exogenous variation in manager turnover risk without affecting investment decisions by managers via other channels.

Our identification strategy relies on the idea that manager replacement does not only occur when a manager's investment performance has been persistently poor. For instance, fund flow (i.e. proportional change in total assets not due to returns) increases assets under management, thereby generating more fees for the fund sponsor, so it is natural that mutual fund companies would want to hire managers who can attract greater flow. Therefore, a board may review and monitor a manager's contribution in terms of attracting a new flow and replace those who are incapable of attracting significant flows. We hypothesize that managers who attract less flow in the family tournament are more likely to get replaced. In short, the manager's fund flow rank within the family should predict manager replacement.

As a proxy for the fund's position in the family tournament, we adopt the "Rank-of-Ranks" approach of Kempf and Ruenzi (2008). The advantage of this method is that it ensures the performance of funds from different segments can be easily compared. This "Rank-of-Ranks" variable signals different but related employment risk fund managers are facing in the tournament, making it more likely that the board will consider replacing the management team.

We first document that fund managers are exposed to the replacement risk if they have peer pressure from the family tournament. Then, we show that the changeability of the fund's position in the family tournament is unlikely to affect the fund's realized volatility directly, in an analysis that controls for various other factors such as fund characteristics and family size. Finally, we use not only the idiosyncratic risk of fund return on Lipper return, but also Carhart 4 factor model adjusted idiosyncratic risk to the measure of the fund's realized volatility. The former one allows us to understand the segment peer adjusted risk, while the latter allows us to understand the market-adjusted realized volatility. We also control for a range of factors shown to influence the fund volatility, including fund and family characteristics.

Our central finding is that there is a robust and significantly positive association between predicted manager turnover risk and the fund realized idiosyncratic risk. Across various regression specifications, the results indicates a one percentage point increase in replacement risk is associated with about 1% greater fund idiosyncratic volatility. The result is in line with the manager employment concern literature. This study provides an innovative explanation for the relationship between fund risk taking and the family tournament. Fund managers that perform badly in the tournament may have greater career concerns since they are more likely to be replaced. Under this career dismissal pressure, those managers tend to hold more volatile portfolios to improve their relative position in the family. In other words, the manager replacement risk driven by the peer pressure from the tournament is likely to reflect in the fund's idiosyncratic risk.

We use an instrumental variable (IV) approach to study whether fund managers would take into account turnover risk that they face when adjusting the volatility of portfolios. The instrumental variable measures the peer flow pressure that a fund is facing in the tournament, and is constructed by following the "Rank-of-Ranks" approach of Kempf and Ruenzi (2008), which allows the performance of funds from different segments to be easily compared. Generally, we show that the risk-taking behavior of fund managers depends on the competitive situation they face. Tournament losers are facing more career risk than winners and they are more likely to increase the riskiness of their investment portfolios to improve their position. The results remain robust when we account for a more generalized segment (investment style) tournament instead of a family tournament.

To sum, the following research questions are addressed in this chaper:

- Is the peer flow pressure from the fund tournament a significant determinant of whether a mutual fund manager is replaced?

- Do fund managers adjust the risk of their funds based on the career risk that they are facing from the tournament?

The following Section 5.2 includes the discussion of prior literature on the topic of mutual fund tournament and fund manager turnover. The main methodology of the two-stage least squares approach is presented in the next section. The discussion of sample selection and variable construction are included in Section 5.4. The next section includes the main empirical resutl and robustness checks. We close the chapter with some conclusion in the end.

5.2 Prior Literature

We provide the discussion of prior literature in different aspects including the fund tournament, portfolio manager turnover and fund volatility.

5.2.1 Mutual Fund Tournament

According to Conyon et al. (2001), tournament is defined as the competition in a group with the purpose of being rewarded on their relative performance. There are two types of fund tournaments discussed in the prior mutual fund literature: the segment tournament (Brown et al., 1996) and the family tournament (Kempf and Ruenzi, 2008).

It is Brown et al. (1996) who pioneered the idea the mutual fund market may be modeled as a tournament in which all funds having comparable investment objectives compete with one another. This approach undoubtedly provides a useful framework for a better understanding of the portfolio management decision-making process. Later on, Kempf and Ruenzi (2008) take a deeper look at the fund family, and argue that the family tournament also creates career concern for fund managers – portfolio managers decide on the portfolio risk to take based on their current position relative to other funds in the same family (family rank). This offers a novel perspective on fund families, specifically that funds belonging to the same family should not be viewed as coordinated entities, contrary to what has been implicitly assumed in the literature. They should rather be seen as competitors in an intense intra-firm competition.

As shown in Nanda et al. (2004), more than 80% mutual funds belong to the family and the average number of mutual funds included in the family is 7. There are many advantage of being a member of a fund family than being alone, such as economies of scale to the servicing, distribution, human resources allocation and promotion of mutual funds (Nanda et al., 2004). As most mutual funds belong to a family, family tournament phenomenon is observed in many studies. Funds with better performance in the tournament are normally associated with better resources while those with worse performance are facing removal risk. For instance, Gaspar et al. (2006) examine how a fund family allocates resources to promote those funds which have greater potential to improve the profits of the entire fund family. Elton et al. (1996) find that fund families merge funds that are doing poorly into partner funds that have excellent performance.

The best-performing fund (star fund) in the tournament not only attracts significant cash inflow to the fund itself, but also to other peer funds in the same family (Nanda et al., 2004). Being on the top benefits both the fund and the family. Therefore, managers are induced to take riskier investment positions in order to beat their peers if they are currently at the bottom of the tournament (Taylor, 2003). In addition, the position of a fund in the tournament is normally measured as the ordinal ranking of performance measures, since investors care more about rankings than absolute performance (Patel et al., 1994). Therefore, we assume that fund managers have incentives to compete with the peers from the same family to achieve better performance and better rank.

5.2.2 Mutual Fund Manager Turnover

Manager turnover is commonly observed in cooperations as well as fund companies. There are many studies investigating the reasons for manager turnover. For example, Peters and Wagner (2014) assume that the manager's decision to leave the current position is explained by the opportunity cost of departure, which is measured as the compensation that the manager could receive by staying. More recently, Kostovetsky (2017) investigates the determinants of the fund manager's decision to quite the industry. Similarly, managers with greater assets under management are less likely to leave the mutual fund industry, while managers who work in bigger fund families or with more co-managers are more likely to exit the industry (Kostovetsky, 2017).

The past fund performance has long been examined as an essential determinant for fund manager turnover. Many studies reveal an inverse relation between the fund performance and manager turnover, indicating that the manager is more likely to leave the fund if the performance is unsatisfactory (e.g., (Chevalier and Ellison, 1999b; Khorana, 1996)). However, only performance in recent 1 or 2 years matters in determining the managerial replacement probability as mentioned in Khorana (1996). Moreover, Kostovetsky and Warner (2015) raise the concern that it is difficult to distinguish between forced and voluntary manager departures, therefore the noisy manager turnover information is biasing downward any estimate of the true turnoverperformance relation. Also, Adams et al. (2013) argue that fund manager replacement can be endogenous decision from the board by examining the association between the fraction of independent directors in the board and fund manager turnover.

Khorana (2001) finds that the turnover of outperforming managers results in deteriorating performance in the future. Furthermore, manager changes are often followed by a spike in the turnover of holdings, incurring additional transactions costs and tax liabilities for fund investors (Bergstresser et al., 2003). On the other hand, the possibility of promotion to hedge funds can work to mitigate agency problems, by creating additional incentives for managerial effort Kostovetsky (2017).

5.2.3 Risk Taking by Mutual Fund

The empirical findings on the fund risk taking behavior and past performance are somehow mixed. Busse (2001) finds that funds that are ranked above the median fund in their category increase total risk more than below-median funds, a result contradicting Brown et al. (1996).

The incentives for the portfolio manager's risk-taking behavior include employment risk, compensation, and etc. The compensation incentive for the fund manager from the convex performance-flow relationship are examined in great detail by Brown et al. (1996); Kempf et al. (2009); Koski and Pontiff (1999), and Elton et al. (2003). Kempf et al. (2009) also study the impact of employment incentives on the risk taking decisions by mutual fund managers. Typically, mutual fund managers are compensated with a fixed fee based on their assets under management. Taylor (2003) reveals that mutual funds are motivated to maximize the investor's inflow because they funds frequently charge a fixed percentage of the assets invested in the fund as a management fee. Given that Chevalier and Ellison (1997) and Sirri and Tufano (1998) find that a disproportionate amount of investor flow volume is directed toward top-performing funds each year, this "risk-increasing" tournament behavior seems like a rational response by compensation-maximizing managers.

However, there are many previous studies that have examined risk-taking decisions by fund managers, after relative underperformance during the first half year. Brown et al. (1996) are the first to hypothesize and document that mutual fund managers have incentives to alter their second-half-of-the-year risk levels based on their mid-year performance rankings. Specifically, managers who underperformed in the first half year increase their risk levels in an attempt to improve their positions against other managers, while managers who outperformed in the first half year reduce risk levels to preserve their positions (Brown et al., 1996). Similarly, Taylor (2003) mentions that poor-performing funds gamble to "catch up" and high-performing funds moderate risk to "lock in" their leads prior to the calendar year-end. Chevalier and Ellison (1997) finds a positive correlation between past performance in excess of a benchmark during the first three quarters of the year and increases in tracking error volatility in the subsequent quarter.

Taylor (2003) proposes an alternative model of the situation involving competing fund managers during the calendar year. When both winning and losing managers are active, the winning manager is more likely to gamble – especially when the mid-year performance gap is high or when stocks offer high returns and low volatility (Taylor, 2003).

Schwarz (2011) points out that the mixed evidence on this question is due to a "sorting bias" from the existing methodology. The commonly applied methodology sorts managers based on their first-half returns, and then uses managers' first-half return standard deviations as the baseline risk level to measure the second-half-of-the-year risk shifting. However, return sorting will also likely sort risk levels given the dependence of risk and return. Even without risk-shifting behavior, mean reversion of these sorted risk levels results in the detection of tournament behavior. After correcting for this bias, Schwarz (2011) finds evidence supporting the hypothesis that managers who underperformed in the first half year increase portfolio risk during the second half of the year and that this tournament behavior is not dependent on first-half market conditions.

5.3 Methodology

The argument for why greater manager turnover risk increases the idiosyncratic risk is as follows. Fund managers are competing within the family tournament. They are facing greater turnover risk if fund performance is sitting at the bottom of peer funds. What they are attempting to do when faced with a high level of replacement risk is to increase the fund volatility to improve the performance, so as to improve their position in the tournament.

5.3.1 Instrumental Variables

The fundamental challenge to this study is to address that the manager replacement risk is endogenous, which can be used to explain the realized idiosyncratic volatility. In observational data, the causal effect can instead be identified using instrumental variables, which significantly affect the fund manager replacement risk but are unrelated to the fund's risk taking except through their effect on manager turnover. We argue that the flow pressure from the fund's peers in the tournament, provides a valid instrumental variable for fund manager turnover in the analysis.

The manager replacement risk may influence the fund's realized volatility. Instead of directly estimating the relationship using a probit model, we introduce an instrumental variable approach to reduce omitted variable bias. The motivation for the IV comes from the career concerns of fund managers in the tournament. We assume that a fund manager's primary goal is to reach a top position in the tournament by attracting significant inflow. The fund manager observes the fund's current position in the segment (segment rank) or family tournament (family rank) on a continuous basis, and takes decisions in adjusting the risk using the observed flow rank.

5.3.2 Empirical Model

Following Peters and Wagner (2014), our methodology mainly includes a two-stage least squares approach. We present two estimation models in this section, while the detail of each variable construction will be discussed in the next section. We use i to denote each equity fund and t to denote time. The first stage involves the following linear probability regression:

$$MR_{i,t} = \alpha_1 + \beta_1 PeerPressure_{i,t} + \beta_c^{'} Controls_{i,t} + \theta_{1i,t} + \varepsilon_{1i,t} \tag{5.3.1}$$

where $MR_{i,t}$ is a binary variable which equals 1 if the fund manager has been replaced since prior calendar year, and 0 otherwise; $PeerPressure_{i,t}$ is the instrumental variable which measures the flow pressure from the fund tournament in a calendar year; $Controls_{i,t}$ is a vector of control variables including $ExpenseRatio$, $TurnoverRatio$, $FundSize$, $FundReturn$, $Flow$ and $FundAge$; $\theta_{1i,t}$ refers to the year/family dummy applied in the regression; and $\varepsilon_{1i,t}$ refers to the stochastic error term for the first stage regression. The detail of variable construction is presented in Section 5.4.2. We use the linear probability model instead of probit or logit models, as the latter ones can harm consistency of the second-stage estimates and complicates the computation of standard errors (Angrist and Krueger, 2001; Bennedsen et al., 2007; Oyer, 2008).

The second stage model estimates the effect of manager replacement on fund risk taking, and is specified as

$$Risk_{i,t} = \alpha_2 + \gamma_1 \widehat{MR}_{i,t} + \beta_c' Controls_{i,t} + \theta_{2i,t} + \varepsilon_{2i,t} \tag{5.3.2}$$

where the dependent variable $Risk_{i,t}$ is the realized idiosyncratic volatility in each calendar year; $\widehat{MR}_{i,t}$ is the predicted value from the first stage regression; $Controls_{i,t}$ refers to a vector of control variables as described in the context of equation (5.3.1); $\theta_{2i,t}$ is a set of year/family dummies that we included in the regression specification; and $\varepsilon_{2i,t}$ refers to the stochastic error term in the second stage regression.

The coefficient of interest is γ_1, which measures the response of a portfolio's riskiness to fund manager replacement. Because $\widehat{MR}_{i,t}$ is a dichotomous variable, fitted values from the first stage regression are interpreted as predicted probabilities. This means that γ_1 captures the causal effect of one percentage point increase in the probability of fund manager replacement on the riskiness of an investment portfolio.

5.4 Data

5.4.1 Sample Selection

Our analysis is mainly based on the CRSP Survivor-Bias Free U.S. Mutual Fund database. The CRSP Survivor-Bias Free U.S. Mutual Fund database includes information on U.S. open-end mutual funds starting in 1962. It comprises the name of the fund, monthly net returns, total net assets under management, investment objectives, the names of the fund managers, and further fund-specific information (Kempf et al., 2009).

First of all, we select sample funds from CRSP by excluding passively managed annuity funds, ETFs, index funds, sector funds and international funds if their names include relevant words. We mainly focus on actively managed domestic funds and managers. It seems unlikely that equity managers directly compete with the bond or money market managers in the same family. The performance cannot be easily compared among bond, money market and equity managers (Kempf and Ruenzi, 2008). Moreover, following Amihud and Goyenko (2013), we exclude funds if the name is missing since we identify the fund family by the fund name. We only include share classes which have more than 50% of the assets invested in common stocks (CRSP variable *per_com*) as described by Kempf et al. (2009)).

The fund segments are defined by the fund's investment objective categories[17]. We combine different investment objective classifications including Weisenberger and Lipper, and Strategic Insight objective code from CRSP to uniform investment objectives as described by Amihud and Goyenko (2013). If there is no investment style code available for a fund's test period but the fund has the style identified for an earlier period, the fund is assigned for the missing test period the style from the previous period. If the fund style cannot be identified, it is excluded from the sample. There are nine segments included in the sample: (1) aggressive growth, (2) equity income, (3) growth, (4) long-term growth, (5) growth and income, (6) mid-cap, (7) micro-cap funds, (8) small cap, and (9) maximum capital gains.

The CRSP database lists every single share class of a fund as an individual entry. Those share classes only differ with respect to their fee structure or to their minimum investment requirements, but are backed by the same portfolio holdings. According to Kempf and Ruenzi (2008), returns on share classes within the same funds are highly correlated. Therefore, we aggregate the share class data at the fund level, using the MFLINKS data provided by WRDS. We exclude share classes that cannot be mapped with MFLINKS. A fund's return, expense ratio, turnover ratio and management fee are measured as the total of TNA-weighted information of underlying share classes (Amihud and Goyenko, 2013). As to the manager and management company information, we keep information of the oldest share class in the fund until the share class is eliminated in the database. Then we will keep the manager and management company information of the largest share class with the greatest TNA in each year.

We are aware of the importance of team managers, as many papers have docu-

[17]We are aware of that SEC requires that funds report their passive benchmarks along with fund returns from 1999. The passive self-designated benchmark of each fund can be obtained from MorningStar from 1999. We did not use the self-designated benchmark because of database inaccessibility.

mented the growth in team management at mutual funds over the last decade (see for example, Massa et al. (2010) and Qiu (2003)). Sharpe (1981) explores the motivation for employment of multiple managers for a single fund. The idea is that the danger of the overall fund performance being damaged by serious decision errors of a single manager could be mitigated by the employment of multiple managers. Barry and Starks (1984) propose yet another motivation for the employment of multiple managers. They show that due to the risk sharing between managers, the optimal risk level of the fund increases as the number of managers increases, and that investors may benefit from the higher risk taken by multiple managers. However, we focus on individual manager turnover because of the database limitation. Following Chevalier and Ellison (1999a), our analysis focuses on those fund-years in which CRSP records that, as of December 31 of the previous year, a single manager is responsible for the fund. Though the data sometimes list the names of each member of a management team, it is often not clear whether all of the managers listed contribute equally to the management of the fund, or whether one of the listed managers is the lead manager. We thus feel that it would be problematic to generate metrics of manager characteristics in such cases.

Similarly to Kempf et al. (2009), our conceptual framework considers the incentives that a fund manager faces. However, we do our analyses using the fund as the unit of observation. Therefore, we implicitly equate a fund manager with a fund under their management. However, some managers manage more than one fund. In these cases, we implicitly assume that fund managers that manage more than one fund manage each fund independently. All the analysis are done for fund families and segments including more than 2 funds, since fund managers are more likely to be exposed to peer pressure from a tournament containing more competitors (Kempf and Ruenzi, 2008). We also eliminate fund-year observations for which some of the data are missing.

Since we only have data on fund manager names from 1992 onwards, our sample is limited to the years 1992 to 2015. Furthermore, we limit our sample to single-managed funds for the present study, as we cannot identify individual managers for most teams. Overall, these decisions reduce our sample size from 15,734 to 9,923 fund-year observations.

5.4.2 Variable Construction

5.4.2.1 Endogenous Variable: Manager Replacement

The endogenous variables $MR_{i,t}$ (Manager Replacement) is a binary variable, which indicates if the fund has replaced its portfolio manager or not within the calendar year. Specifically, variables $MR_{i,t}$ equals 1 if the current year-beginning manager differs from the prior year-end manager, or there is manager replacement happening within this calendar year, and 0 otherwise. It is rare but there are a small number of funds that has multiple episodes of manager replacement within one year. We treat multiple replacement in the same way as single replacement[18].

The main issue of using manager information from CRSP is that it does not report every manager's name if the fund is managed by multiple managers. Our method has an obvious shortcoming – it can only capture the manager replacement if the fund switches from one individual to another individual manager, or if the fund switches from individual to multiple managers or the opposite.

We also need fund family information since we perform the analysis from the perspective of the family tournament. The detail of how we identify the mutual fund family is presented in Appendix B. It is possible that a fund has multiple families identified within a calendar year due to fund acquisition or fund company takeover. We keep the first company reported in the calendar year.

5.4.2.2 Instrumental Variables: Peer Pressure

The main objective of this study is to estimate the casual effect of fund manager's replacement risk on the risk taking. In this study, we assume that the manager's career concern mainly comes from the flow pressure generated by peers. Therefore it is essential to identify "peer" at the first place. Specifically, we use two classifications – "Segment" peers identified as funds that use the same Lipper objective code and "Family" peers identified as funds that are using the same objective code and from the same fund family.

We use ranks based on fund flow rather than fund flow itself, since fund investors mainly care about ranks in making their investment decisions (Patel et al., 1994; Sirri and Tufano, 1998). Consequently, ranks seem the best measure to capture the

[18] Observations with multiple manager turnover make up 2.3% of the full sample. The results remain both qualitatively and quantitatively unchanged if we drop the multiple manager turnover observations.

influence of fund managers' incentives. Furthermore, using normalized ranks has the advantage that fund observations from segments of different sizes become directly comparable (Kempf et al., 2009).

We firstly calculate the fund annual flow which is defined as the growth rate of the total net asset ($TNA_{i,t}$) under management after adjusting for the appreciation of the mutual fund's assets ($R_{i,t}$) in each calendar year following Huang et al. (2011):

$$Flow_{i,t} = \frac{TNA_{i,t} - TNA_{i,t-1}(1 + R_{i,t})}{TNA_{i,t-1}(1 + R_{i,t})} \tag{5.4.1}$$

Then, we use the annualized fund flow to construct two rankings of a fund i at the beginning at year t. The factor *Segment Flow Rank* is determined by the fund flow relative to the total flow of the competing funds in the same segment. The rank is calculated by ordering the funds in a segment according to their annual flows. We then calculate the fractional segment rank for each fund to obtain evenly-distributed rank between 0 and 1. A higher *Segment Flow Rank* denotes a better position in the flow competition within a segment. Segment ranks are calculated separately for each segment so as to control for risk differences across various segments.

In the next step, we order all equity funds of a family according to their segment ranks to measure the *Family Flow Rank* of a fund. Based on this ordering of the segment ranks, we then assign a family rank number to each fund. This "Rank-of-Ranks" method is adopted from Kempf and Ruenzi (2008), and it ensures that the flow of funds from different segments can easily be compared. Also, the *Family Flow Rank* is evenly distributed between 0 and 1.

5.4.2.3 Idiosyncratic Risk

There are many previous papers analyzing the fund risk taking behavior using fund return data (e.g. Brown et al. (1996) and Elton et al. (2003)). Busse (2001) argues that daily returns produce much more efficient estimates of fund volatility compared to monthly data. However, CRSP only reports fund daily returns from 1999 which would largely reduce the sample size. Therefore, we choose monthly returns in our main volatility measurement.

The idiosyncratic risk measures the volatility that is endemic to a particular fund. There are two types of idiosyncratic risk measures used in this study – the segment peer-adjusted and the Carhart-adjusted idiosyncratic risk. The former measures the

the volatility that is endemic to a particular fund and cannot be explained by the segment benchmark, while the later captures the fund-specific risk which cannot be explained by the Carhart factors.

The first step in getting the the segment peer-adjusted idiosyncratic risk measure is to identify the peer benchmark return in each segment. We follow the method of Lipper fund index construction to create our peer return in each segment, with the purpose in providing measurements of the central tendency of similar investments objectives[19]. To be specific, we determine the component funds in each segment using the previous year-end total net asset values. Thirty component funds with largest year-end TNA are selected in a single investment segment in each calendar year. Finally, we calculate the average monthly return of the selected 30 funds as the benchmark peer return. The equally weighted return of component funds is used to prevent dominance of an index by a single fund.

Next, we perform the regression using 12 monthly returns against peer returns for each fund and each calendar year. We keep the residuals from the regression, and take the standard deviation of the saved residuals. Therefore, the idiosyncratic risk is computed as the standard deviation of the residuals saved from each regression at the fund-year level.

As a robustness check, we also use an alternative measure to describe the fund's yearly risk. We obtain the Carhart-adjusted idiosyncratic risk as the standard deviation of the residuals from regressing the fund's monthly excess return against Carhart four factors, following the Carhart (1997) 4 factor model:

$$\begin{aligned} R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,m}(R_{m,t} - R_{f,t}) + \beta_{i,smb}SMB_t + \beta_{i,hml}HML_t \\ +\beta_{i,mom}MOM_t + \varepsilon_t^j \end{aligned} \tag{5.4.2}$$

5.4.2.4 Control Variables

There are many fund or fund family characteristics that are considered as potential determinants of manager turnover, including fund size, turnover ratio, age and expenses (Kempf and Ruenzi, 2008; Kempf et al., 2009). We include them as control variables in this study as follows.

[19]The Lipper fund indices are used to describe the returns that an investor could reasonably have expected to achieve in the past. The detail of creating Lipper indices of U.S. funds can be obtained from the official descriptive document: Thomson Reuthers Lipper Index Policies

The factor *Segment Return Rank* and *Family Return Rank* are calculated following Kempf and Ruenzi (2008), which is similar to the instrument variable construction. Firstly, *Segment Return Rank* is calculated by ordering the funds in a segment according to their annual return, and take the fractional rank for each fund to make it an evenly distributed number between 0 and 1. Next, we order all funds from the same family according to their segment return ranks to measure the *Family Return Rank*. Also, the *Family Return Rank* is evenly distributed between 0 and 1.

Factors *Expense Ratio* (CRSP variable name *exp_ratio*) and *Turnover Ratio* (CRSP variable name *turn*) are already reported in the CRSP $fund\_hdr$ data file. Variable *Fund Age* is computed as the natural logarithm of the difference between the current year and the fund's inception year as reported in CRSP. *Fund Size* is the natural logarithm of the fund's total net asset in millions. *Annual Return* is computed as the geometric mean of the fund's monthly returns in each calendar year. *Fund Flow* refers to the percentage change in fund's total net asset adjusted to the return growth within each calendar year. The *Load Dummy* is a binary variable indicating the load status of a fund which takes on the value 1 if any of the share classes of the fund charges a load in the calendar year, and 0 otherwise (Kempf et al., 2009). Factor *Multiple Share Classes* is also an indicator variable equals 1 if the fund includes more than one share class in the calendar year, and 0 otherwise. Moreover, there are two fund family character – *Family Size* and *Number of Funds in Family*, which is calculated as the natural logarithm of the fund family's total net assets and the number of funds included in each family in the calendar year, respectively.

We also pay attention to the time period over which all control variables are measured. Studies on fund manager turnover as determinants of manager replacement typically use fund information measured either in the current or previous years. There are both pros and cons of using explanatory variables in contemporaneous or previous periods. When using the current calendar year information, the measurement often overlaps with the replacement date and thus includes performance that should be attributed to the new manager, instead the manager who has been replaced. On the other hand, when using lagged variables, there may be a significant gap between the manager departure date and variable measurement date. For instance, if the manager replacement happens in November, lagged control variables would neglect the most recent performance realized under the departing manager.

Table 5.1: Summary Statistics

Panel A: Frequency of Manager Replacement			
	# Fund Years	# Manager Replace	% Manager Replace
Sample Size and # of Replace	9,923	2029	20.45

Panel B: Fund Characteristics					
	Obs	Mean	Std. Dev.	Min	Max
Idiosyncratic Risk	9,832	0.018	0.014	0.000	0.170
Carhart-adj. Idiosyncratic Risk	9,832	0.013	0.011	0.000	0.158
Manager Replacement	9,923	0.204	0.403	0	1
Segment Flow Rank	9,781	0.489	0.278	0	1
Family Flow Rank	9,781	0.492	0.331	0	1
Segment Return Rank	9,865	0.506	0.284	0	1
Family Return Rank	9,865	0.497	0.331	0	1
Expense Ratio	9,730	0.012	0.005	-0.005	0.135
Fund Age (year)	9,923	14.747	11.259	1	55
Turnover Ratio	9,730	0.898	1.442	0	91.5
Fund Total Net Asset (million)	9,781	1511	4918	10	111095
Fund Size (log TNA)	9,781	5.714	1.746	2.398	11.618
Fund Return (annual)	9,865	0.075	0.220	-1.998	1.085
Fund Flow	9,781	0.210	1.064	-11.981	38.591
Load Dummy	9,923	0.647	0.478	0	1
Multiple Share Classes	9,923	0.517	0.500	0	1
# Funds	1,642				

Panel C: Fund Family Characteristics					
	Obs	Mean	Std. Dev.	Min	Max
Fund Family TNA (million)	9,894	53,523	116,924	10	440,208
Fund Family Size (log TNA)	9,894	8.215	2.515	2.303	12.995
Number of Funds in Family	9,923	21.331	26.283	3	91
# Fund Families	343				

This table summarizes the descriptive statistics of relevant variables used in the study. Panel A presents the number of observations and the frequency of manager replacement in the sample. Panel B demonstrates the descriptive statistics including mean, standard deviation, minimum and maximum of fund characteristics which are applied in the analysis. Panel C shows the statistics of fund family characteristics.

To address these timing convention issues, we perform our analysis using both contemporaneous and lagged explanatory variables.

5.4.3 Descriptive Statistics

Table 5.1 reports the summary statistics for the sample, including fund characteristics of the fund-year sample. All variables definitions can be found in Appendix C. The final sample used in the main analysis contains 9,923 fund-year observations, spanning from year 1992 to 2015. In total, there are 1,642 domestic equity funds, 343 fund families and 9 Lipper Objective Codes (investment styles). Panel A reports the basic manager replacement statistics. There are 2,029 fund-year observations that have manager replacement representing 20.45% of the 9,923 final sample observations. Panel B summarizes fund characteristics while Panel C summarizes fund family characteristics.

We use two types of fund realized volatility in this chapter, namely Lipper peer returns adjusted idiosyncratic volatility (Idiosyncratic Volatility) and the Carhart (1997) 4 factor model idiosyncratic risk (Carhart-adj. Idiosyncratic Volatility). We apply the former one as the main risk measure and the latter in the robustness check. The mean of *Idiosyncratic Volatility* is 1.8%, which is slightly greater than the *Carhart-adj. Idiosyncratic Volatility* 1.3%. The correlation coefficient between these two idiosyncratic volatility measure is over 80%. The main instrumental variable *Family Flow Rank* is also highly-correlated to the alternative instrumental variable *Segment Flow Rank*, with the mean of both being around 0.49.

The average annual expense ratio of our sample is 1.2%, ranging from -0.5% to 13.5%[20]. The average fund age in our sample is around 14.7 years. The average turnover ratio is 89.8% which indicates the funds are actively managed equity funds. The fund size measure is volatile and ranges from $10 million to $111 billion in terms of total net assets under management. Therefore we take the natural logarithm of it to reduce the outlier effect. The mean annualized fund return is 7.5% and the mean annualized flow is around 21%. Finally, 64.7% of the sample observations charge fund loads, and 51.7% fund-year observations are from multi-share class funds. There are averagely 21 funds managed by each family, which indicates that we select relatively large families for the analysis. Consistently, the mean of fund family TNA is $53.5 million.

5.5 Empirical Result

We present and discuss our empirical results in this section, including the main estimation result as well as the robustness check output. The robustness checks explore the use of alternative measures of the fund's realized risk, and also the use of alternative instrumental variables. We also test for lagged effects of instrumental variables by using one period lagged explanatory variables in estimation specifications.

[20]The expense ratio refers to the ratio of total investment that shareholders pay for the fund's operating expenses, which include 12b-1 fees. It may include waivers and reimbursements, which can lead to negative expense ratio.

Table 5.2: First Stage Regression of Manager Replacement (Instrument Variable: Family Flow Rank)

Dependent Variable	Manager Replacement Dummy							
	(1)		(2)		(3)		(4)	
Family Flow Rank	-0.0788	***	-0.0769	***	-0.0764	***	-0.084	***
	(-5.53)		(-5.42)		(-5.34)		(-5.38)	
Segment Return Rank	0.0032		-0.0204		-0.0068		0.056	
	(0.11)		(-0.7)		(-0.23)		(1.33)	
Family Return Rank	0.0210		0.0350	*	0.0218		-0.006	
	(1.1)		(1.83)		(1.12)		(-0.22)	
Expense Ratio	-1.2585		-0.4736		4.1179	***	3.432	**
	(-1.29)		(-0.49)		(-3.49)		(2.56)	
Fund Age	0.0232	***	0.0250	***	0.0400	***	0.044	***
	(3.32)		(3.59)		(-4.82)		(5.12)	
Turnover Ratio	0.0317	***	0.0228	***	0.0089		0.009	
	(6.38)		(4.54)		(-1.58)		(1.39)	
Fund Size	-0.0096	***	-0.0197	***	-0.0218	***	-0.024	***
	(-3.42)		(-5.91)		(-6.11)		(-6.72)	
Fund Return	-0.1072	*	-0.0997	*	-0.1007	*	-0.187	***
	(-1.83)		(-1.71)		(-1.73)		(-2.87)	
Fund Flow	0.0170	**	0.0108		0.0071		0.013	
	(2.19)		(1.39)		(-0.89)		(1.42)	
Load Dummy	0.0443	***	0.0299	***	0.0209	*	0.031	**
	(4.63)		(3.09)		(-1.67)		(2.24)	
Multiple Share Classes	-0.0042		0.0117		-0.0151		-0.028	**
	(-0.46)		(1.27)		(-1.3)		(-2.16)	
Fund Family Size			0.0044		0.0122	**		
			(1.36)		(-2.26)			
Number of Funds in Family			0.0352	***	0.025			
			(4.52)		(1.21)			
Constant	0.006		-0.0478		-0.113		0.207	***
	(0.19)		(-0.16)		(-0.8)		(6.14)	
Observations	9,729		9,729		9,729		9,729	
Year Fixed Effects	Yes		Yes		Yes		No	
Family Fixed Effects	No		No		Yes		No	
Family$\times$Year Fixed Effects	No		No		No		Yes	
Statistics on Predicted Manager Replacement Probability								
25th	0.112		0.110		0.086		0.000	
75th	0.303		0.305		0.315		0.341	
Standard Deviation	0.127		0.132		0.172		0.274	

This table presents estimations of the first stage regression following equation 5.3.1, using the Family Flow Rank as the instrument variable. The upper part of the table shows the first-stage least-squares regressions of a dummy variable "Manager Replacement" indicating the fund manager turnover on controls. The lower section of the table presents the summary statistics for the predicted manager replacement probability. The idiosyncratic risk on peer returns are winsorised at 1% level in model specifications (1), (2) and (3), and 5% level in model (4) as the outcome is largely affected by outliers. t-statistics are reported in parentheses. *, ** and *** denotes the significance at 10%, 5% and 1% level, respectively.

5.5.1 Determinants of Fund Manager Replacement

Table 5.2 presents the main results from the first stage regression which models the probability of fund manager replacement. We use the term "specification" to refer to the column reported in each table. In specification (1), we include controls at the fund level, including the fund's return rank in the Lipper segment, expense ratio, fund age, fund size, turnover ratio, annualized return, yearly flow, load dummy and multiple share-class dummy. As analysis proceeds, we add fund family control variables such as *Family Size* and *Number of Funds in Family* in specification (2). In specification (3), we apply the same set of control variables as in specification (2) but with additional fund family fixed effects. Finally, we consider the interacted fund family$\times$year fixed effects in specification (4).

Concerning the control variables, we find that unsurprisingly funds with worse annual returns are more likely to be replaced, given that variable *Fund Return* is negatively associated with the manager replacement dummy across all model specifications. We also find that younger funds, smaller funds, funds which charge loads are more likely to replace the portfolio manager. Replacement risk for larger families are greater than their smaller counterparts, though the significance level differs under different types of fixed effects.

Our main interest is the explanatory power of the instrument variable shown at the top of the table. The main instrumental variable – *Family Flow Rank* – is highly statistically significant and correlated with manager replacement in the predicted direction. Funds with lower ranking within segment and family are facing higher replacement risk.

Most of the existing work on the determinants of fund manager turnover risk does not control for both flow and return ranks in peer groups. It is also noteworthy that the effects of the instrumental variable is economically significant. For instance, a 0.08 change in the family flow rank (which corresponds to about $\frac{0.08}{0.33}$= 0.24 standard deviation) is associated with a decrease in the probability of dismissal of 1%. The negative impact of flow rank is consistent across 4 model specifications using different sets of control variable and different types of fixed effects.

The bottom part of the Table 5.2 reports the interquartile range of predicted manager replacement rates in the base model (5.3.1), which is between 0.195 to 0.345. The linear probability model which is used to ensure consistency of the second-stage estimates sometimes predict negative probabilities. For example, in model (1), 7% of the sample has negative predicted probabilities. The economic effects of the instrumental variable and other controls remain the same in terms of magnitude and statistical significance.

In sum, we find that funds with worse flow ranking within segment and family are exposed to higher risk in manager replacement. The strong correlation between the ranking and manager turnover establishes the relevance of the instruments and alleviates concerns over weak instruments.

5.5.2 Manager Turnover Pressure and Risk Taking

A first set of second-stage regressions is presented in Table 5.3. We begin by presenting the regressions of realized idiosyncratic risk on predicted manager turnover probabilities from Table 5.2 and a range of control variables and fixed effects. As mentioned in Focke et al. (2017), including a range of fixed effects in addition to a large set of control variables allows us to control for unobserved heterogeneity. Apart from estimated coefficients, the F-statistics for instrument relevance are reported in the bottom part of the table.The F-statistics are well above the threshold of 10 suggested by Stock et al. (2002), which indicates that the instrumental variable is highly relevant to the first stage model. Generally, we find that manager turnover has a significantly positive association with fund idiosyncratic risk in all 4 regressions.

Column (1) presents the baseline specification and suggests that on average, the annual realized idiosyncratic risk is 1.25% greater for a fund which has the manager replaced than a fund which does not. As expected, fund age measured as the natural logarithm of the age in years is significantly positively related to the fund volatility. Similarly, expense ratio also shows a positive coefficient of 0.4, which probably picks up higher-order effects and is difficult to interpret on its own given the range of other fund fee controls we include. Fund size measured as the natural logarithm of year-beginning TNA is significantly negatively related to fund volatility. We add fund family control variables in specification (2), because families with more employed managers are more flexible to change fund managers. The *Fund Family Size* presents a positive coefficient, which indicates that larger families are associated with greater realized risk. In specification (3) we raise the hurdle by adding family fixed effects

Table 5.3: Second Stage Regression of Fund Risk Taking (Dependent Variable: Idiosyncratic Risk on Peer Return)

Dependent Variable	Idiosyncratic Risk on Peer Return							
	(1)		(2)		(3)		(4)	
Manager Replacement Prob.	0.0125	**	0.0132	***	0.0107	**	0.0072	*
	(2.56)		(2.6)		(2.3)		(1.74)	
Segment Return Rank	0.0010		0.0006		-0.0002		-0.0004	
	(1.28)		(0.73)		(-0.25)		(-0.41)	
Family Return Rank	-0.0007		-0.0005		-0.0003		-0.0001	
	(-1.42)		(-0.94)		(-0.58)		(-0.1)	
Expense Ratio	0.4015	***	0.4116	***	0.3118	***	0.3372	***
	(14.78)		(15.33)		(8.9)		(10.14)	
Fund Age	0.0005	**	0.0005	**	0.0010	***	0.0010	***
	(2.18)		(2.13)		(3.44)		(3.43)	
Turnover Ratio	0.0001		-0.0001		0.0001		0.0001	
	(0.5)		(-0.29)		(1.01)		(0.9)	
Fund Size	-0.0003	***	-0.0007	***	-0.0008	***	-0.0007	***
	(-3.33)		(-4.89)		(-6.09)		(-5.44)	
Fund Return	-0.0012		-0.0010		0.0009		0.0009	
	(-0.72)		(-0.63)		(0.57)		(0.53)	
Fund Flow	0.0007	***	0.0006	***	0.0004	**	0.0002	
	(4.02)		(3.07)		(2.11)		(1.2)	
Load Dummy	0.0020	***	0.0018	***	0.0037	***	0.0045	***
	(6.06)		(5.81)		(11.36)		(13.32)	
Multiple Share Classes	-0.0063	***	-0.0060	***	-0.0049	***	-0.0054	***
	(-25.55)		(-23.13)		(-16.48)		(-17.19)	
Fund Family Size			0.0005	***	0.0000			
			(5.55)		(0.01)			
Number of Funds in Family			-0.0003		0.0003			
			(-1.14)		(0.57)			
Constant	0.0127	***	0.0117	***	0.0057	*	0.0129	***
	(14.18)		(11.87)		(1.69)		(12.62)	
Observations	9,729		9,729		9,729		9,729	
Year Fixed Effects	Yes		Yes		Yes		No	
Family Fixed Effects	No		No		Yes		No	
Family×Year Fixed Effects	No		No		No		Yes	
F-stat of Excluded Instrument	30.58		29.38		28.52		28.94	
Endogenous Variable	Manager Replacement							
Instrument Variable	Family Flow Rank							

This table presents the result of the second stage least-square regressions of fund's idiosyncratic risk on the fund manager replacement probability and control variables. The dependent variable Risk is calculated as the standard deviation of the residual from regressing fund return against peer Lipper objective returns. The idiosyncratic risk on peer returns are winsorised at 1% level in specifications (1), (2) and (3), and 5% level in model (4) as the outcome is largely affected by outliers. Manager replacement probability is the predicted value from the first-stage least-squares regressions presented in Table 5.2. t-statistics calculated from robust standard errors are reported in parentheses. *, ** and *** denotes the significance at 10%, 5% and 1% level, respectively.

in addition to specification (2). This controls for the variation across different years as well as across families. The key estimate decreases slightly to 1.07%. Finally, the specification (4) helps us to better control for unobserved time-varying family characteristics by applying an interaction of family and year fixed effects. We expect to see weaker results in the ladder as the pressure is likely to be dependent on time within family. The point estimate declines numerically to 0.72%, but it still remains significant at the 10% level. This is because that the family and year interacted fixed effects absorb a significant portion of variation in the fund risk. Though the estimate of the effect is numerically smaller than what we saw in the baseline specifications, it is more precisely estimated. The family control variables are omitted in specification (4) because those factors are largely correlated with the year×family ID.

Consistently with our main hypothesis, the probability of manager replacement is positively associated with the fund's realized idiosyncratic risk in four regression specifications, with different sets of control variables and fixed effects applied. In other words, the fund is expected to show higher idiosyncratic volatility when the manager is exposed to greater replacement risk. The estimation results on control variables remain very similar across different specifications. For instance, we find that fund age is positively associated with the fund risk. Similarly, funds that charge front or end loads, as well as higher expenses are expected to show higher risk. Single share funds are more likely to present higher idiosyncratic risk, given the control variable *Multiple Share Class* has a coefficient estimate of around -0.006. The fund size factor also has a negative coefficient estimate, indicating that smaller funds tend to exhibit higher risk. The flow is positively associated with fund volatility.

5.5.3 Robustness Check

In this section, we provide empirical results of robustness analysis, including the use of alternative idiosyncratic risk measurement, alternative instrumental variable and lagged explanatory factors.

5.5.3.1 Alternative Idiosyncratic Volatility Measure

It is possible that part of the result shown in Table 5.3 is due to the classification of segments (peers), since the realized idiosyncratic volatility relies on peer returns. To alleviate this concern, we use an alternative dependent variable. Instead of using

Table 5.4: Second Stage Regression of Fund Risk Taking (Dependent Variable: Carhart-Adjusted Idiosyncratic Volatility)

Dependent Variable	Carhart-Adjusted Idiosyncratic Risk							
	(1)		(2)		(3)		(4)	
Manager Replacement Prob.	0.0085	**	0.0092	**	0.0082	**	0.0078	**
	(2.33)		(2.43)		(2.29)		(2.36)	
Segment Return Rank	-0.0006		-0.0008		-0.0012	**	-0.0017	**
	(-0.95)		(-1.3)		(-2.11)		(-2.26)	
Family Return Rank	-0.0003		-0.0002		-0.0001		0.0002	
	(-0.77)		(-0.46)		(-0.26)		(0.48)	
Expense Ratio	0.3295	***	0.3336	***	0.2822	***	0.2793	***
	(16.3)		(16.64)		(10.45)		(10.53)	
Fund Age	0.0004	**	0.0004	**	0.0005	**	0.0004	*
	(2.33)		(2.2)		(2.2)		(1.77)	
Turnover Ratio	0.0005	***	0.0004	***	0.0006	***	0.0006	***
	(3.44)		(3.29)		(5.02)		(5.19)	
Fund Size	0.0000		-0.0003	***	-0.0004	***	-0.0002	**
	(-0.74)		(-3)		(-3.35)		(-2.37)	
Fund Return	-0.0007		-0.0006		0.0006		0.0017	
	(-0.55)		(-0.46)		(0.48)		(1.3)	
Fund Flow	0.0008	***	0.0007	***	0.0006	***	0.0004	***
	(5.52)		(4.6)		(4.08)		(2.93)	
Load Dummy	0.0018	***	0.0017	***	0.0029	***	0.0032	***
	(7.36)		(7.44)		(11.56)		(11.94)	
Multiple Share Classes	-0.0045	***	-0.0044	***	-0.0036	***	-0.0038	***
	(-24.59)		(-22.42)		(-15.66)		(-15.02)	
Fund Family Size			0.0004	***	0.0000			
			(6.13)		(0.17)			
Number of Funds in Family			-0.0005	**	-0.0004			
			(-2.39)		(-1.07)			
Constant	0.0067	***	0.0062	***	0.0018		0.0072	***
	(10.12)		(8.41)		(0.7)		(8.82)	
Observations	9,729		9,729		9,729		9,729	
Year Fixed Effects	Yes		Yes		Yes		No	
Family Fixed Effects	No		No		Yes		No	
Family×Year Fixed Effects	No		No		No		Yes	
F-stat of Excluded Instrument	30.58		29.38		28.52		28.94	
Endogenous Variable	Manager Replacement							
Instrument Variable	Family Flow Rank							

This table presents the result of the second stage least-square regressions of fund's idiosyncratic risk on the fund manager replacement probability and control variables. The dependent variable Risk is calculated as the standard deviation of the residual from regressing fund return on Carhart 4-factor model. The idiosyncratic risk on Carhart model is winsorised at 1% level in model specifications (1), (2) and (3), and 5% level in model (4) as the outcome is largely affected by outliers. Manager replacement probability is the predicted value from the first-stage least-squares regressions presented in Table 5.2. t-statistics calculated from robust standard errors are reported in parentheses. *, ** and *** denotes the significance at 10%, 5% and 1% level, respectively.

the fund realized idiosyncratic volatility that are net from the segment benchmark, we use the Carhart 4 factor model adjusted idiosyncratic risk. This alternative dependent variable captures the realized fund risk without relying on the segment classification.

In Table 5.4, we only report the second stage estimation results using the alternative idiosyncratic risk measure, since the first stage results are identical to Table 5.2. Though the coefficients on the manager replacement probability (0.008) decrease slightly compared to the previous analysis (0.01), they still remain statistically and economically significant – the likelihood of manager turnover is a determinant of the fund's realized Carhart-adjusted volatility.

The four model specifications in Table 5.4 still use the predicted manager replacement probabilities from Table 5.2 as the key explanatory variable for Carhart-adjusted idiosyncratic risk. Similarly, the F-statistics reported in the bottom part are also above the threshold of 10. Most of the empirical findings remain qualitatively unchanged when using the Carhart-adjusted risk as the dependent variable. However, one thing that is worth noticing is that variable *Turnover Ratio* becomes significantly positive in this analysis. Therefore, the turnover ratio of fund holdings is yet another effective determinant in fund volatility adjusted using the Carhart model.

Taken together, we find that the empirical findings remains unchanged when we use the Carhart-adjusted idiosyncratic risk measure, that does not depend on segment classifications, as the dependent variable in the second stage regression.

5.5.3.2 Alternative Instrument Variable

As a robustness check, we examine the peer pressure from the more generalized segment tournament instead of the family tournament. The segment flow rank measures the fund's current position in the segment tournament. A fund with a higher rank is considered to have less peer pressure whereas a lower ranking fund is considered to face greater tournament pressure and career risk.

We present the first- and second-stage estimation results using the alternative instrumental variable in Table 5.5 and 5.6 separately. As before, we report estimation results under 4 different specifications using different sets of control variables and fixed effects. Generally, we find the result remains very similar comparing the

Table 5.5: First Stage Regression of Manager Replacement (Instrument Variable: Segment Flow Rank)

Dependent Variable	Manager Replacement Dummy							
	(1)		(2)		(3)		(4)	
Segment Flow Rank	-0.1461	***	-0.1452	***	-0.1396	***	-0.1529	***
	(-7.08)		(-7.07)		(-6.61)		(-6.54)	
Segment Return Rank	0.0235		-0.0004		0.0100		0.0695	*
	(0.81		(-0.01)		(0.33)		(1.66)	
Family Return Rank	0.0088		0.0232		0.0125		-0.0119	
	(0.46		(1.22)		(0.64)		(-0.43)	
Expense Ratio	-1.2698		-0.4815		4.1356	***	3.4300	**
	(-1.3)		(-0.49)		(3.51)		(2.57)	
Fund Age	0.0201	***	0.0219	***	0.0386	***	0.0428	***
	(2.86)		(3.12)		(4.65)		(4.92)	
Turnover Ratio	0.0299	***	0.0210	***	0.0086		0.0087	
	(6.03)		(4.18)		(1.53)		(1.42)	
Fund Size	-0.0081	***	-0.0182	***	-0.0207	***	-0.0234	***
	(-2.88)		(-5.48)		(-5.8)		(-6.51)	
Fund Return	-0.1125	*	-0.1051	*	-0.1069	*	-0.1893	***
	(-1.92)		(-1.81)		(-1.84)		(-2.9)	
Fund Flow	0.0403	***	0.0342	***	0.0278	***	0.0298	***
	(4.36)		(3.72)		(2.97)		(2.85)	
Load Dummy	0.0444	***	0.0299	***	0.0200		0.0313	**
	(4.63)		(3.1)		(1.61)		(2.24)	
Multiple Share Classes	-0.0043		0.0117		-0.0141		-0.0283	**
	(-0.47)		(1.27)		(-1.21)		(-2.17)	
Fund Family Size			0.0045		0.0123	**		
			(1.39)		(2.29)			
Number of Funds in Family			0.0353	***	0.0237			
			(4.53)		(1.17)			
Constant	0.0233		-0.0307		-0.1031		0.2333	***
	(0.7)		(-0.91)		(-0.77)		(6.79)	
Observations	9,729		9,729		9,729		9,729	
Year Fixed Effects	Yes		Yes		Yes		No	
Family Fixed Effects	No		No		Yes		No	
Family×Year Fixed Effects	No		No		No		Yes	
Statistics on Predicted Manager Replacement Probability								
25th	0.111		0.109		0.086		0.000	
75th	0.304		0.304		0.316		0.341	
Standard Deviation	0.128		0.133		0.172		0.274	

This table presents estimations of the first stage regression following equation 5.3.1, using the Segment Flow Rank as the instrument variable. The upper part of the table shows the first-stage least-squares regressions of a dummy variable "Manager Replacement" indicating the fund manager turnover on controls. The lower section of the table presents the summary statistics for the predicted manager replacement probability. t-statistics are reported in parentheses. *, ** and *** denotes the significance at 10%, 5% and 1% level, respectively.

previous analysis which uses the *Segment Flow Rank* as the instrumental variable.

In Table 5.5, we report the first stage estimation results using the Segment Flow Rank as the instrumental variable. Firstly, the main factor of interest *Segment Flow Rank* is highly statistically significant and negatively correlated with manager replace, with the coefficient standing around -0.14. In terms of magnitude, the estimate is greater than what we found earlier in Table 5.2. But the results still agree with our hypothesis that funds with greater pressure from the segment tournament are facing greater replacement risk. Unsurprisingly, fund performance is negatively associated with the manager replacement across all model specifications, consistent with other literature. Smaller funds are more likely to replace the portfolio manager as the negative coefficient on *Fund Size* suggests. *Fund Age* is positively associated with manager turnover. Therefore, we conclude that in the segment tournament, managers who manage older funds are facing larger replacement risk. The bottom part of Table 5.5 presents the interquartile range of predicted probabilities of manager replacement, using the base model specification 5.3.1, which is between 0.11 to 0.34. The linear probability model, which is used to ensure consistency of the second-stage estimates, sometimes predicts negative probabilities. For example, in specification (1), 7% of the sample has negative predicted probabilities. The economic effects of the instrumental variable and other controls remain the same in terms of magnitude and statistical significance.

Table 5.6 reports the estimation results for the second stage regression, which includes 4 specifications with a range of control variables and fixed effects. Also, F-statistics reported in the bottom part of the table indicates that the instrumental variable is highly relevant. We find very similar results using *Segment Flow Rank* as the alternative instrumental variable. Specifically, the coefficients on the predicted probability of manager replacement improve slightly using a different IV, both numerically and statistically. We mainly focus on the discussion of specification (4) as it provides the most robust and precise estimation results, with the family and year interacted fixed effects. On average, the annual realized idiosyncratic risk is 0.82% greater for a fund which has replaced the portfolio manager within the calendar year.

Table 5.6: Second Stage Regression of Fund Risk Taking (Dependent Variable: Idiosyncratic Risk on Peer Return)

Dependent Variable	Idiosyncratic Risk on Peer Return							
	(1)		(2)		(3)		(4)	
Manager Replacement Prob.	0.0138	***	0.0143	***	0.0075	**	0.0082	**
	(3.52)		(3.61)		(2.08)		(2.36)	
Segment Return Rank	0.0010		0.0006		-0.0002		-0.0004	
	(1.26)		(0.75)		(-0.31)		(-0.45)	
Family Return Rank	-0.0007		-0.0005		-0.0002		-0.0001	
	(-1.42)		(-0.98)		(-0.52)		(-0.09)	
Expense Ratio	0.4030	***	0.4121	***	0.3251	***	0.3340	***
	(14.69)		(15.07)		(10.26)		(10.24)	
Fund Age	0.0005	**	0.0005	**	0.0011	***	0.0009	***
	(2.13)		(2.11)		(4.51)		(3.54)	
Turnover Ratio	0.0001		-0.0001		0.0002		0.0001	
	(0.34)		(-0.47)		(1.29)		(0.83)	
Fund Size	-0.0003	***	-0.0006	***	-0.0009	***	-0.0007	***
	(-3.33)		(-5.26)		(-7.74)		(-5.82)	
Fund Return	-0.0011		-0.0009		0.0006		0.0010	
	(-0.65)		(-0.56)		(0.39)		(0.64)	
Fund Flow	0.0007	***	0.0006	***	0.0003	**	0.0002	
	(3.98)		(3.11)		(1.99)		(1.28)	
Load Dummy	0.0020	***	0.0017	***	0.0037	***	0.0044	***
	(6.29)		(5.88)		(12.27)		(13.37)	
Multiple Share Classes	-0.0063	***	-0.0060	***	-0.0049	***	-0.0054	***
	(-25.05)		(-22.98)		(-17.56)		(-17.26)	
Fund Family Size			0.0005	***	0.0000			
			(5.44)		(0.25)			
Number of Funds in Family			-0.0004		0.0004			
			(-1.39)		(0.78)			
Constant	0.0127	***	0.0118	***	0.0053	*	0.0128	***
	(13.95)		(12.08)		(1.64)		(13.38)	
Observations	9,729		9,729		9,729		9,729	
Year Fixed Effects	Yes		Yes		Yes		No	
Family Fixed Effects	No		No		Yes		No	
Family×Year Fixed Effects	No		No		No		Yes	
F-stat of Excluded Instrument	50.13		49.98		43.69		42.77	
Endogenous Variable	Manager Replacement							
Instrument Variable	Segment Flow Rank							

This table presents the result of the second stage least-square regressions of fund's idiosyncratic risk on the fund manager replacement probability and control variables. The dependent variable Risk is calculated as the standard deviation of the residual from regressing fund return against peer Lipper objective returns. The idiosyncratic risk on peer returns are winsorised at 1% level in model specifications (1), (2) and (3), and 5% level in model (4) as the outcome is largely affected by outliers. Manager replacement probability is the predicted value from the first-stage least-squares regressions presented in Table 5.5. t-statistics calculated from robust standard errors are reported in parentheses. *, ** and *** denotes the significance at 10%, 5% and 1% level, respectively.

Table 5.7: First Stage Regression of Manager Replacement (Lagged Effect)

Dependent Variable	Manager Replacement Dummy					
	(1)		(2)		(3)	
Family Flow Rank in t-1	-0.0463	***	-0.0422	***	-0.0598	***
	(-3.47)		(-3.28)		(-4.41)	
Segment Return Rank in t-1	-0.0426	*	-0.0894	***	-0.0991	**
	(-1.67)		(-3.03)		(-2.36)	
Family Return Rank in t-1	0.0080		0.0162		0.0162	
	(0.4)		(0.84)		(0.58)	
Expense Ratio in t-1	3.2483	***	3.1353	***	2.0324	
	(2.91)		(2.89)		(1.64)	
Fund Age in t-1	0.0003		0.0011	**	0.0015	***
	(0.64)		(2.08)		(2.89)	
Turnover Ratio in t-1	-0.0008		-0.0027		-0.0014	
	(-0.26)		(-0.94)		(-0.45)	
Fund Size in t-1	-0.0155	***	-0.0180	***	-0.0218	***
	(-4.65)		(-5.39)		(-6.43)	
Fund Return in t-1	-0.0379	*	0.0740		0.0908	
	(-1.72)		(1.38)		(1.49)	
Fund Flow in t-1	0.0000		0.0000		0.0000	
	(0.97)		(1.24)		(0.72)	
Load Dummy in t-1	0.0207		0.0194		0.0210	
	(1.54)		(1.5)		(1.42)	
Multiple Share Classes in t-1	-0.0515	***	-0.0369	***	-0.0463	***
	(-4.37)		(-3.02)		(-3.33)	
Fund Family Size in t-1			0.0111	**		
			(2.09)			
Number of Funds in Family at in t-1			0.0081			
			(0.49)			
Constant	0.3643	**	0.5151		0.3685	***
	(2.23)		(1.64)		(12.16)	
Observations	8,994		8,994		8,994	
Family Fixed Effects	Yes		Yes		No	
Year Fixed Effects	No		Yes		No	
Family×Year Fixed Effects	No		No		Yes	
Statistics on Predicted Manager Replacement Probability						
25th	0.123		0.091		0.000	
75th	0.293		0.319		0.350	
Standard Deviation	0.136		0.175		0.276	

This table presents estimations of the first stage regression following equation 5.3.1, using the one period lagged family flow rank as the instrument variable and one period lagged control variables. The upper part of the table shows the first-stage least-squares regressions of a dummy variable "Manager Replacement" indicating the fund manager turnover on controls. The lower section of the table presents the summary statistics for the predicted manager replacement probability. The idiosyncratic risk on peer returns are winsorised at 1% level in model specifications (1), (2) and (3), and 5% level in model (4) as the outcome is largely affected by outliers. t-statistics are reported in parentheses. *, ** and *** denotes the significance at 10%, 5% and 1% level, respectively.

Table 5.8: Second Stage Regression of Fund Risk Taking (Lagged Effect)

Dependent Variable	Idiosyncratic Risk on Peer Return					
	(1)		(2)		(3)	
Manager Replacement Prob.	0.0195	**	0.0150	*	0.0093	*
	(2.16)		(1.86)		(1.83)	
Segment Return Rank in t-1	-0.0011		0.0004		0.0003	
	(-1.17)		(0.36)		(0.28)	
Family Return Rank in t-1	0.0008		0.0006		0.0007	
	(1.25)		(1.13)		(1.05)	
Expense Ratio in t-1	0.2760	***	0.3220	***	0.3281	***
	(5.87)		(8.18)		(10.82)	
Fund Age in t-1	0.0000	**	0.0000	**	0.0000	**
	(-2.27)		(2.33)		(2.06)	
Turnover Ratio in t-1	0.0000		0.0000		0.0000	
	(0.46)		(0.27)		(-0.46)	
Fund Size in t-1	-0.0003	*	-0.0007	***	-0.0006	***
	(-1.9)		(-4.22)		(-4.86)	
Fund Return in t-1	-0.0001		-0.0041	***	-0.0039	***
	(-0.14)		(-2.63)		(-2.73)	
Fund Flow in t-1	0.0000		0.0000		0.0000	*
	(-0.61)		(-1.04)		(-1.73)	
Load Dummy in t-1	0.0028	***	0.0036	***	0.0046	***
	(6.11)		(9.56)		(12.99)	
Multiple Share Classes in t-1	-0.0051	***	-0.0048	***	-0.0053	***
	(-8.39)		(-10.75)		(-13.4)	
Fund Family Size in t-1			0.0000			
			(0.26)			
Number of Funds in Family at in t-1			0.0008	*		
			(1.84)			
Constant	0.0070		-0.0008		0.0135	***
	(1.18)		(-0.09)		(7.51)	
Observations	8,994		8,994		8,994	
Family Fixed Effects	Yes		Yes		No	
Year Fixed Effects	No		Yes		No	
Family×Year Fixed Effects	No		No		Yes	
F-stat of Excluded Instrument	12.04		10.76		19.45	
Endogenous Variable	Manager Replacement					
Instrument Variable	Family Flow Rank					

This table presents the result of the second stage least-square regressions of fund's idiosyncratic risk on the fund manager replacement probability and control variables. The dependent variable Risk is calculated as the standard deviation of the residual from regressing fund return against peer Lipper objective returns. All explanatory variables are one period lagged. The idiosyncratic risk on peer returns are winsorised at 1% level in model specifications (1), (2) and (3), and 5% level in model (4) as the outcome is largely affected by outliers. Manager replacement probability is the predicted value from the first-stage least-squares regressions presented in Table 5.7. t-statistics calculated from robust standard errors are reported in parentheses. *, ** and *** denotes the significance at 10%, 5% and 1% level, respectively.

5.5.3.3 Lagged Effect

The previous results are done within the contemporaneous time. In this robustness test, we lag the main instrumental variable *Family Flow Rank* and control variables by one fiscal year to reduce potential simultaneity concerns. As before, estimation results from first- and second-stage regressions are presented separately in Table 5.7 and 5.8. Overall, the *Family Flow Rank* remains a significantly negative predictor for the manager replacement in the next year, as shown across 3 model specifications in Table 5.7. In the second stage regression, funds with manager changed in the prior calendar year is more likely to be associated with greater idiosyncratic risk.

We also report the estimates for 3 model specifications, and the results are similar to what we obtained using the contemporaneous specification. Specifically, column (1) in both tables presents the estimation results using lagged fund-level control variables and family fixed effects. In this specification, differences in the family characteristics are accounted for. Specification (2) adds lagged family control variables and year fixed effects in addition to specification (1). The fixed effects in specification (2) control for the variation across different years as well as across families. Interestingly, we find a negative relation between manager turnover and prior fund performance, as in previous studies (e.g. (Kostovetsky and Warner, 2015)). But the negative effect from past year return becomes insignificant when the year fixed effect is considered. Finally, column (3) considers the family and year interacted fixed effects. Consistently, we expect the analysis in the last column is the weakest since the family$\times$year fixed effects absorb a significant amount of variation in the fund volatility. A half of the coefficient estimates for the control variables are significant, showing that there are some time series variation exists in these variables to have an effect in a regression with a large array of fixed effects.

5.6 Summary

This chapter makes the simple point that mutual fund manager replacement explains an important part of the fund's realized volatility of domestic equity funds in U.S.. The empirical magnitude of the manager turnover risk premium – about 1% greater realized volatility for a one percentage point increase in manager replacement risk – is in line with calibrated theoretical predictions. The manager replacement risk driven by the peer pressure is likely to be reflected in the fund's idiosyncratic risk.

We use an instrumental variable (IV) approach to study whether fund managers would take into account turnover risk that they face when adjusting the volatility of portfolios. The instrumental variable measures the peer flow pressure that a fund manager is facing in the tournament, by following the "Rank-of-Ranks" approach of Kempf and Ruenzi (2008). This method allows the performance of funds from different segments to be compared easily, and signals different but related employment risk fund managers are facing in the tournament. In the IV analysis using different sets of control variables and fixed effects, we find that *Family Flow Rank* is a highly statistically significant determinant of manager replacement, which means that funds with a lower flow ranking in the family tournament are facing higher replacement risk. Such peer pressure would lead the fund to increase the idiosyncratic volatility. The finding is robust to the use of an alternative instrumental variable *Segment Flow Rank*, an alternative measure of realized risk *Carhart-adjusted Idiosyncratic Risk* and one-period lags of explanatory factors in both first- and second-stage regressions.

Both mutual fund families and relevant regulatory authorities could potentially benefit from the findings of this study. Specifically, fund families should pay attention to the rebalancing costs caused by the risk adjustment behavior in the fund tournament. In addition, fund families suffer from the in-family tournament negatively because fund managers compete with others in the same family for inflows according to Kempf and Ruenzi (2008). Finally, regulatory authorities may take an interest in the fund tournament since, as James and Isaac (2000) find, tournament behavior may lead to irrational price formation in asset markets.

Chapter 6

Conclusion

This chapter concludes the thesis, with main empirical finding and contributions to the literature. This thesis comprises three empirical studies on mutual funds, ranging from fund manager career concerns to fund creation and asset allocation. The main conclusions and implications of each study may be summarized as follows.

The first essay examines the relationship between the mutual fund manager's past experience and mutual fund performance. The skills and knowledge acquired from prior working experience may be transferred to the current working context, thereby influencing the current job performance (Schmidt et al., 1986). Researchers have explored this topic from the perspectives of both applied psychology and empirical finance, where the latter particularly pertains to the CEO behavior analysis (Custódio et al., 2013). Building on this literature, we investigate the relationship between the mutual fund manager's past experience and mutual fund performance. Using U.S. mutual fund data of fund managers' work experience ranging from 1993 to 2012, the first essay introduces a new method to evaluate mutual fund performance from the perspective of the manager's lifetime working experience. Specifically we use the Principal Component Analysis (PCA) to construct a Managerial Experience Index (MEI) based on 3 professional experience factors from the past career history of each manager: (i) investment objectives of the funds that s/he has managed (Zambrana and Zapatero, 2017), (ii) fund companies that s/he has worked for and (iii) industries of stocks in which s/he has invested (Kacperczyk et al., 2005). The MEI would increase along with the experience accumulation for each mutual fund manager. We group the sample based on the MEI into 5 quintiles from the lowest MEI score (most concentrated experience) to the highest MEI score (most diversified experience). Therefore, the "Specialist" refers to portfolio managers with a more concentrated professional history while the "Generalist" refers to those with more diversified experience in mutual fund management. Both the univariate and multivariate estimation findings suggest that "Specialist" managers outperform "Generalist" managers. In addition, the "Specialist" tends to exhibit stock-picking ability while the "Generalist" tends to exhibit market-timing ability.

This essay considers an individual's past working experience as an essential determinant of their current career performance and provides a new method to evaluate the mutual fund performance from the perspective of the manager's lifetime working experience. The findings of this study are expected to be particularly useful for individual investors, since an observable managerial characteristic such as managerial past experience would allow them to more appropriately choose where to allocate their money for investment purposes.

This essay can be further improved in several aspects. Firstly, we only include individual fund managers due to the database limitation. The effort can be made in the future to construct a more comprehensive managerial bibliography dataset. Secondly, we currently analyze the manager's stock selection and market timing ability based on the assumption that only one type of skill exists. However, according to Ferson and Mo (2016), it would be difficult to distinguish one skill from the other if a fund manager attempts to adopt both skills. Moreover, Ferson and Mo (2016) mention that it is necessary to consider both market level and volatility timing behavior, as well as security selection ability, when measuring the portfolio performance. Therefore, further improvement can be made by applying the methodology which accommodate all three components as discussed in Ferson and Mo (2016).

The second essay analyzes the performance patterns of new funds during the early stage after their creation, and provides potential explanations for their short-lived outperformance. Instead of investigating the overall fund performance, this chapter concentrates on the emerging period of mutual funds (the first 6 months after creation of new funds) using an event time approach, where the event is the date when the fund is initiated. Using a sample of incubation-free mutual fund data from 1996 to 2015, we address the questions of (i) whether new mutual funds outperform the market and (ii) if they do what may explain their superior performance. We find evidence of outperformance for the new funds during their emerging period defined here as the first 6 months of their existence, both before and after fund expenses are taken into account. This finding is consistent with prior literature which provides evidence that new US equity mutual funds outperform their peers by 0.15% per month over the first 3 years (Karoui and Meier, 2009). This outperformance, however, only lasts for a short term and disappears soon after the emerging period. The short-term outperformance during the emerging period is negatively related with the fund size, which is consistent with the finding in Karoui and Meier (2009) that funds start by investing more actively in small-cap stocks and gradually increase their exposure to market risk. We also find that IPO access is a significant explanation for the short-term outperformance, which indicates that newly created funds with IPO allocations provide an attractive investment opportunity, especially during the first 6 months of their lives. However, we do not find significant heterogeneity in the outperformance with respect to managerial characteristics such as team managers and prior experience in equity fund management. We also provide evidence on the flow-performance relationship.

The evidence of outperformance for the new funds during their emerging period is particularly useful for mutual fund investors. Our conclusions also have implications for portfolio managers and fund companies, as we show that IPO allocation is an effective strategy in enhancing investment flows during the emerging period of a new fund. In addition, we find that funds created by team managers attract more flows than funds created by individual managers.

However, this chapter can be enhanced in the future. The first direction to look at is the expense analysis of IPO, which can be seen as the reward of IPO allocation. Malhotra and McLeod (1997) already conclude that that expenseconscious investors should pay attention to some fund characteristics such as the fund size, age, turnover ratio and cash holding as key determinants of expenses. We can further examine if IPO allocation dummy is the additional determinant for fund expenses in the emerging period. The next further analysis we can do is to perform a multinominal probit model to investigate the fund family's decision in opening an IPO new fund following Khorana and Servaes (1999).

The third chapter investigates the idea that fund managers would take into account turnover risk that they face when adjusting the volatility of portfolios under their management. We use an instrumental variable (IV) approach to avoid omitted variable bias from the usual probit regression. We assume that a fund manager's primary goal is to reach a top position in the tournament to secure or improve the career status. Specifically, each fund manager observes the position of her funds relative to other funds in the same family (family rank) on a continuous basis which is reflected in the turnover probability. Therefore, fund managers decide on the amount of risk to take based on the career risk resulting from the tournament. The empirical magnitude of the manager turnover risk premium – about 1% greater realized volatility for a one percentage point increase in manager replacement risk – is in line with calibrated theoretical predictions. Across various regression specifications, the results indicate that funds which change portfolio managers during the calendar year are subject to about 1% greater idiosyncratic volatility than funds which do not change managers. The result is in line with the manager employment concern literature. This study provides an innovative explanation for the linkage of fund risk taking and the family tournament. Fund managers who perform badly in the tournament face greater career risks since they are more likely to be replaced. Under the resulting pressure, those managers tend to hold more volatile portfolios to improve their positions within the family tournament. In other words, the manager replacement risk driven by the peer pressure from the tournament is likely to be incorporated into the fund's idiosyncratic risk.

The central finding of third empirical study has several implications for mutual fund investors, fund families as well as relevant regulatory authorities. According to Kempf and Ruenzi (2008), the purpose of risk adjustment in the tournament is not about optimizing an optimal portfolio for investors. Fund families should pay attention to the rebalancing costs caused by the risk adjustment behavior in the fund tournament. Secondly, a fund family also suffers from the in-family tournament negatively because fund managers compete with others in the same family for inflows. Such uncoordinated behavior of individual fund managers will lead to considerable agency costs (Bär et al., 2011; Massa et al., 2010). Finally, regulatory authorities may take an interest in the fund tournament since, as James and Isaac (2000) find, tournament behavior may lead to irrational price formation in asset markets.

We are aware that this chapter can be further improved in the following aspects. First, we can focus on the question of why the fund manager departs from the current fund – forced or voluntary departures. One possible solution is applied in Kostovetsky and Warner (2015) by identifying portfolio managers as in-house employees or subadvisors. Manager departures by in-house managers are more likely to be voluntary, because good performance gives in-house managers better opportunities, such as joining hedge funds (see (Kostovetsky and Warner, 2015)), causing them to leave.

In contrast, outperforming subadvisors can take advantage of expanded opportunities by simply adding clients. Thus, subadvisor data may help reduce classification error in distinguishing between voluntary and involuntary turnover.

Appendix

A Mutual Fund Manager Identification

The manager information is not fully disclosed in the CRSP since the manager information is not required to disclose by the SEC prior to 1988. Even after 1988, funds are not required to disclose detailed information of each manager in the team by the SEC. Until February 2006, funds are required to disclose information about each manager in a team (up to at least four of the members) by the SEC.

CRSP rarely reports more than three manager names; during the majority of that time, for most of the funds for which Morningstar lists four or more manager names, CRSP simply reports "Team Managed". This suggests that the CRSP manager name variable does not allow researchers reliably to distinguish co-managed funds with more than three managers from anonymously managed funds

We capture the variable *mgr_name* which refers to the portfolio manager name from the *fund_hdr* data file. CRSP documents the fund managed by individual manager directly as the manager name such as "John Smith". However, if the fund is managed by more than one manager, CRSP might report the manager information in different ways "John Smith and Jane White", "John Smith and Team Managers" or "Team Managed". Most of them are impossible to identify each manager's identity. Therefore, we keep only the individual fund managers and manually correct typos or abbreviations. Next, we assign each individual manager a unique ID number (integer starting from 1); we assign multiple managers with the ID equals 0.

B Mutual Fund Family Identification

CRSP provides two unique identifiers, *crsp_fundno* and *crsp_portno*. Neither identifier is unique to "families" of funds, or groups of fund share classes with the same holdings portfolio and management company. CRSP provides an imperfect way to identify fund family – to parse common syntax used in the *fund_name* field. It is based on the convention of using semicolon (;) to distinguish fund class from fund family. However, it fails for many funds who do not have a semicolon (;) in their names. Alternatively, we use the CRSP reported management company information (variable name *mgmt_name*) if we cannot identify the fund family based on fund name.

We manually correct typos and possible duplicates in the company names and assign each management company with a unique ID as we did for portfolio managers in Appendix A. We notice that many funds change the management company because of fund merge or acquisition throughout the whole reporting period. We attempt to manually merge it to the parent corporation. However, it is still not perfectly accurate.

C Variable Description for Chapter 5

We present description and usage of factors from Chapter 5 in the following tables.

Table 1: Variable Description for Chapter 5 (part 1)

Variable Name	Definition	Variable Usage
Manager Replacement (MR)	Manager Replacement indicator equals 1 if the current year-beginning manager differs from the prior year-end manager, or there is manager replacement happening within this calendar year, and 0 otherwise (see Section 5.4.2.1 for a more detailed description)	Dependent Variable in the First-Stage Regression
Segment Flow Rank	The fractional rank which measures the fund flow relative to the total flow of the competing funds in the same segment. The rank is calculated by ordering the funds in a segment according to their annual flows, and then calculate the fractional segment rank for each fund to obtain evenly-distributed rank between 0 and 1.	Instrumental Variable
Family Flow Rank	The fractional rank which measures the fund flow relative to the total flow of the competing funds in the same segment and in the same fund family. It is captured by a "Rank-of-Ranks" method, and is measured by ordering the funds in a family according to their *Segment Flow Rank* as described previously, and then calculate the fractional family rank for each fund to obtain evenly-distributed rank between 0 and 1.	Instrumental Variable
Idiosyncratic Volatility	The yearly risk that is endemic to a particular fund and cannot be explained by the segment peer benchmark. It is calculated as the standard deviation of the residuals saved from regressing 12 monthly fund returns against segment benchmark returns.	Dependent Variable in the Second-Stage Regression
Carhart-adjusted Idiosyncratic Volatility	The yearly risk that is endemic to a particular fund and cannot be explained by the Carhart asset-pricing factors. It is calculated as the standard deviation of the residuals saved from regressing 12 monthly fund returns against Carhart factors.	Dependent Variable in the Second-Stage Regression
Segment Return Rank	The fractional rank which measures the fund return relative to the total return of the competing funds in the same segment. The rank is calculated by ordering the funds in a segment according to their annual returns, and then calculate the fractional segment rank for each fund to obtain evenly-distributed rank between 0 and 1.	Control Variable
Family Return Rank	The fractional rank which measures the fund return relative to the total return of the competing funds in the same segment and in the same fund family. It is captured by a "Rank-of-Ranks" method, and is measured by ordering the funds in a family according to their *Segment Return Rank* as described previously, and then calculate the fractional family rank for each fund to obtain evenly-distributed rank between 0 and 1.	Control Variable

Table 2: Variable Description for Chapter 5 (part 2)

Variable Name	Definition	Variable Usage
Expense Ratio	The ratio of total investment that shareholders pay for the funds operating expenses, which include 12b-1 fees. It is reported in CRSP.	Control Variable
Turnover Ratio	The percentage of a mutual fund's holdings that have been replaced in a given year. It is reported in CRSP.	Control Variable
Fund Age	The natural logarithm of the difference between the current year and the fund's inception year as reported in CRSP.	Control Variable
Fund Size	The natural logarithm of the fund's total net asset in millions.	Control Variable
Annual Return	The geometric mean of the fund's monthly returns in each calendar year.	Control Variable
Fund Flow	The percentage change in fund's total net asset adjusted to the return growth within each calendar year.	Control Variable
Load Dummy	A binary variable indicating the load status of a fund which takes on the value 1 if any of the share classes of the fund charges a load in the calendar year, and 0 otherwise.	Control Variable
Multiple Share Classes	An indicator variable equals 1 if the fund includes more than one share class in the calendar year, and 0 otherwise.	Control Variable
Family Size	The natural logarithm of the fund family's total net assets.	Control Variable
Number of Funds in Family	The number of funds included in each family in the calendar year.	Control Variable

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