Fang, Rong (2011) Liquidity and performance of actively managed equity funds. PhD thesis, University of Nottingham.

Nottingham University Business School

Accounting and Finance Division

Liquidity and Performance of Actively Managed Equity Funds

by

Rong Fang

Supervisors:

Prof. David P. Newton

Prof. Weimin Liu

Examiners:

Dr. Chun Yu Mak

Dr. Ghulam Sorwar

Thesis submitted to the University of Nottingham for the Degree of Doctor of Philosophy

August, 2011

ACKNOWLEDGEMENTS

Admittedly, the writing of this Ph.D. thesis can be a very lonely and tough experience, yet it is obviously impossible to complete without the personal and practical support from many people. Thus, my sincere gratitude goes to my family, all my friends, and my supervisors and companions in the Nottingham University Business School (NUBS) for their love, support, and patience over the last few years.

First, I wish to thank my supervisors, Prof. David Newton and Prof. Weimin Liu, for inspiring and encouraging me to pursue academic studies. Prof. Newton was responsible for involving me in the Ph.D. programme in the first place. He taught me how to use different approaches to deal with a research question and enlightened my horizon through his wide knowledge and deep intuitions. I also thank Prof. Liu, who was readily available for me anytime. He always read and responded to the drafts of my work more quickly than I could have expected. Although he was not a man of many words, his oral and written comments were forever extremely perceptive, useful, and appropriate.

Many people on the faculty and staff of the NUBS assisted and encouraged me in various ways during my research. Also I benefited from conversations with numerous colleagues and participants at a series of Nottingham-Manchester Finance-Math seminars. Moreover, my research was made more efficiently by the use of SAS programming language and here I gladly express my gratitude to the staff and net friends at www.pinggu.org/bbs, a famous economics forum website in China, especially for their assistance in solving various problems of my data processing.

My thanks go out to Shenhwee Chua, Kai Dai, and the rest people in the Accounting and Finance group at NUBS. We not only studied and had meetings together but also they were willing to discuss some sections of my thesis and provided very useful input. My enormous debt of gratitude can hardly be repaid to my office-mate and close friend Lei Zhang, who provided many constructive suggestions and substantive challenges to help me improve my research topic and clarify my arguments.

Especially, I also would like to give my thanks to my external examiner Dr. Chun Yu Mak from Birmingham Business School and internal examiner Dr. Ghulam Sorwar from NUBS, who offer their helpful suggestions for improvement of this thesis.

Looking back, I am surprised and at the same time very grateful for all I have received these last few years. It has certainly shaped me as a person and has led me to where I am now. All these years of Ph.D. studies at NUBS are full of such gifts.

ABSTRACT

Most scholars have concluded that actively managed equity mutual funds as a whole underperform their passively managed counterparts, linked to some benchmarks. In other words, active equity fund managers on average do not have enough significant stock-picking abilities to add value for investors. However, earlier investigations may be flawed through failure to give adequate consideration to liquidity. Hence, this research pays much attention to liquidity effects on mutual fund performance and argues that it is a preference for holding highly liquid stocks which results in the perceived underperformance.

First, we find no significant liquidity premium at fund level, no matter the holding period returns or risk-adjusted performance. This indicates that all or almost all active equity fund managers in effect pay considerable attention to liquidity. We also examine the effects of liquidity on fund performance among actively managed equity funds. In contrast with earlier research, we find that actively managed equity funds in the aggregate perform close to the passive strategy. That means, on average, active equity fund managers do at least have talent sufficient to generate returns to cover costs that their funds impose on investors. This we attribute to the liquidity requirement of mutual funds. Moreover, using bootstrap simulation, we discover that many more mutual funds can be classified as skilled funds rather than lucky funds, once a liquidity factor has been included. Thus, our research provides a new insight into mutual fund performance, and highlights liquidity as an important and non-negligible determinant in the evaluation of mutual fund performance.

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CHAPTER 1: INTRODUCTION

Mutual funds are created and managed by professional companies which are registered with the Securities and Exchange Commission (SEC) in the U.S.[1] Hence, they are also called professional collective investment schemes that pool money from mass investors and invest this money in capital markets to realize capital gains through qualified management and skillful investment strategies. For mass investors, a motivation for investing in mutual funds is the common belief that fund managers can do better than they could. Additionally, individual investors are able to enjoy the benefits of diversification and economies of scale through investing in mutual funds. Investors can participate in mutual funds by purchasing shares issued by these professional mutual fund companies. Subsequently, investors also are able to cash in fund by redemption of mutual fund shares.

1.1. Research Incentives

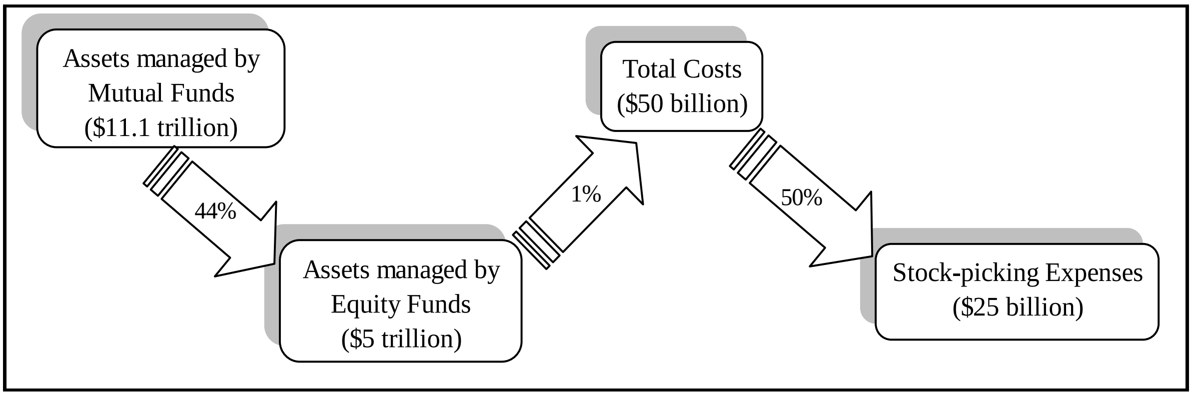
Over the recent decades the mutual fund industry has increased dramatically and now plays a significant role in global financial markets. According to the latest 2010 Investment Company Fact Book (ICI, 2010), U.S. mutual funds had $11.1 trillion in assets under management at the end of 2009. They managed about $371 billion at the end of 1984, so this figure grew by around 30 times in 25 years. Of the $11.1 trillion, roughly $5 trillion was managed in equity funds at year-end 2009. As a result, equity mutual funds were the largest group of investors in U.S. companies, since they held nearly one-fourth of outstanding stocks of U.S. companies in 2009. For this

[1] In the U.K., mutual funds are often referred to as Unit Trusts although their correct designation is Open Ended Investment Companies, OEIC. They are managed by companies registered with the Financial Services Authority (FSA).

professional investment management, a typical equity fund normally charges certain fees and expenses to investors. Based on the ICI (2010), investors in equity funds paid fees and expenses of 1.98% of fund assets in 1990, and this figure had fallen by half to 0.99% by 2009. Conservatively, let us assume that the fees and expenses of these actively managed equity funds average about 1% of the assets; then this suggests business of the order of $50 billion in equity funds in 2009. Amongst the effort expended in providing various services, "more than half of the expenses of mutual funds arise because of their stock selection efforts" according to Daniel et al. (1997). In this case, at least $25 billion in 2009 were expended by these active fund managers in pursuit of underpriced stocks (see Figure 1.1). Given the magnitude of these expenses, re-examination of the stock-picking talent of the fund managers is a highly worthwhile activity. Thus, it becomes our practical incentive to research mutual fund performance.

Figure 1.1

Stock-picking Expenses of Actively Managed Equity Funds in the U.S. (2009)



Data Source: 2010 Investment Company Fact Book, Investment Company Institute.

As far as our academic incentive is concerned, it is to test once again the efficient market hypothesis (EMH). The study of mutual fund performance is actually a derivative of EMH testing. If this hypothesis holds, the existence of active fund management will never be justified. In the 1960s, Prof. Eugene Fama introduced the

EMH into the economics and finance literature. He argued persuasively that, in an efficient market that includes many well-informed and intelligent investors, stocks will be appropriately priced and reflects all available information. Thus, no information or analysis can be expected to result in outperformance if a market is efficient. However, some economists noted problems with the hypothesis in 1980s. Grossman and Stiglitz (1980) showed that a perfectly efficient market was impossible because, in such a market, nobody would have any incentive to collect the information needed to make the market efficient. After the market crash of 1987, Shiller (1989), one of the founders of behavioural finance, even called the EMH one of the most remarkable errors in the history of economic thought. During the global financial crisis of 2008-2009, the EMH became a hot topic again for academics and practitioners. For investors, the issue of market efficiency reduces boils down to whether professional fund managers have the ability to outperform the market as a whole. Following Malkiel (1973), “if market prices were determined by irrational investors and systematically deviated from rational estimates of the present value of corporations, and if it was easy to spot predictable patterns in security returns or anomalous security prices”, then professional fund managers are supposed to be able to outperform the market. Thus, in academic circles, it has been widely accepted that direct testing of the performance of actively managed equity fund should provide the most convincing evidence of market efficiency.

1.2. Debate Topics

Although investors, in practice, seem to trust the selectivity ability of these professionals and try to select such active fund managers, academics have repetitively questioned this trust. So far, three key topics have been central to academic debates in the area.

The core issue is whether mutual fund managers who actively trade stocks are able to add value for investors; in other words, whether abnormal fund performance, after expenses are taken into account, is positive or negative. Thus far, most academic studies have concluded that, on average, actively managed mutual funds underperform their benchmarks, net of costs and expenses. For example, Jensen (1968), in the seminal paper on mutual fund performance, first reports that mutual funds cannot forecast stock prices well enough to recover expenses and fees, even for an individual fund. Malkiel (1995) and Gruber (1996) further emphasize that mutual funds on average offer a negative risk-adjusted return and so, in the aggregate, underperform benchmark portfolios. Grinblatt and Titman (1989) attribute underperformance on net returns to high expense and fees. They show that superior gross performance may exist, but mutual funds have higher expenses eliminating abnormal returns and, as a result, do not exhibit abnormal performance net of all expenses. Subsequently, Daniel et al. (1997) and Wermers (2000) also find that, on net returns, mutual funds underperform the market index, although the performance on gross returns is better than the market. They attribute much of fund performance to the characteristics of the stocks held by funds. In this thesis, we will examine the issue of performance of mutual funds via two approaches: (i) to conduct a simple time-series regression for each fund and (ii) to examine fund performance as a whole by constructing a portfolio of funds in each month. Moreover, we will apply regression models to examine the mutual fund performance. For example, we will present the results for those conventional asset pricing models (capital asset pricing model - CAPM, Fama-French three-factor model - FF3F, and Carhart four-factor model - FF+Mom) and liquidity-based asset pricing models (Pastor-Stambaugh four-factor model - FF+PS and Liu liquidity-augmented two-factor model - LCAPM). We hope to find a new reason or a new angle to explain the outperformance or underperformance of mutual funds.

From a variety of press and media, mass investors may now be familiar with Fidelity Magellan Fund and Schroder Ultra Fund, the two brightest stars in the history of the mutual fund industry. They surely cannot help wondering, however, whether these star funds reflect unusual wisdom in identifying undervalued stocks or are simply endowed with luck. This has become a hot debate (the second topic in our study) in recent academic research. Through the bootstrap method, a kind of Monte Carlo simulation, it is possible to examine the difference between all funds that exhibit a certain alpha in value-added and those funds that exhibit the same alpha by luck alone. Kosowski et al. (2006) introduce bootstrap simulation analysis (residual-only resampling) into fund performance research to distinguish the performance of best and worst funds not solely due to luck, where results cannot be explained by sampling variability alone. More recently, Fama and French (2010) infer the existence of superior and inferior managers in the cross section of fund returns through a joint resampling method, another bootstrap simulation. Although the main inference is less positive than that of Kosowski et al. (2006), they conclude that few active funds produce sufficient returns to cover their costs and star managers are hidden by the mass of managers with insufficient skill. Since these two bootstrap simulation methods, residual-only resampling and entire cases (joint) resampling, have their respective pros and cons, we will apply each successively to evaluate the performance of mutual funds and to reveal the lucky and skilled funds in our research. Accordingly, by comparing any ex-post t-statistics of fund alphas, $\hat{t}_{\hat{\alpha}i}$, with their appropriate luck distribution $f(\hat{t}^{b}_{\hat{\alpha}i})$, we are able to reject or not reject the null hypothesis that performance is due to luck at some confidence level and infer that the best funds have or do not have selectivity skill.

As is well known, besides satisfying investors' financial goals, mutual fund managers also meet their liquidity needs. Liquidity has been listed as one of four main advantages of mutual funds in the website of SEC.[2] Recently, an increasing number of fund managers paid much attention to the liquidity management in their investment decisions. For instance, aggressive profit-oriented fund managers will tend to hold fewer liquid securities,[3] while those capital safety-oriented funds will be likely to hold more liquid securities. However, we notice that prior academic studies on mutual funds give less consideration to the impact of liquidity on fund performance. Perhaps the first notable paper considering a liquidity factor on mutual fund performance is Edelen (1999). By examining funds' abnormal return and fund investor flows, Edelen argues that flow adversely affects a fund's performance because the position acquired in a liquidity-motivated trade has a negative impact on the fund's abnormal return. Hence, he attributes negative return performance to the costs of liquidity-motivated trading. Subsequently, Massa and Phalippou (2005) construct and use a new portfolio liquidity ratio, based on a micro-level fund liquidity concept. After considering short-term divergences from the optimal level and market-wide liquidity shocks, they conclude that portfolio liquidity does not affect performance in a predictable way, but note that mutual funds' better performance in bad (illiquid) times might be partially or totally driven by liquidity. Since there is no consensus on the relationship between liquidity and mutual fund performance, finding an appropriate liquidity factor and investigating how it might affect mutual fund performance is deserving of further study. Hence, we finally analyze the third research topic - whether there is liquidity premium at fund level and to what extent it affects fund performance. In this research, we will first

[2] See the website of U.S. SEC at http://www.sec.gov/investor/pubs/inwsmf.htm.

[3] Such as Zebra Capital Management which establishes a liquid investment strategy that captures liquidity premium. See http://www.zebracapm.com/strategies.htm.

construct fund liquidity measures (FLMs) based on the value-weighted average of the liquidity measure of stocks held by a fund. Then, we will test fund liquidity premium by sorting all qualified equity funds into ten portfolios based on their FLMs and controlling for risk using various asset pricing models. If the least liquid portfolio consistently outperforms the most liquid portfolio, this is a strong evidence of the presence of a liquidity premium at fund level. More importantly, it is necessary to make clear that the analysis above only focuses on the fund liquidity level, rather than fund liquidity risk. When examining mutual fund performance, we will emphasize the effect of the fund liquidity factor on performance through observing the loading of liquidity factor in Liu liquidity-augmented two-factor model (i.e. fund liquidity risk). As Liu (2009) points out, liquidity level and liquidity risk are two related but different concepts. Thus, it is imperative to distinguish them successfully.

1.3. Potential Contributions

Nearly all earlier academic research on mutual fund performance gives little consideration to fund managers having to provide liquidity to investors through the holding of considerable quantities of liquid stocks. It makes sense, however, that fund managers always prefer stocks with high liquidity in readiness to response to unexpected and contingent fund share redemptions. To fill this gap, our research not only constructs new fund liquidity measures and analyzes the liquidity characteristics of actively managed equity funds but also examines the existence of a fund liquidity premium, as well as effect of the liquidity factor on fund performance.

First of all, this thesis takes a new look at returns of 2417 diverse actively managed U.S. equity funds during the period of 1984 to 2008 and utilizes a new data sample that includes the liquidity measures of stocks held by funds in each month over the 25-year period. Initially using the classification of Thomson Reuters CDA/Spectrum, we then apply our own standard (based on proportion of the stock-holdings in a mutual fund) to identify the equity funds, which effectively avoids the fund classification confusion. Thus, it appears that our actively managed equity fund sample is purer and more accurate than any in the existing literature.

Next, through the mutual fund stock-holdings' data, it is possible for us to define and construct new fund liquidity measures (FLMs) from a micro perspective. That is, our fund liquidity indicates the liquidity comes from stock-holdings, rather than Edelen (1999)'s macro-level fund liquidity, which is defined as fund investors' flow, i.e. cash flow including new sales and redemptions. To a large extent, Edelen's macro-level fund liquidity could not be controlled directly by fund managers, while our micro-level fund liquidity is able to tell us exactly the liquidity preference of fund managers. Thus, we believe the weighted average liquidity of stocks held by funds might be more suitable as a factor for investigating performances of mutual funds, since stock-holdings can be managed effectively by fund managers.

Then, we present the liquidity characteristics of actively managed equity funds over the period 1984 to 2008. By analyzing the four fund liquidity measures and two fund stock-holdings characteristics, we find that the equity funds now favour highly liquid stocks more than ever. In particular, a typical equity fund is likely to hold stocks with fewer no-trading days (Liu's LM12), higher trading turnover ratio (TO12), lower price-impact ratio (Amihud's RtoV12), and slightly lower effective cost of trading (Hasbrouck's EC). In addition, we notice that the market capitalization of stock-holdings (MV) increases almost ninefold during the 25-year period; meanwhile the book-to-market ratio of stock-holdings (B/M) falls markedly. These phenomena indicate that, especially in recent times, liquidity has been paid increasing attention by fund managers when making investment decisions. Moreover, according to the micro-level fund liquidity concept, above, we can further examine liquidity premium at fund level and we find that fund liquidity premium does not exist, no matter the holding period returns or risk-adjusted performance. The absence of a fund liquidity premium is consistent with our expectation. As a matter of fact, almost all actively managed equity funds pay much attention to liquidity and hold a large volume of highly liquid stocks. As a result, it is impossible to find a significant liquidity premium within these notably liquid portfolios.

Subsequently, we use conventional asset pricing models (CAPM, FF3F, and FF+Mom) and liquidity-based asset pricing models (FF+PS and LCAPM) to measure and examine the mutual fund performance and try to offer new outcomes and explanations from fund liquidity consideration. Through analyzing the performance (yearly alpha) of aggregate wealth invested in funds (value-weighed returns of portfolio of funds) relative to passive benchmarks, we discover two different stories. If we use CAPM, FF3F, FF+Mom, and FF+PS models, the fund performance is poor, because the models' annualized intercepts are negative, ranging from -0.721% to -1.057% per year, with t-statistics from -2.37 to -3.23. These significant negative alphas tell us that, on average, actively managed equity funds do not have the ability to generate sufficient returns to cover the costs and expenses. However, the result from Liu LCAPM is completely different. Not only is the model's annualized intercept negative nearly zero (-0.116% per year), but also its t-statistic is insignificant (only -0.34). That means the aggregate portfolio of funds is mimicking the performance of benchmarks. These results echo our expectations. The underperformance in the first story arises because the liquidity factor is not considered properly in those models. In contrast, in our new story, to a large extent fund performance is affected by fund liquidity requirements. If the liquidity factor is taken into account, it cannot be rejected that actively managed equity funds as a whole perform close to the benchmarks.

With the Shapiro-Wilk W test for normality, we find that roughly half of equity funds have alphas that are drawn from a distinctly non-normal distribution.[4] This finding of non-normal residuals challenges the validity of earlier research that relies on the normality assumptions. Accordingly, this finding strongly indicates the need to bootstrap, especially in the tails, to determine whether significant performance is due to fund manager's ability or to luck alone. Thus, this thesis distinguishes skill from luck for individual funds using two different bootstrap simulation methods, residual-only resampling and entire cases resampling. We find that the performance of these best and worst funds can not be explained solely by sampling variability, which indicates these fund managers' performance is not due to luck alone. We uncover the substantial effect of liquidity factor on performance again. For example, in residuals-only resampling bootstrap simulation, we discover that the top 20% funds can be called skilled funds with genuine stock-picking ability if we apply Liu LCAPM. In contrast, using other asset pricing models, we find only the top 5% to 10% of funds show genuine skills. Put another way, without considering the liquidity factor, around 10% to 15% of funds are classified into lucky funds away from skilled. That exactly tells us that these funds pay a certain attention to liquidity which, in turn, weakens their performance.

Basically we suppose this thesis contributes to the literature by addressing these aspects above. Our research offers a new insight into the mutual fund performance and detects the liquidity factor as an important and non-negligible determinant in asset

[4] In this research, if the p-value is less than 0.05 (i.e. at 5% significance level), we reject the null hypothesis that the residual is normally distributed. In our tests, the normality is rejected for around 43.5% to 59.3% of funds when using various asset pricing models.

pricing. Our results emphasize the importance of understanding liquidity in the evaluation of mutual fund performance.

The remainder of this thesis continues as follows. In Chapter 2, we briefly take a bird's eye view of the evolution in mutual fund industry, as well as the motivations of investing in mutual funds, and then explain some essential elements in mutual fund investment. Besides introducing the efficient market hypothesis and models applied in our research, in Chapter 3 we review the literature on mutual fund performance and liquidity. The data sources, data processing, fund sample construction and statistics description are in Chapter 4. Chapter 5 details the regression models and methodologies in this research, explaining the necessity and advantages of using bootstrap simulation methods. Chapter 6 presents empirical results on the fund liquidity premium, after forming fund liquidity measures. Chapter 7 provides empirical results for mutual fund performance by examining the cross-sectional performance of portfolio of funds and separating skilled funds from lucky funds via bootstrap simulation. Additional robustness tests, such as subsample and subperiod analyses, are given in Chapter 8. Chapter 9 summarizes and suggests some future work in this research area.

CHAPTER 2: INDUSTRY PERSPECTIVE

2.1. The Evolution of Mutual Fund Industry

Although mutual funds have been particularly popular in recent several decades, they have existed for more than 230 years. The origin of mutual funds dates back to Netherlands in the late of 18th century. According to Rouwenhorst (2004), “In 1774, the Dutch merchant and broker Adriaan Van Ketwich invited subscriptions from investors to form a trust named Eendragt Maakt Magt - the maxim of the Dutch Republic. The founding of the trust followed the financial crisis of 1772-1773 and Van Ketwich’s aim was to provide an opportunity to diversify for small investors with limited means.” Eendragt Maakt Magt, the name of the first fund, translates to “unity creates strength”, which reflects the spirit of pooled investing.

Thereafter, the idea of pooling resources and spreading risk using closed-end investment soon made its way to Great Britain and United States (McWhinney, 2005). In 1868, the Foreign and Colonial Government Trust was founded in London and, subsequently, the Boston Personal Property Trust, the first closed-end fund in the U.S., formed in 1893. The arrival of the modern fund (mutual fund or open-end fund) dates back to Boston in 1924. Massachusetts *Investor’s* Trust, the first mutual fund, introduced significant innovations to the pooled investment concept, such as by “establishing a simplified capital structure, continuous offering of shares, the ability to redeem shares rather than hold them until dissolution of the fund, and a set of clear investment restrictions and policies” (ICI, 2010).

With the stock market crash of 1929 and the Great Depression that followed, the growth of mutual funds was greatly hampered until a series of landmark government regulations. After creating the SEC, the U.S. legislature passed the Securities Act of

1933 and the Securities Exchange Act of 1934, which aims to safeguard the investors' interest. Later, the Investment Company Act of 1940 added regulations that "required mutual funds to register with the SEC, provide disclosure in the form of a prospectus, and sought to minimize conflicts of interest" (McWhinney, 2005). All of these reinvigorated investor confidence.

With these numerous innovations and renewed investor passion, the mutual fund industry was able to continue to expand. The 1960s saw the rise of aggressive growth funds. In the 1970s, a series of index funds were established after the introduction of the efficient market theory. Believing in passive investment strategy, John Bogle founded the Vanguard Group (renowned for low-cost index funds) in 1974 and started the First Index Investment Trust at the end of 1975. The 1970s also saw the rise of the no-load fund, which had an enormous impact on the way mutual funds were sold and would make a major contribution to the industry's success (McWhinney, 2005). In recent several decades, with baby boomers marching towards retirement and the growth of defined contribution pensions, such as 401(k) plans, abundant money poured into the mutual fund industry and fund managers perhaps even became household superstars, for instance, Peter Lynch and his Fidelity Magellan Fund.

The mutual funds' objectives and compositions are greatly disparate, both domestically and internationally, and range from specialty funds to index funds. As a main portion of the U.S. mutual funds, equity funds held 44% of total \$11.1 trillion mutual fund assets in 2009 (domestic stock funds and international stock funds held 33% and 11% respectively). Moreover, the money market funds reached a relatively high level and accounted for 30% of U.S. mutual fund assets at the end of 2009.[5] For the remainder of the total assets in mutual fund industry, bond funds and hybrid funds

[5] That might be most mutual fund investors redeemed equity funds and invested into the money market funds for liquidity and safety during the global financial crisis of 2008-2009.

held 20% and 6% respectively. Although industry scale declined somewhat during the global financial crisis of 2008-2009, mutual funds have still been noted as the fastest growing investments over recent decades. At the end of 1984, they only managed about $371 billion in assets, but this figure had grown to $11.1 trillion at the end of 2009; mutual fund industry scale has grown by 30 times during these 25 years. Moreover, with roughly $5 trillion managed in equity funds (including domestic and international stock funds), which has grown by 62 times over the 25 years, equity fund is the fastest growing category in this industry (see Appendices 1 and 2).

2.2. The Motivations for Investing in Mutual Funds

Even though mutual funds have constantly and gradually evolved over time, the main motivations for investors to invest in mutual funds remain unchanged. Just as an adage says “Don't put all your eggs in one basket”, the most important motivation for small-scale investors to invest in mutual funds should be diversification. Theoretically, the highest degree of diversification for an investor is obtained by holding a market portfolio that includes a share of all tradable assets. However, there are several practical problems an individual investor is faced with when trying to hold such an optimally diversified portfolio. For instance, it requires a large investment budget to purchase a sufficiently large number of securities. Moreover, managing such a portfolio involves significant transaction costs. By pooling large amount of capital, mutual funds can offer individual investors an immediate benefit of instant diversification through economies of scale.

In addition, as investment professionals, fund managers (or portfolio managers) are expected to be familiar with what is available, the gains and risks possible, and the laws and regulations in the industry. Most investors are likely to believe that fund managers have the ability to select profitable investments (selection ability) and earn money by buying and selling securities at the right time (timing talent). As a result, fund managers can charge certain service fee to investor for their professional management. This leads to two key disputes in academia. The first is whether mutual funds are able to add value to investors through active trading, i.e. whether they are genuine professionals. The other is whether, if mutual funds with superior talent claim high fees, these high expenses to their investors eliminate abnormal returns and result in no outperformance for the investors. So far, academics have reached contradictory conclusions regarding these disputes. Nevertheless, in practice, the mass of investors seem to believe fund managers possess some professional talent, at least sufficient to outperform those individual investors.

Another motivation is that investors are provided liquidity by mutual funds, because they are able to get in and out mutual funds easily. Liquidity has been listed as one of four main advantages of mutual funds by the SEC. In general, all mutual funds constantly offer shares to the public. That is, mutual fund shares can be bought and sold between the investors and the mutual funds without any difficulty on each trade date. However, unlike stocks transaction, in which investors know the sale price when they trade, mutual funds transact only at the net asset value (NAV) of each trade date, such that investors must wait until the following day to discover the trade price. The motivation of providing liquidity also involves a problem: fund managers have to hold a large amount of cash or highly liquid assets for dealing with possible share redemption, which is at the cost of performance. Therefore, fund managers face a tough trade-off between getting better performance and meeting the liquidity requirement.

2.3. The Essential Elements of Mutual Funds

2.3.1. Structure and Category

Mutual funds are created under state laws either as a corporation or as a trust in the U.S. On the one hand, mutual funds have officers and directors or trustees, just as any other companies. On the other hand, mutual funds "typically rely on third parties or service providers, either affiliated organizations or independent contractors, to invest fund assets and carry out other business activities" (ICI, 2010). For instance, an Administrator operates the fund company and oversees the performance; a Custodian (generally a bank) holds the fund's assets and protects shareholder interests; an Investment Adviser manages the fund's portfolio; a Principal Underwriter, known as the fund's distribution channel, sells fund shares; an Accountant certifies the fund's financial statements, and so on (see Appendix 3).

The categories of mutual funds are typically characterized by their investment goals or strategies. Usually, there are four basic categories of mutual funds: money market, bond, hybrid (or balanced, mix of stocks and bonds) and equity. A money market fund's goal is to preserve principal while yielding a modest return by investing in short-term bank notes that pay a modest rate of interest and are very safe; a bond fund aims to generate income while preserving principal as much as possible by investing in medium and long term bonds issued by corporations and governments; a hybrid fund tries to grow the principal and generate income by investing in both stocks and bonds, which enables to investors reduce their market risk effectively because of highly diversification; an equity fund's goal is to obtain long-term growth through capital appreciation, meanwhile dividends and interest are also sources of revenue.

Some specific equity funds may focus on a certain kind of corporation or sector, for example, growth funds, value funds, large-cap funds, mid-cap funds, small-cap funds, and so on. Based on the classification of Thomson Reuters CDA/Spectrum database, an equity fund's investment objectives are classified as aggressive growth, growth, as well as growth and income, respectively. An aggressive growth fund's goal is to produce capital growth as much as possible and neglect the dividend income. This kind of fund invests in stocks that have the potential for explosive growth (these companies commonly never pay dividends); accordingly such stocks also have the potential to go bankrupt suddenly. A growth fund's target is to acquire both capital growth and dividend income. This type of fund buys those stocks that are growing rapidly but have less probability of bankruptcy. A growth and income fund aims to preserve the principal and generate some dividend income - hence, this style of fund purchases stocks that have modest growth prospect but pay fat dividend yields.

Similarly, Investment Company Institute, MorningStar, Lipper, and other organizations also have their own classification standards. The standard of classification is generally broad enough to allow a wide range of different investment policies. As Brown and Goetzmann (1997) argue, "given this broad latitude, it is not surprising to find widely divergent behaviour among funds pursuing the same objective. As a result, existing classifications do a poor job of forecasting differences in future performance." Therefore, in this research, besides using the classification of the Thomson Reuters CDA/Spectrum, we apply a new standard (based on the proportion of the stock-holdings in a fund) to classify the equity funds, so as to avoid the classification confusion as much as possible. Our new classification criterion is based on the SEC rule 35d-1. In 2002, the SEC adopted and proposed a requirement that "an investment company with a name that suggests the company focuses its investments in a particular type of investment or in investments in a particular industry must invest at least 80% (originally 65%, later raised to 80%) of its assets in the type of investment suggested by the name”. For example, ABC Equity Fund has to invest at least 80% of assets in stocks; and XYZ Bond Fund must invest at least 80% of its assets in bonds. Investment companies have had to comply with the rule, if they want to keep the investment objective and style unchanged. Thus, we propose using the proportion of stock-holdings as a standard to identify equity funds.

2.3.2. Pricing, Sales, Fees & Share-classes

Since investors’ purchase and redemption is based on the net asset value (NAV) per share of each trade date, mutual funds must ensure the accuracy of NAV. Actually mutual funds release the NAV only after confirming by the Custodian. In the context of mutual funds, NAV is the current market value of all the holdings of the fund, minus liabilities, and then divided by the total number of outstanding shares:

$$\text{Net Asset Value (NAV)} = \frac{\text{Market Value of Holdings} - \text{Liabilities}}{\text{No. of Outstanding Shares}}.$$

The value of these holdings is determined “either by a market quotation for those securities in which a market quotation is readily available or, if a market quotation is not readily available, at fair value as determined in good faith by the fund” (ICI, 2010).

There are two methods to sell or distribute the mutual fund shares. The main sales method is through distribution channels such as broker-dealers, banks, and insurance companies. In this way, a sale load fee is often involved, which is retained by the distribution channels as compensation to the investment advice provided. In addition, mutual funds always offer a portion of their management fee as an additional compensation or encouragement to distribution channels. That is known as 12(b)-1 fee in the U.S., which was originally used to pay for advertising, marketing and other sales promotion activities (this fee is limited to 1% p.a. of the fund’s asset by the National Association of Securities Dealers, Inc.). Nevertheless, recently most of the 12(b)-1 fee collected by funds is used to compensate financial advisers and other financial intermediaries for assisting fund investors before and after purchases of fund shares. As a matter of fact, the 12(b)-1 fee used for advertising implies, to some extent, that current shareholders bear the cost of attracting new shareholders (Cuthbertson et al., 2006). Another sales method is direct marketing via fund supermarkets and fund management companies (such as online, call centre, and direct marketing department). Unlike the first method, direct marketing is not only convenient and easy but also has low costs (even no load fee). These directly marketed funds may only use the 12(b)-1 fee to pay for advertising or shelf space at a fund supermarket.

Since mutual funds provide professional investment service but, meanwhile, need to compensate third parties for investment advice at sales, a typical equity fund normally charges two primary kinds of fees and expenses to investors: sales loads and ongoing expenses. The former are one-time fees, paid by investors either at the time of share purchase (front-end loads), or when shares are redeemed (back-end loads). The latter cover "portfolio management, fund administration, daily fund accounting and pricing, shareholder services such as call centres and websites, distribution charges known as 12(b)-1 fee, and other miscellaneous costs of operating the fund" (ICI, 2010).

Partly, no doubt, because of competition within the mutual fund industry, mutual fund fees and expenses that investors pay have trended downward since 1990. According to 2010 Investment Company Fact Book, investors in equity funds paid fees and expenses of 1.98% of fund assets in 1990. However, this figure had fallen by half to 0.99% by 2009 (see Appendix 4). Besides competition, another reason for the dramatic decline in the fees and expenses arises from a significant change in the manner of some fund sales. An increasing number of mutual funds sell shares through employer-sponsored retirement plans that usually are not charged sale loads for purchases of fund shares. As a result, the investors pay much less in sales loads than previously. In 2009, no-load mutual funds obtained the bulk of net new cash, accounted to $323 billion of the total $388 billion in net cash, whilst load funds only attracted $39 billion (see Appendix 5). Additionally, the levels of fees and expenses are influenced by fund investment objective and fund size. In general, money market and bond funds tend to have lower expenses ratios than equity funds. Among equity funds, aggressive growth funds and international funds may choose to focus more on small- or mid-cap stocks and broader stocks, which cause them to be more costly to manage. As a result, both expense ratios are more than 1% (see Appendix 6). As to the fund size's influence, intuitively, large mutual funds are apt to have lower expense ratios due to economies of scale.

Since the 1990s, mutual funds usually design different fee structures and offer more than one share-classes to investors with several ways to pay for the services of financial advisers. For example, class A shares normally have a front-end load, a sales charge payable when investors buy the fund share; class B shares have a back-end load, payable when investors redeem fund shares. If fund shares are redeemed before a given number of years of ownership (usually six or seven years), a contingent deferred sales load is triggered[6]; class C shares have no front-end load and a very low back-end load, but have relatively high 12(b)-1 marketing fees (normally 1%) and a contingent deferred sales load (also around 1%). As to other share-classes, they might be designed for institutional shares, and not available to individual investors. For instance, the Growth Fund of America owns 14 share-classes, the highest number of share-classes[7]. From another angle, these share-classes above are also called load share-classes. The

[6] Contingent deferred sales load (CDSL) decreases the longer the investor owns the shares and reaches zero typically after shares have been held six or more years.

[7] The 14 share-classes include class A, class B, class C, class F, class 529-A, class 529-B, class 529-C, class 529-E, class 529-F, class R-1, class R-2, class R-3, class R-4, and class R-5 shares, respectively.

no-load share-classes are originally offered by mutual fund sponsors and sold directly to investors. Now investors can purchase no-load share-classes through employer-sponsored retirement plans, mutual fund supermarkets, as well as directly from mutual fund sponsors. Because no-load share-classes have no front-end load, and only have a low 12(b)-1 fee of 0.25% or less, they are paid much more attention by investors and have collected much new cash flow. Although a mutual fund generally has a series of share-classes, these share-classes are based on same pool of securities and managed by same fund manager, and only differ in the fee structures. Since the net returns are reported at share-class level in some mutual fund databases, we must switch them to fund level by weighting share-class level returns by the proportion of each share-class total net asset at the beginning of each period.

2.3.3. Performance Measures

It is known that fund return alone should not be considered as the basis of measure of the performance of a mutual fund scheme; it should also include the risk taken by the fund manager because different funds have different levels of risk attached to them. Risk associated with a fund may commonly be defined as variability in the returns generated by it. The higher the fluctuations in the returns of a fund during a given period, the higher will be the risk associated with it (presuming future variability related to past). These considerations on risk-return relationship suggest that risk-adjusted return is a desirable way to measure the fund performance.

Methods of risk-adjusted performance evaluation using mean-variance criteria came on stage simultaneously with the Capital Asset Pricing Model (CAPM). Development of the CAPM involved several eminent academics[8] in the 1960s. Treynor (1965) produces a composite measure of portfolio performance. He measures

[8] Especially Jack L. Treynor (1965), William F. Sharpe (1966) and Michael C. Jensen (1968, 1969).

portfolio risk with beta (systematic risk), and calculate portfolio's market risk premium relative to its beta:

$$\text{Treynor's measure} = (R_p - R_f) / \beta_p ,$$

where R_p is portfolio's actual return during a specified time period, R_f is risk-free rate of return, β_p is the beta of the portfolio. This measure is a ratio of return generated by the fund over and above risk-free rate of return, during a given period and the systematic risk associated with it (beta). All risk-averse investors would like to maximize this measure. A high and positive Treynor's measure indicates a superior risk-adjusted performance of a fund. Afterward, Sharpe (1966) develops a composite measure which is very similar to the Treynor's measure, the difference being its use of standard deviation (total risk), instead of beta, to measure the portfolio risk:

$$\text{Sharpe's measure} = (R_p - R_f) / \sigma_p ,$$

where σ_p is the standard deviation of the portfolio. According to Sharpe's measure, it is the total risk of the fund that the investors are concerned about. For a completely diversified portfolio, Treynor's measure and Sharpe's measure would give identical results, as the total risk is reduced to systematic risk. The trouble with both measures for evaluating risk-adjusted returns is that they measure risk with short-term volatility. Hence, these measures may not be applicable in evaluating the long-term investments.

Subsequently, Jensen (1968, 1969) proposes the following formula in terms of realized rates of return, assuming that CAPM is empirically valid:

$$R_{p,t} - R_{f,t} = \beta_p (R_{m,t} - R_{f,t}) + \varepsilon_{i,t} .$$

In this formula, we would not expect an intercept for the regression equation, if all stocks are in equilibrium. However, if a superior portfolio manager can persistently earn positive risk premiums on their portfolios, the error term $\varepsilon_{i,t}$ will always have a positive value. In such a case, an intercept value which measures positive differences from the formula must be included in the equation as follows:

$$\text{Jensen's measure} = \alpha_p = R_p - [R_f + \beta_p (R_m - R_f)],$$

where R_p is the returns that the fund has generated, $R_f + \beta_p (R_m - R_f)$ is the returns actually expected out of the fund given the level of its systematic risk. The surplus between the two returns is called α_p (known as Jensen's measure or Jensen's alpha), which measures the performance of a fund compared with the CAPM return for the level of risk over the period. A superior portfolio manager would have a significant positive alpha because of the consistent positive residuals. Thus, if Jensen's measure is positive, then the portfolio is earning excess returns over those expected if the CAPM holds. In other words, a positive Jensen's alpha implies that a fund manager has beaten the market with his stock selection skills. We have to bear in mind that Jensen's measure uses systematic risk based on the premise that the unsystematic risk is diversifiable. It is suitable for large institutional investors, such as mutual funds, because they have high risk taking capacities and can readily invest across a number of stocks and sectors.

In practice, the information ratio (IR) or Modigliani squared measure (M^2) are commonly used to evaluate the fund performance. The IR is defined as expected active return divided by tracking error, where active return is the difference between the return of the security and the return of a selected benchmark index, and tracking error is the standard deviation of the active return:

$$\text{IR} = \text{active return} / \text{tracking error} = E(R_p - R_b) / \sqrt{\text{var}(R_p - R_b)}.$$

The Modigliani squared measure (M^2) is a variant of Shape's measure. It focuses on total volatility as a measure of risk. To compute this measure, we imagine that a managed portfolio (P) is mixed with a position in T-bills so that the adjusted portfolio (P*) matches the volatility of a market index:

$$M^2 = r_{p*} - r_m ,$$

where $r_{p*} = \frac{\sigma_m}{\sigma_p} r_p + (1 - \frac{\sigma_m}{\sigma_p}) r_{T.bill}$. For example, if the managed portfolio has 1.5 times the standard deviation of the market index, the adjusted portfolio would be 2/3 invested in the managed portfolio and 1/3 invested in bills.

In academic studies, applying the alpha (α_p) as fund performance measure has been the mainstream approach. With the further development of asset pricing models, the fund’s alpha becomes defined as the intercept term in a regression of the fund’s excess returns on the excess returns of one or more benchmark factors (e.g. market, size, book-to-market, momentum, liquidity risk, liquidity factor, etc.). In the following chapter, we will describe specifically the progress in the development of asset pricing models, as well as the differences between them.

CHAPTER 3: LITERATURE REVIEW

In this chapter, besides introducing hypothesis and models relevant to mutual fund performance (such as the efficient market hypothesis and asset pricing models), we mainly review the literature on mutual fund performance, persistence of performance, and liquidity effect on mutual fund performance.

3.1. Efficient Market Hypothesis (EMH)

The Efficient Market Hypothesis (EMH) asserts it is impossible to “beat the market” because market efficiency causes existing stock prices always to incorporate and reflect all relevant information. Our research on mutual fund performance is actually a derivative of EMH testing. If this hypothesis holds, the existence of active fund management will never be justified on the basis of returns. According to the EMH, stocks always trade at their fair value, making it impossible for fund managers either to purchase undervalued stocks or to sell overvalued stocks based on their expectations. As such, it is also impossible to outperform the overall market through fund managers’ stock selection or market timing.

The introduction of the term “efficient market” is usually attributed to Prof. Eugene Fama. In his earlier papers,[9] Fama tests the theory of random walk in stock market and introduces the efficient market concept. Through study of serial correlations in daily price changes of 30 stocks that comprise the Dow Jones Industrial Average index, he concludes that successive price changes are extremely close to zero,

[9] Fama’s Ph.D. thesis “The behavior of stock market prices” was published in the Journal of Business (1965a). Subsequently the work was rewritten into a less technical article “Random walks in stock-market prices”, which was published in the Financial Analyst Journal (1965b).

which supports the independence assumption of the random walk. An efficient market is defined by Fama (1965b) as

> "a market where there are large number of rational profit-maximizers actively competing, with each trying to predict future market values of individual securities, and where important current information is almost freely available to all participants".

In an efficient market, he claims that the effects of new information on intrinsic value will be reflected "instantaneously" in actual prices because of severe competition. Subsequently, Fama (1970) develops the EMH, and introduces the three versions in which the EMH is now commonly stated: the weak, semi-strong, and strong forms of the hypothesis. In weak form efficiency, stock prices already reflect information that can be derived from the history of past prices; that is, future prices cannot be predicted by analyzing past prices. Hence, technical analysis will not be able consistently to produce excess returns; trend analysis is fruitless. The semi-strong form hypothesis states that stock prices reflected all publicly available information about a firm's prospect (including the firm's product, management quality, balance sheet composition, earning forecasts, and etc.). This variant of the hypothesis implies that neither fundamental analysis nor technical analysis will be able reliably to produce excess returns. Last, the strong form hypothesis asserts that all information relevant to firms, public and private, are reflected in the stock prices. Evidently, this variant is quite extreme, since it assumes that company insiders cannot profit from trading on that information. Preventing insider trading has always been, of course, one of the core activities of worldwide securities authorities.

Fama's work suggests that a simple policy of buying and holding the securities will be as good as any more complicated mechanical procedure for timing buys and sales. Based on the EMH, in the 1970s Jack Bogle invented Vanguard index funds, tracking the performance of the stock market as a whole and keeping ordinary investors from wasting their money trying to beat it. At the same time, in academia, economists and finance scholars cleared the way for a new approach to investing and risk management that included risk-weighted portfolio allocation and mathematical models to price options and other derivatives.

However, it didn't take long time before some economists came to reveal problems with the EMH. Grossman and Stiglitz (1980) argue that a perfectly efficient market is impossible because, in such a market, nobody would have any incentive to collect the information needed to make the market efficient. This line of reasoning has become known as Grossman-Stiglitz paradox. Additionally, Shiller (1981) tests changes in dividends and their effect on stock prices, and suggests that stock prices jump around a lot more than corporate fundamentals do. This phenomenon is known as "excess volatility". After market crash of 1987, Shiller (1989) further criticizes that the logical leap from observing that markets are unpredictable to concluding that prices are right is "one of the most remarkable errors in the history of economic thought." Recently, the global financial crisis of 2008-2009 has brought renewed scrutiny of the EMH. In his book, The Myth of the Rational Market, Justin Fox (2009), an economics of columnist for Time, tells the story of the scholars who enabled abuses under the banner of the financial theory of EMH. He goes as far as to state that belief in EMH caused financial leaders to have an underestimation of the dangers of asset bubbles breaking and that the hypothesis is responsible for the current financial crisis. Thus in this area, informed inquiry will be likely pay more attention to the conditions that explain and improve the informational efficiency of markets than to whether markets are efficient.

For fund investors and researchers, the issue of market efficiency, to a large extent, reduces to whether professional fund managers have ability to outperform the market as a whole. As Malkiel (1973) proposed, "if market prices were determined by irrational investors and systematically deviated from rational estimates of the present value of corporations, and if it was easy to spot predictable patterns in security returns or anomalous security prices", then professional fund managers would be supposed to be able to outperform the market. Thus, in academia it has been widely accepted that direct testing of the performance of fund managers (especially the active equity fund managers) should represent the most convincing evidence of market efficiency, since these professionals have the strongest incentives to beat the market.

3.2. Asset Pricing Models

3.2.1. Conventional Models

In order to measure abnormal performance by mutual funds, it is necessary to have a benchmark for normal performance. Modern portfolio theory offers such a standard of comparison, that combination of the market portfolio and the riskless asset which is of comparable risk. The first model used to evaluate risk-adjusted fund performance is the Capital Asset Pricing Model (hereafter CAPM) derived independently by Sharpe (1964) and Lintner (1965). Given a few important assumptions[10], these authors provide the following expression for the expected one period return $E(R_i)$, on any fund i[11]:

[10] For instance, (1) all investors are averse to risk, and are single period expected utility of terminal wealth maximizers; (2) all investors have identical horizons and homogeneous expectations regarding investment opportunities; (3) all investors choose among portfolios solely based on expected returns and variance of returns; (4) the capital market is in equilibrium.

[11] Actually, the asset i could be any security or any portfolio. Since this thesis studies fund performance, we just let the asset i be fund i.

$$E(R_i) = R_f + \beta_i[E(R_m) - R_f],$$

where R_f is the one-period risk-free rate; $E(R_m)$ is the expected return on market proxy portfolio; $\beta_i = \frac{\mathrm{cov}(R_i, R_m)}{\mathrm{var}(R_m)}$ is the beta coefficient (also called systematic risk). Jensen (1968, 1969) extends the single period model to a multi-period world where investors are allowed to have heterogeneous horizon periods and trading takes place continuously through time:

$$E(R_{i,t}) = R_{f,t} + \beta_i[E(R_{m,t}) - R_{f,t}],$$

where the t denotes an interval of time. Then Sharpe's (1964) market models are given:

$$R_{i,t} = E(R_{i,t}) + \beta_i \pi_t + \mu_{i,t},$$

$$R_{m,t} = E(R_{m,t}) + \pi_t,$$

where $R_{i,t}$ and $R_{m,t}$ are realized returns on fund i and market portfolio during time period of t; π_t is an unobservable market factor which to some extent affects the returns on all funds; and the $\mu_{i,t}$ is the random error term, which has an expected value of zero. Through reorganizing the three equations above, Jensen obtains an equation can be used directly for empirical estimation:

$$R_{i,t} = R_{f,t} + \beta_i(R_{m,t} - R_{f,t}) + \mu_{i,t} \quad \text{or}$$

$$R_{i,t} - R_{f,t} = \beta_i(R_{m,t} - R_{f,t}) + \mu_{i,t}.$$

This equation says that the realized returns on any fund can be expressed as a linear function of its systematic risk, the realized returns on the market portfolio, the risk-free rate and a random error. If a fund manager is a superior forecaster, he will tend to select systematically securities which realize $\mu_{i,t} > 0$. Allowance for such forecasting ability can be made by simply not constraining the estimating regression to pass through the origin. Hence Jensen allows for such possible existence of a non-zero constant in equation above by using following as the estimating equation:

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_i (R_{m,t} - R_{f,t}) + \varepsilon_{i,t} ,$$

where $R_{i,t} - R_{f,t}$ is the excess return on fund i in period t, $R_{m,t} - R_{f,t}$ is the excess return on the market proxy portfolio in period t, $\varepsilon_{i,t}$ is a new error term, which has $E(\varepsilon_{i,t}) = 0$, and should be serially independent. Then Jensen (1968) argues that if the portfolio manager has stock selection ability, the intercept, α_i will be positive. In contrast, a naïve random selection buy and hold policy should be expected to yield a zero intercept.

However, Roll (1977, 1978) forcefully argues that “the use of CAPM as a benchmark in performance evaluation is logically inconsistent under the assumptions of the model since any measured abnormal performance can only occur when the market proxy is inefficient”. Moreover, CAPM uses a single factor, beta, to compare the excess returns of a fund with the excess returns of the market portfolio. It apparently oversimplifies the complex market. Also it cannot account for non-index stock-holdings, such as small-cap stocks or value stocks. The obvious inefficiency of the usual market proxies, coupled with concern over the testability of the CAPM, has led researchers to explore alternative theories of asset pricing.

One theory which has stimulated much recent research is the Fama-French three-factor model (hereafter FF3F) from Fama and French (1992, 1993). The systematic factors in their model are firm size, book-to-market ratios (B/M), as well as the market portfolio. These two firm-characteristic variables are chosen due to long-standing observations that firm size and B/M seem to be predictive of average stock returns. Hence, Fama and French suggest that size or the B/M may be proxies for exposures to sources of systematic risk not captured by CAPM beta and, thus result in the return premium associated with these factors. For instance, firms with high B/M are more likely to be in financial distress and small stocks may be more sensitive to changes in business conditions. It is reasonable to infer these variables may capture sensitivity to risk factors in the macro-economy. To construct portfolios to track the firm size and B/M factors, Fama and French (1993) sort firms into two groups on firm size (Small and Big groups) and three groups on B/M (Low, Median, and High groups). From the intersections of the two size and three B/M groups, six portfolios (S/L, S/M, S/H, B/L, B/M, and B/H) are constructed. The size premium, SMB (for small minus big), is the difference in returns of an equally weighted long position in the three small-stock portfolios and an equally weighted short position in the three big-stock portfolios:

$$SMB = \tfrac{1}{3}(S/L + S/M + S/H) - \tfrac{1}{3}(B/L + B/M + B/H).$$

Similarly, the book-to-market effect, HML (for high minus low), is calculated from the difference in returns between an equally weighed long position in the high B/M portfolios and an equally weighted short position in the low B/M portfolios:

$$HML = \tfrac{1}{2}(S/H + B/H) - \tfrac{1}{2}(S/L + B/L).$$

Then, they obtain FF3F as:

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_i(R_{m,t} - R_{f,t}) + s_i SMB_t + h_i HML_t + \varepsilon_{i,t},$$

where β_i, s_i, and h_i are the factor loadings on the three relevant risk factors.

Subsequently, academics developed asset pricing models using diverse risk factors based on their different research purposes. As Fama and French (1996) also admit, their three-factor model cannot explain cross-sectional variation in momentum-sorted portfolio returns. Hence, Carhart (1997) constructs a four-factor model (hereafter FF+Mom) using Fama-French three-factor model plus an additional factor, one-year momentum anomaly, introduce by Jegadeesh and Titman (1993):

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_i (R_{m,t} - R_{f,t}) + s_i SMB_t + h_i HML_t + p_i PR1YR_t + \varepsilon_{i,t},$$

where $PR1YR_t$ (momentum factor) is the difference in return between a portfolio of past winners and a portfolio of past losers; past winners are the firms with the highest 30% eleven-month returns lagged one month and past losers are the firms with the lowest 30% eleven-month returns lagged one month. Carhart finds that four-factor model can explain sizeable time-series variation, and SMB, HML, and PR1YR factors could account for much cross-sectional variation in the return on stock portfolios. Thus he suggests that the momentum factor is statistically significant in explaining returns on mutual funds, and the four-factor model substantially improves on the average pricing errors of the CAPM and FF3F.

3.2.2. Liquidity-Based Models

Later, Pastor and Stambaugh (2003) show the liquidity risk is also related to expected return differences that are not explained by stocks' sensitivities to market, size, B/M, and momentum factors. First, they sort stocks on the basis of values of liquidity beta (β_i^L) and form 10 portfolios, then they construct a traded liquidity risk factor (LIQ_V), which is the value-weighted return on the 10-1 portfolio (i.e. highest minus lowest liquidity-beta decile). By adding LIQ_V to market factor, SMB, HML, and PR1YR, they find LIQ_V prominently in the ex post tangency portfolio, at the cost of PR1YR especially. That is, the momentum factor's importance is reduced by their liquidity risk factor. Therefore, in order to include a more dramatic role for a liquidity risk factor, in this research we add traded liquidity factor, LIQ_V, only to the Fama-French factors as Pastor-Stambaugh four-factor model (hereafter FF+PS):

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_i (R_{m,t} - R_{f,t}) + s_i SMB_t + h_i HML_t + l_i LIQ\_V_t + \varepsilon_{i,t}$$

where LIQ_V_t (liquidity risk factor) is the difference in return between the highest liquidity risk decile and lowest liquidity risk decile; and the factor loading l_i captures the asset's comovement with aggregate liquidity.

Since Pastor and Stambaugh (2003) provide evidence that liquidity risk is a state variable, whilst the Fama-French three-factor model and Carhart four-factor model fail to explain the liquidity premium, Liu (2006) develops a new liquidity-augmented two-factor model. He argues that his liquidity-augmented model not only explains the size, book-to-market, and fundamental to price ratios, but also captures the liquidity risk, which is not properly explained by prior models.

First of all, he defines a new liquidity measure, LM12, as the standardized turnover-adjusted number of zero daily trading volumes over the prior 12 months:

$$\mathrm{LM12} = [\text{No. of zero daily volumes in prior 12 months} + \frac{1/(\text{12-month turnover})}{\text{Deflator}}] \times \frac{21 \times 12}{\mathrm{NoTD}},$$

where 12-month turnover is the sum of daily turnover over the prior 12 months; daily turnover is the ratio of the number of shares traded on a day to the number of shares outstanding at the end of the day; NoTD is the total number of trading days over the prior 12 months. The number of zero daily trading volumes over the prior 12 months captures the discontinuity of trading, that is, the absence of trade indicates a security's degree of illiquidity. Then based on this trading discontinuity measure of liquidity (LM12), Liu sorts all common stocks in ascending order, and forms two portfolios (low-liquidity and high-liquidity portfolios). Through buying one dollar of equally weighted low-liquidity portfolio and selling one dollar of equally weighted high-liquidity portfolio, the liquidity factor (LIQ) is constructed. Adding LIQ to CAPM, he develops the liquidity-augmented two-factor model (hereafter LCAPM):

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_{m,i}(R_{m,t} - R_{f,t}) + \beta_{l,i}\mathrm{LIQ}_t + \varepsilon_{i,t},$$

where LIQ_t (liquidity factor) is the difference in return between the bottom liquidity decile and top liquidity decile; $\beta_{l,i}$ is the loading of liquidity factor, i.e. fund liquidity risk. Then, by substituting $r_{i,t} = R_{i,t} - R_{f,t}$ and $r_{m,t} = R_{m,t} - R_{f,t}$, he transforms equation above into the following:

$$r_{i,t} = \alpha_i + \beta_{m,i} r_{m,t} + \beta_{l,i} LIQ_t + \varepsilon_{i,t},$$

where $r_{i,t}$ is the excess return on fund i in period t; $r_{m,t}$ is the excess return on the market proxy portfolio in period t.

During the examination of mutual fund performance, we will emphasize the effect of fund liquidity on performance through observing this loading of liquidity factor. Liu (2009) asserts that it is essential to distinguish concepts, since liquidity level and liquidity risk are related but different. Moreover, the Liu LCAPM implies that the expected excess return of a fund is explained by the covariance of its return with the market and the liquidity factors. As Liu (2006) emphasizes, this model explains well the cross-section of stock returns, especially captures the liquidity risk.

All these models above (either conventional models or liquidity-based models) are unconditional models, because they assume that “both investors and fund managers use no information about the state of the economy to form expectations” (Otten and Bams, 2004). However, an active fund manager may alter portfolio holdings and weights and, consequently, portfolio betas depending on publicly available information. So if a fund manager trades on this information and employs dynamic strategies, these unconditional models may generate unreliable results. For this reason, Ferson and Schadt (1996) advocate conditional performance measurement. They use time-varying conditional expected returns and conditional betas instead of the usual, unconditional betas:

$$\beta_{i,t} = \beta_{i,0} + B_i^{'} Z_{t-1},$$

where $B_i^{'}$ is a vector of response coefficients of the conditional beta with respect to the instruments in Z_{t-1}; Z_{t-1} is a vector of lagged predetermined instruments (including the 1-month T-bill rate, dividend yield on the market index, the slope of the term structure, and the quality spread). Moreover, Christopherson et al. (1998) and Christopherson et al. (1999) assert that alpha may also be dynamic since beta can be dynamic. Assuming that alpha may depend linearly on Z_{t-1}, so that:

$$\alpha_{i,t} = \alpha_{i,0} + A_i^{'} Z_{t-1},$$

where $\alpha_{i,0}$ measures abnormal performance after controlling for publicly available information (Z_{t-1}) and adjustment for the factor loadings ($A_i^{'}$) based on this information. Introducing time-variation in alpha makes it possible to examine whether managerial performance is indeed constant, or if it varies over time as a function of information.

However, what we have to emphasize here is that capturing time variation in the regression slopes and intercept poses thorny problems, and we leave this potentially important issue for future research. In addition, as documented by Barras et al. (2010), using unconditional or conditional modelling has no material impact on their results for fund performance. Therefore, in this thesis, we only employ these unconditional models and present results from them.

3.3. Mutual Fund Performance

The performance of actively managed equity funds is of key concern in mutual fund research, particularly because they try to beat the market and their passively managed counterparts. Do mutual fund managers add value for investors through actively trading? This question has been asked for a long time. Although the number of studies on mutual fund performance has increased substantially with the rapid growth of the mutual fund industry, academics remain with contradictory conclusions regarding the mutual fund performance on net and gross returns, as well as whether certain factors have effects on fund performance.

3.3.1. Evidences of Underperformance, on Net Return

As the seminal paper on mutual fund performance, Jensen (1968) emphasizes, the absolute measure of fund performance is used to refer to a fund manager's predictive ability, i.e. the skill to earn returns through successful prediction of security prices. Employing the CAPM as estimating equation, he suggests using the intercept in the CAPM, Jensen alpha, to assess performance. Thus, if a fund manager has an ability to forecast security prices, the alpha will be positive, and a naïve random selection buy and hold policy could be expected to yield a zero alpha. After evaluating 115 mutual funds' performances relative to the S&P 500 index in the period of 1945-1964, he finds that the funds' mean value of alpha is -0.011, that is on average the funds earned 1.1% per year less than expected given their level of systematic risk. Also, he finds only three funds that have performance measures which are significantly positive at the 5% level, based on the t-statistic of alpha. Consequently, he claims that not only are these funds not able to forecast future security prices well enough to recover expenses and fees, but also there is very little evidence that an individual fund is able to do significantly better than that mere random chance.

Later studies start with looking for the reasons of underperformance through testing returns at different levels and improving study data and methodologies. For example, Grinblatt and Titman (1989) consider negative performance for the average mutual fund unsurprising from an economic perspective. If fund managers have superior stock-picking talent, they may be able to claim higher fees and expenses for their talent. Thus, Grinblatt and Titman use gross portfolio returns as well as actual (net) returns in their research. Employing the data that contain quarterly equity holdings of mutual funds, they are able to construct hypothetical mutual fund returns, i.e. approximate gross returns.[12] In addition, they examine the effect of investment objectives and fund size on performance and suggest that both are determinants of abnormal performance. Finally, they report that superior gross performance may exist among growth funds, especially aggressive growth funds and smaller funds but these funds have the higher expenses, eliminating abnormal returns and resulting in underperformance net of all expenses. In a comprehensive work, Malkiel (1995) uses all diversified equity mutual fund data (from Lipper Analytic Service), which allows him to examine more precisely performance and the extent of survivorship bias. For all funds in existence during the 21-year time period of 1971-1991, he calculates the funds' alpha of excess performance using the CAPM, and finds the mean of alpha is -0.06% but the t-statistic is only -0.21, so it is indistinguishable from zero. For the funds in 10-year period of 1982 to 1991, he obtains similar results; the average alpha with net returns is negative (-0.93%) and positive (0.18%) with gross returns, but neither alpha is significantly different from zero. As a result, he concludes that funds in the aggregate have not outperformed benchmark portfolios both after management expenses and even before expenses. To some extent, his study does not provide any reason to abandon a belief that securities markets are efficient. Also, he suggests that investors would be considerably better off by buying an index fund, than by trying to select an active fund manager who appears to possess selectivity skill. Subsequently,

[12] Specifically, their gross returns are constructed by multiplying portfolio weights (can be equally weighted or value weighted) by the monthly excess returns of securities and sum up. Therefore, these data have no expenses, fees or transaction costs subtracted from them.

Gruber (1996) uses a sample of 270 mutual funds listed in Wiesenberger's Mutual Funds Panorama during the period 1985-1994, and employs three different measures of performance (return relative to the market, excess return from CAPM, and excess return from a four index model). His study shows that mutual funds underperform the market by 1.94% per year. The risk adjusted return is estimated to be -1.56% per year using the CAPM model and -0.65% per year using the four index model, which leads to more accurate performance evaluation he thinks. Also, Gruber finds that the average fund's expense is 1.13% per year, which suggests that active management funds charge the investors more than the value added.

All of the aforementioned studies assess the performance of mutual funds by examining the actual returns that investors realize from holding the funds. In contrast, a study by Daneil et al. (1997) develops a new measure of fund performance, that is, to use benchmarks based on the characteristics of stocks held in the portfolio to measure fund performance. Specifically, the benchmarks are constructed from the returns of 125 passive portfolios that are matched with stocks held in the evaluated portfolio on the basis of the market capitalization, book-to-market, and prior-year returns. The authors apply these measures to a new database of mutual fund holdings covering over 2500 equity funds from 1975 to 1994. Taking the characteristic-based approach, they decompose the overall excess return of a fund into characteristic selectivity (CS), characteristic timing (CT), and average style (AS) measures, which capture the selectivity, timing, and style aspects of performance. As a result, they suggest that the funds as a group possess some stock selection ability, but that funds exhibit no timing ability. For a closer look, they break down the performance by fund types. The aggressive-growth and growth funds exhibit the highest performance on hypothetical returns (gross returns), and also generate the largest costs. Similarly, using a new widely-cited fund database[13], Wermers (2000) empirically decompose performance into several components to analyze the value of active fund management. By a series of complicated matching,[14] Wermers obtains the merged database which has 1788 distinct funds that existed sometime during 1975 to 1994. With these data, he decomposes fund returns into several factors such as selectivity, style timing, long-term style-based returns, expense ratios, and transaction costs. The first three components correspond to CS, CT, and AS in Daniel et al. (1997). He finds that mutual funds' stock portfolios outperform a market index on average by 1.3% per year (therein 0.6% is due to the higher returns associated with the characteristics of stocks held by the funds; the remaining 0.7% is due to talents in picking stocks that beat their characteristic benchmark portfolios). However, the funds' net return is about 1% lower than market index. Therefore, he attributes the difference of 2.3% between the funds' stock returns and net returns to non-stock portfolio components: expense ratios and transaction costs. To sum up, these two studies both attribute much of fund performance to the characteristics of the stocks held by funds, yet, their results are similar to previous studies: the fund performance on funds' stock returns (or hypothetical returns, gross returns) is better than market, whereas on net returns the mutual funds underperform the market index.

So far, most academic studies primarily use two approaches to assess fund performance: examining the actual fund returns that investors realize and using characteristic-based benchmarks. No matter which approach is used, a consensus has been reached that, on average, actively managed funds underperform their passively managed counterparts, net of costs, despite some evidence showing that they might be

[13] The new database comes from the merging of Thomson Reuters CDA/Spectrum mutual fund holdings database with Center for Research in Security Prices (CRSP) mutual fund database (inc. mutual fund net returns, expenses, turnover levels, and other characteristics).

[14] See Appendix A in Wermers (1999) and Appendix A in Wermers (2000).

able to earn positive return before expenses and fees.

More recently, an increasing number of papers in this area have switched their research topic to verify whether certain subgroups of fund managers have superior stock-picking ability. For instance, whether the star fund managers are genuine stock-pickers or are simply endowed with luck. Through bootstrap simulation (a kind of Monte Carlo method), it is possible to examine the difference in value added between all funds that exhibit a certain alpha and those funds that exhibit the same alpha by luck alone. Kosowski et al. (2006) were first to use the bootstrap method into fund performance study. They propose many reasons why the bootstrap in necessary for proper inference. For example, individual funds exhibit non-normally distributed returns, and the cross section of funds represents a complex mixture of these individual fund distributions. Applying the bootstrap can reduce the difference between true and nominal probabilities of correctly rejecting a given null hypothesis. They investigate the performance of 1788 equity funds that survive for at least 5 years during 1975-2002. For testing whether the estimated Carhart four-factor alphas of star fund managers are due only to luck or to genuine stock-picking skill, they examine the statistical significance of the performance of best and worst funds based on a flexible bootstrap procedure (residual-only resampling) applied to a variety of unconditional and conditional Carhart four-factor models of performance. The basic idea of their bootstrap procedure is, for each fund, to construct artificial return with a true alpha that is zero through residual-only resampling. Since the results cannot be explained by sampling variability alone, they conclude that the performance of these best and worst funds is not solely due to luck. Moreover, they also find strong evidence of superior performance among growth-oriented funds using bootstrap tests, but no evidence among income-oriented funds. Similarly, using another bootstrap simulation method, joint sampling of entire cases, Fama and French (2010) aim to infer the existence of superior and inferior managers in the cross section of fund returns during 1984-2006. They first estimate monthly returns on equally weighed and value weighted portfolios of the funds. In terms of net returns, they find fund performance is poor. The Fama-French three-factor and Carhart four-factor intercepts for equally weighed and value weighed on net returns are negative, ranging from -0.81% to -1.00% per year, with t-statistics from -2.05 to -3.02. These findings are in line with earlier studies (i.e. mutual funds on average underperform benchmarks on net returns). To distinguish between luck and skill, they then compare the distribution of t-statistics of alpha from actual fund returns with the distribution from bootstrap simulations in which all funds have zero true alphas. Their finding is that only top 3 percentile funds have enough skill to cover costs; that is managers of these funds do have stock-picking talent. Moreover, they also give hints about whether manager skill affects expected returns by comparing the percentiles of t-statistics of alpha for actual fund returns with the simulation averages. This likelihoods analysis confirms that skill sufficient to cover costs is rare. Even for the portfolio of funds in the top percentiles, the estimate of net return three-factor true alpha is about zero, which indicates that its performance is not better than the efficiently managed passive funds.

With the recently introducing bootstrap simulation approach, the question of whether the apparent superior performance of a small group of funds is from genuine talent or from amazing luck is answered well. Although there are a few active funds (only 3% - 5%) produce sufficient returns to cover their costs, “these star managers are hidden by the mass of managers with insufficient skill” (Fama and French, 2010). Overall, the results of mainstream research on fund performance conclude that true alpha on net returns to investors is negative for most if not all actively managed equity mutual funds.

3.3.2. Other Issues

In the mutual fund industry, another major issue is whether abnormal performance can persist. Persistence means that past winners or losers tend to stay winners or losers in the future. If persistence exists, investors could allocate additional money to winner funds and withdraw from loser funds.

In early studies, Grinblatt and Titman (1992) wonder whether past performance provides useful information to an investor, and analyze the relationship between mutual fund future performance and past performance on the basis of securities characteristics. They follow a three-step procedure: split the 10-year (1975-1984) returns sample of 279 funds into two 5-year subperiods; use ordinary least squares to estimate the abnormal returns (alphas) for each 5-year subperiod; estimate the slope coefficient in a cross-sectional regression of alphas computed from the last 5 years of data on alphas computed from the first 5 years of data. They find that mutual funds in the second 5-year are expected to realize a 0.281% greater alpha for every 1% alpha achieved in the first 5-year. Moreover they use the same chronological sorting and random sorting to examine the average alpha of the top 10% and bottom 10% performing funds in a 5-year period. Their research indicates that there is positive persistence in mutual fund performance, with stronger evidence among past losers over 5 to 10 years horizons. As to the persistence in the short-term horizon, Hendricks et al. (1993) examine quarterly net returns data on a sample of open-end, no-load, growth-oriented equity funds (listed in the Wiesenberger Mutual Funds Panorama) over the period of 1974-1988. They first rank funds into eight performance-ranked portfolios (octiles) on the basis of the most recent four quarters' returns, and then find that mean excess returns, Sharpe's measure and Jensen's alpha rise monotonically with octile rank. That is, a portfolio of better recent four quarters' performance is better in the next four quarters than the mean fund performance. Lastly, they suggest a strategy of selecting: every quarter, the top performers based on the last four quarters can significantly outperform the average mutual fund. Because it is a short-term phenomenon, roughly a one-year period, they attribute the persistence to "hot hands"[15]. Subsequently, Goetzmann and Ibbotson (1994) using data for 728 mutual funds over the 1976-1988 examine 2-year, 1-year, and monthly gross and risk-adjusted returns. They find support for the winner-repeat question for funds overall, and the top-quartile and lower-quartile funds experience the greatest performance persistence. Similar finding are also reported by Brown and Goetzmann (1995). They show evidence of statistical persistence for a 1-year and 3-year period, using a database free of survivorship bias, rather than a database including only surviving funds as prior studies. Meanwhile, Malkiel (1995) also examines the 'hot hand' phenomenon. Following the Goetzmann and Ibbotson (1994) method, he analyzes the persistence of performance by constructing two-way tables showing successful performance over successive periods. He finds that hot hands (winning followed by winning) during the 1970s, occur much more often than a win followed by a loss (65.1% repeat winners); the relationship is considerably weaker during the 1980s (only 51.7% repeat winners).

Perhaps, the most influential paper on fund performance persistence is Carhart's (1997). He uses a comprehensive database of 1892 diversified equity mutual funds and 16109 fund-years covering the period 1962-1993, and employs two models to measure performance: the CAPM and Carhart four-factor model. After sorting funds into deciles based on past 1-year or past 3-year four-factor alpha, he finds some evidence of 1-year persistence for the top and bottom deciles ranked funds using a contingency

[15] "Hot hands", comes from the argot of the sports world. In mutual fund research, it indicates that the winner funds could still be the winners in the future, especially in the short-term.

table of initial and subsequent 1-year mutual fund rankings. Then, he tracks each decile fund's gross returns over the following 1-5 years and finds persistence of up to 3 years occurs for the lowest decile ranked fund but for all other decile there is little or no evidence of persistence. According to his research, buying last year's top-decile mutual funds and selling last year's bottom-decile funds yields a return of 8% per year (0.67% per month). Finally he suggests several rules for investors, such as avoiding funds with persistently poor performance; funds with high returns last year have higher-than-average expected returns next year, but not in years thereafter. His general result is that persistence in superior fund performance is very weak and he attributes persistence to fund expenses and momentum factors.

As to the current papers on performance persistence, using some new approaches, their results are to some extent different with Carhart's findings. Following the Bayesian framework of Pastor and Stambaugh (2002), a totally different approach, Busse and Irvine (2006) estimate the persistence of mutual fund performance. They claim that incorporating a long time series of passive asset returns in a Bayesian method estimates fund performance more precisely and find that Bayesian alphas based on single-factor CAPM are particularly useful for predicting future standard CAPM alphas. Hence, they suggest investors do not adhere to a strategy of investing in the lowest expense fund (index fund) but instead focus on past performance net of expenses. More recently, Cremers and Petajisto (2009) advocate using both active share (emphasizing stock selection) and tracking error volatility (emphasizing systematic factor risk timing) as convenient empirical proxies, to quantify portfolio management. They show strong evidence for performance persistence of the funds with the highest active share: the prior one-year winners within the highest active share quintile are very attractive, with a benchmark-adjusted 5.1% annual net return and a

3.5% annualized alpha with respect to the four-factor model. Overall, the literature frequently reaches conflicting conclusions regarding the persistence of mutual fund performance, which provides academics with a controversial question yet to be answered.

Other issues of interest are the effects of characteristics such as fund scale and fund liquidity on fund performance. Chen et al. (2004) investigate the effect of scale on performance in the active mutual funds and explore the idea that fund returns decline with lagged fund size because of the interaction of liquidity and organization diseconomies. They use the Center for Research in Security Prices (CRSP) mutual fund database from 1962 to 1999, giving 3439 distinct funds and a total 27431 fund-years in their analysis. After sorting all funds into size quintile, they find that the gross return of all funds is 0.01% per month, which means fund managers have the ability to beat or stay even with market before management fees; but the net return is -0.08% per month (-0.96% per year), which indicates mutual fund investors are apparently willing to pay much in fees for limited stock-picking ability. More importantly, they also notice that smaller funds appear to outperform their larger counterparts. Adopting cross-sectional variation, they analyze the effect of past fund size on performance in Fama and MacBeth (1973) regression, and find that fund performance declines with own fund size but increases with the size of the other funds in the family. Moreover, they attribute the fund size erosion of performance to liquidity (transaction costs) and organizational diseconomies (hierarchy costs). Lately, it has been a trend to research mutual fund investment behaviour from the characteristics of mutual fund and fund family. Pollet and Wilson (2008) investigate the effect of asset growth on aspects of fund investment behaviour, to identify the constraints acting on funds as they grow. Using the matched Thomson Reuters CDA-CRSP mutual fund sample from 1975 to 2000, they sort all funds into quintiles by fund scale and fund style measure (the weighted average market capitalization of companies owned by the fund) for every year. They discover (i) the average number of stocks held by a fund increases with fund total net asset (TNA), but very slowly; (ii) the smallest-cap funds tend to have lower TNA and account for less market share, while the largest-cap funds are not always the largest funds or the largest market segment. Meanwhile, they examine the relationship between diversification and subsequent performance. Using the procedure of Fama and MacBeth (1973), they estimate cross-sectional regressions of risk-adjusted fund returns on a constant and fund characteristics, and then average the coefficients across months. They conclude that higher fund TNA is associated with lower returns, while higher family TNA is associated with higher returns. In addition, they document a positive relationship between diversification and subsequent returns and this relationship is stronger for small-cap funds.

Academic studies on mutual fund have given little consideration to the impact of liquidity on performance, yet it could seem sensible that fund managers have to hold considerable volumes of liquid stocks for providing liquidity to investors and dealing with possible share redemptions. Perhaps the first influential paper considering a liquidity factor on mutual fund performance is Edelen (1999). He considers the effect between funds' abnormal return and fund investor flows. At first, he argues that fund managers need to provide a great deal of liquidity to investors, thus having to engage in a material volume of uninformed liquidity-motivated trading in which they will be unable to avoid below-average performance. According to informational efficient market theory of Grossman and Stiglitz (1980), equilibrium is attained only when uninformed traders sustain losses to informed traders. Edelen's research argues that flow adversely affects a fund's performance because the position acquired in a liquidity-motivated trade has a negative impact on the fund's abnormal return. His sample consists of 166 equity funds selected randomly from the Morningstar's Sourcebook (1987 summer edition). Calculating from a single-factor market model, he exhibits the unconditional average net abnormal return (α) equals to -1.63%, but after controlling for the detrimental effects of flow-related liquidity trading the conditional net annual abnormal return is only -0.26%. Hence, he attributes the negative return performance to the costs of liquidity-motivated trading. Subsequently, Massa and Phalippou (2005) construct and use a new portfolio liquidity ratio (PLIQ), which is based on the average of the individual stock illiquidity ratios of Amihud (2002) (ILLIQ). Using a large sample of active equity mutual funds over the period of 1983-2001, they estimate a cross-sectional relation between portfolio liquidity and the fund characteristics related to the liquidity. They find out several most important determinants of liquidity: fund size, manager's trading frequency, and portfolio concentration. Then they consider two cases that portfolio liquidity can affect performance: (i) short-term divergences from the optimal level; (ii) market-wide liquidity shocks. In the first case, they find funds that fall in the decile that deviate most underperform funds that fall in the decile that deviate least by over 0.10% per month on average. As these deviations are uncorrelated over time, investors cannot use them to select funds. In the second case, they find liquid funds outperform illiquid funds by as much as 1.4% per month during the most illiquid months. Also investors cannot use this information to select funds since this would require knowing future liquidity shocks. As a result, they conclude that portfolio liquidity does not affect performance in a predictable way but note that mutual funds' better performance in bad (illiquid) times might be partially or totally driven by liquidity. More recently, Shawky and Tian (2010) revisit successfully the issue of fund liquidity but in the context of small-cap equity mutual funds. They consider that small-cap funds commonly tend to buy less liquid stocks and sell the more liquid stocks, which is called as “liquidity creation” to the market. Then they examine the role small-cap fund managers play as providers of liquidity and the mechanism by which they create liquidity in the market. Lastly, their empirical results show that small-cap mutual fund managers are able to earn an additional 1.5% return per year as compensation for providing such liquidity services to the market. Obviously, their study confirms that there is a strong relationship between the fund scale and the fund liquidity characteristics.

Since there is no consensus on the relationship between liquidity and mutual fund performance, finding an appropriate liquidity factor and showing how it might affect mutual fund performance is deserving of further study. Accordingly, from a new perspective, this thesis will offer re-examination of mutual fund performance and the effect of liquidity on fund performance.

CHAPTER 4: DATA & SAMPLE

4.1. Data Sources

Consistent with most academic papers in this field, our research data of U.S.-based equity mutual funds are primarily from three sources.

(1) The return information of mutual funds comes from the Center for Research in Security Prices mutual fund database (hereafter CRSP-MF). Besides fund monthly net returns, monthly total net asset, monthly net asset value per share, it provides other fund characteristics, such as fund's name, investment style, expense ratio, investor flows, turnover, and so on.[16] Although the CRSP-MF provides information on survivor-bias-free fund data, which enables us to escape survivorship bias in measuring mutual fund returns, a selection bias (or incubation bias) does exist. The SEC has begun permitting some funds with prior returns histories as private equity funds to add these returns onto the beginning of their public histories. Thus, successful private equity fund (surviving incubated fund) histories are included in the CRSP-MF database.[17]

(2) The information on the stock-holdings of each fund is derived from the Thomson Reuters mutual funds holdings database (also known as CDA/Spectrum database, hereafter TR-CDA). From the TR-CDA, we can collect the details on the stock-holdings of funds (such as stock name, share price, and shares held at end of some quarter).[18] Additionally, this database consists of management company name,

[16] The fund information provided by the CRSP-MF database is based at share-class level, rather than at fund level. We will adjust it in later data processing.

[17] To lessen the effects of incubation bias, we will limit the tests to mutual funds reach $25 million in total net assets in the chapter of Robustness Tests.

[18] In the TR-CDA database, only the equity portion of funds is reported. Neither bond nor other types of securities are reported.

fund name, total net asset under management, and the self-declared investment objective for mutual funds investing in the U.S. markets. The database provides holdings data at quarterly intervals, although some funds report their holdings during these years semi-annually as required by the SEC in the early 1980s. Moreover, these data are collected not only from reports filed by mutual funds with the SEC but also from voluntary reports generated by the fund companies. Therefore, the data unfortunately have reporting gaps for many mutual funds. Inevitably, there is a selection bias since some funds' reports are voluntary.

(3) Given the two databases above provide distinctly different fund identifiers (CRSP_FUNDNO and FUNDNO, respectively), to merge them, we have to depend on the third database, MFLinks file[19], from Wharton Research Data Services (WRDS), since it provides a uniform and unique fund identifier (Wharton Financial Institution Center Number, WFICN). Also, it provides other fund information, such as fund name, management company abbreviation, investment objective code and country. The last two items are useful for us to identify U.S. equity mutual funds. More importantly, the MFLinks file solves some significant problems in the CRSP-MF and TR-CDA databases, such as re-used FUNDNO, arbitrary change in FUNDNO, and multiple share-classes of same fund. As Rabih Moussawi declared at a WRDS users meeting in 2007, "MFLinks file focuses on U.S. domestic equity funds and covers 15268 share-classes (in the CRSP-MF) and 6037 funds (in the TR-CDA). Thus the MFLinks database is of a much higher quality today" (Moussawi, 2007).

As far as the stock data and liquidity data are concerned, we collect them from two other sources.

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[19] The MFLinks file was originally developed by Prof. Russ Wermers in 2000, and updated by WRDS. There are two sub-databases in the MFLinks file: MFLinks-CRSP and MFLinks-CDA, which are used to match the CRSP-MF and TR-CDA respectively.

(4) The data on the general information about stocks are derived from the Center for Research in Security Prices NYSE/AMEX/NASDAQ stock file (hereafter CRSP-STK). This provides information on individual securities such as stock identity information (company name, permanent number, and CUSIP identifier), share type, share code, price, returns, trading volumes, shares outstanding, and so forth. In this research, we focus on all common and ordinary stocks (whose stock type code, SHRCD, equals to 10 or 11) traded on the NYSE, AMEX, and NASDAQ markets.

(5) The stock liquidity information is collected from the stock liquidity database (hereafter LIQ-STK) provided by Prof. Weimin Liu. It includes four liquidity measures for each share: Liu's trading discontinuity measure of liquidity (LM12), turnover ratio (TO12), Amihud's price impact ratio (RtoV12), and Hasbrouck's effective cost (EC)[20]. Meanwhile, it also provides two firm characteristics: stock's market capitalization (MV) and book-to-market-value ratio (B/M). Specifically, LM12 is defined by Liu (2006) as the standardized turnover-adjusted number of zero daily trading volumes over the prior 12 months; TO12 is the average daily turnover over the prior 12 month[21]; RtoV12 is defined by Amihud (2002) as the daily absolute-return-to-dollar-volume ratio averaged over the prior 12 months; and EC is defined by Hasbrouck's (2009) as Gibbs estimate of cost from Basic Market-Adjusted model.

In this thesis, to obtain a fund's abnormal performance, we estimate intercepts from five asset pricing models (CAPM, Fama-French three-factor model - FF3F, Carhart four-factor model - FF+Mom, Pastor-Stambaugh four-factor model - FF+PS, and Liu liquidity-augmented two-factor model - LCAPM). Thus, we also need to collect these models' factors. The factors of the first four models are derived from the

[20] Some of data in this database are provided by the original authors or collected from their websites. For example, the data of effective cost are collected from Hasbrouck's website at www.stern.nyu.edu/~jhasbrou.

[21] The daily turnover is the ratio of the number of shares traded on a day to the number of shares outstanding on that day.

Fama-French portfolios and factors database from WRDS. Such factors include risk-free return rate (RF), excess return on the market (MKTRF), size factor (small minus big size return, SMB), book-to-market factor (high minus low B/M return, HML), momentum factor (high minus low prior 1-year return portfolio return, PR1YR), and traded liquidity factor (high minus low liquidity beta portfolio return, LIQ_V). Actually, RF is the Ibbotson one month Treasury bill rate; MKTRF, SMB, HML, and PR1YR are from Kenneth French's data library at Dartmouth[22]; and LIQ_V is the PS_VWF in Pastor and Stambaugh (2003). As to the liquidity factor (LIQ) in the Liu LCAPM, this comes from the liquidity factor database provided by Prof. Liu. Similar to the construction of factors in the other asset pricing models, the LIQ is the illiquidity minus liquidity portfolio return.

4.2. Data Processing & Sample Construction

Although mutual fund common information in the CRSP-MF database has been reported since 1962, we focus on the period from 1984. As Fama and French (2010) claim, during 1962-1983 about 15% of funds in the CRSP-MF report only annual returns, and after 1983 almost all funds report monthly returns. Elton et al. (2001) also discuss the data problems in the CRSP-MF database for the period before 1984. They argue that, before the mid-1980s, differences in alpha are sufficiently large that conclusions might well be affected by the use of different fund databases. As to the data in the LIQ-STK and liquidity factor databases, they are all updated by the year-end of 2008. Therefore, our research time period is from January 1984 to December 2008, 25 years in total.

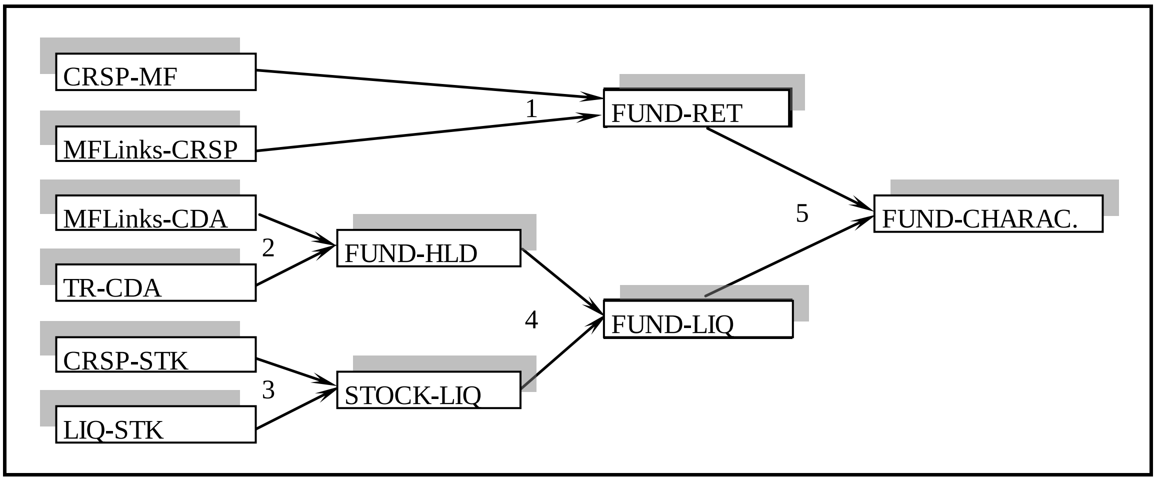
In data processing (see Figure 4.1), we employ six identifiers to combine all

[22] Kenneth French's data website: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

databases. CRSP_FUNDNO, FUNDNO, and WFICN are used as the fund (or share-class) identifiers, PERMNO and CUSIP as the stock identifiers, as well as YYYYMM (year and month) as time identifier.

Figure 4.1

Data Sources & Data Processing



First of all, based on a fund identifier, CRSP_FUNDNO, we combine the CRSP-MF and MFLinks-CRSP databases to attain a new fund return database with identifier WFICN (i.e. FUND-RET database). In the CRSP-MF database, the return values are calculated as a change in net asset value (NAV)[23]. Thus the returns values actually are net returns category at here. Net returns are calculated as follows:

$$R_t = (NAV_t / NAV_{t-1}) - 1.$$

According to the mutual fund database guide of CRSP, the t-1 may be up to 3 periods prior to t. This means that, if we observe a missing return, we need to remove the return of the following month, because CRSP-MF has filled this with the cumulated return since the month of last non-missing return. Similar to the method in Kosowski et al. (2006) and in Barras et al. (2010), we delete these cumulated returns. In fact, there are two aims in this step: (i) to let WFICN be fund identifier instead of

[23] The net asset value (NAV), including reinvested dividends, is net of all management expenses and 12(b)-1 fees, as well as the front and rear load fees are excluded.

CRSP_FUNDNO; (ii) to calculate the fund monthly return (RET) and total net asset (TNA) at fund level, rather than at share-class level. A mutual fund could enter the CRSP-MF database multiple times if it has diverse share-classes. These portfolios are independently listed but they have both the same pool of securities and fund manager, and only differ in the fee structures they charge (Massa and Phalippou, 2005). Thus, we calculate the monthly fund-level returns through weighting share-class-level returns by the proportion of each share-class monthly TNA at the beginning of each period. Meanwhile, we also compute the monthly fund-level TNA as the fund scale, summing of the TNA at each share-class-level.

Next, based on another fund identifier, FUNDNO, we merge the TR-CDA and MFLinks-CDA databases to achieve a new funds' stock-holdings database with identifier WFICN (i.e. FUND-HLD database). Indeed the purposes of this step are to let WFICN become fund identifier instead of FUNDNO in the fund holdings database; and to realize the data conversion from quarterly to monthly. Basically, the TR-CDA database provides fund holdings data quarterly, while we need monthly fund holdings data to match monthly fund returns data. The core idea of data conversion is that when observing a missing-month, we let the holdings data of this missing-month be the same as the last non-missing month. That is, if the datum of a month is missing, the datum of the prior non-missing month is carried forward. We also need to deal with some problems in the MFLinks-CDA database. For example, the data in the MFLinks-CDA were updated only to December 2006. So we have to assume that the variable SDATE2 (the end date) was December 2008 if it was December 2006. This might be a reasonable assumption, because if some fund appeared from January 2007, it would be at most 24 months survival-periods, which does not meet at least 36 months survival-period requirement in our research. Thus, it means that any new funds started from January 2007 would be excluded in our sample. Another problem in the MFLinks-CDA is there are a couple of different FUNDNOs with overlapped time periods for a same fund. Thus, we have to remove these faulty FUNDNO observations. Mainly based to fund's survival periods (the fund name and fund size also are used during the filtering process), we identify 212 fault FUNDNOs in total 1045 overlapped observations. Additionally, in this step we create a new variable AMT (dollar amount of stock-holdings, given by shares of holdings times stock price). This variable tells us the exact dollar amount of a stock held by a fund. As a result, we are able to calculate the weight of each stock in a fund.

Then, applying a stock identifier, PERMNO, we combine the CRSP-STK and LIQ-STK databases to gain a new stock liquidity database with CUSIP (i.e. STOCK-LIQ database). The CUSIP information will be used as the stock identifier later when we link this new database to the fund holdings database (FUND-HLD). Actually, the functions of the step are to let CUSIP be stock identifier instead of PERMNO in stock liquidity database; and to identify whether a stock is an ordinary common stock by matching share code (SHRCD). To be more accurate, we utilize the variable CUSIP from the TR-CDA database, and the variable NCUSIP from the CRSP-STK database (rather than the variable CUSIP, which means Head-CUSIP in the CRSP-STK database), just as Schwarz (2009) declares.

Accordingly, we move to the fourth step of generating the fund-level liquidity database (i.e. FUND-LIQ database), by combining the FUND-HLD and STOCK-LIQ databases based on another stock identifier, CUSIP. Through the value-weighted average of the liquidity measure of individual stock held by a fund, we acquire four fund liquidity measures: LM12, TO12, RtoV12, and EC, and two fund stock-holdings characteristics: MV and B/M, respectively. Because Hasbrouck's (2009) effective cost

(EC) is estimated over all trading days in a year, we cannot obtain the EC until the end of the year. For achieving the monthly data, we assume that the values of January to November of a year were same as the value of last December, since the data of EC are given once in December of each year. Furthermore, for observing the macro-level fund liquidity, we produce two new variables about fund cash flow: FLOW1 (the change in log TNA not attributable to the portfolio return), and FLOW2 (the difference between current TNA and previous TNA with attributable to the portfolio return). Using these two variables, it is straightforward to identify the direction and quantity of fund cash flow.

Lastly, we merge the FUND-RET and FUND-LIQ databases based on the unique fund identifier, WFICN, and then obtain a database containing the core characteristics of funds (i.e. FUND-CHARAC. database). It includes the monthly net return, monthly total net asset, diverse fund liquidity measures, and investment objectives, which are all at fund level. Moreover, for getting more fund characteristics, we define and generate new variables: STKPCT (percentage of stock-holdings in a fund) and STKNUM (number of stocks in a fund). Then we compute their time series averages for each fund and get another two new variables: STKPCTAVE (average of the percentage of stock-holdings) and STKNUMAVE (average of the number of stocks). These new variables are vital guides for identifying actively managed equity funds.

After a series of data processing steps, our preliminary sample has been obtained. There are still some essentials we need to stress. Because our attention is on actively managed U.S. equity funds, we eliminate funds with unknown objectives, and exclude money market funds, bond funds, balanced funds, international funds, mortgage-backed funds, funds that invest in precious metals, as well as specialized funds.[24] In addition, we exclude index funds in various databases. A fund is identified as an index fund if its fund name has the word "index" in the TR-CDA database. In the MFLinks database, we delete index funds that have "index", "indx", "inde", "idx", "ind", and "in" in their names. At the same time, we delete non-U.S. funds whose country names don't contain "United States". Moreover, as in Chen et al. (2004), we rule out funds with fewer than ten different stocks, i.e. we require the time series average of number of stock-holdings of a fund (STKNUMAVE) be not less than ten.[25] More importantly, besides using the classification of Thomson Reuters CDA/Spectrum, we apply a new standard (the proportion of the stock-holdings in a fund) to identify the equity funds, so as to avoid the fund classification confusion as much as possible. According to the SEC new rule 35d-1 in 2002, "an investment company with a name that suggests the company focuses its investments in a particular type of investment must invest at least 80% of its assets in the type of investment suggested by its name". Since then, investment companies have to raise the 65% threshold to 80% in order to comply with the rule, if they want to keep the investment objective and style unchanged. Thus, we require the time series average of percentage of stock-holdings of a fund (STKPCTAVE) be at least 70%.[26] That is, only if a fund invests 70% or more of its assets in stocks on average, it can be called as an actively managed equity fund. Furthermore we select only funds having at least 36 monthly return observations in order to obtain precise fund performance estimates. This requirement for return

[24] We exclude funds with the following several investment objectives (IOC) in the TR-CDA database: international (IOC=1), municipal bonds (IOC=5), bond & preferred (IOC=6), balanced (IOC=7), and metals (IOC=8).

[25] The Investment Company Act, 1940, section 5b-1 defines a fund as diversified if no more than 5% of its assets is invested in a company's securities and it holds no more than 10% of the voting shares in a company. Therefore, funds at least need to hold more than ten stocks, if diversified.

[26] The SEC rule 35d-1 must be complied with by July 31, 2002. Before then, the threshold is 65%, and after then is 80%. Since our data cover the time period from 1984 to 2008, after weighted averaging, 70% is a sound and reasonable threshold for identifying equity funds in our research.

observations is at least 60 months in Kosowski et al. (2006) and in Barras et al. (2010). However, Barras et al. (2010) conclude that reducing the minimum fund return requirement to 36 months has no material impact on their main results, so they believe that any biases introduced from the 36-month requirement are minimal.[27]

4.3. Sample Statistics Description

Our research universe contains fund-level monthly net returns data and liquidity data on 2417 distinct actively managed U.S. equity mutual funds and 318378 fund-month observations during the 25-year period (1984-2008).

Most existing related studies obtain the equity fund sample by matching funds in the CRSP-MF and TR-CDA databases using WFICN in the MFLinks file. Wermers (2000) firstly combines the TR-CDA database with the CRSP-MF database over the period from 1975 to 1994, and his sample includes 1788 equity funds. Kosowski et al. (2006) merge same databases over the period 1975 to 2002 and extract 2118 U.S. equity funds. Jiang et al. (2007) manually match the funds in the CRSP-MF and TR-CDA databases using a matching procedure similar to Wermers (2000). Besides using investment objective to identify each equity fund, they also require that a fund has a minimum of 8 quarters of holdings data and 24 monthly return observations. Their final matched dataset has 2294 unique funds over the period from 1980 to 2002. Kacperczyk et al. (2008) exclude funds which hold less 80% or more than 105% in stocks, hold less than 10 stocks, and whose scale are less than $5 million. In addition, they use a series of investment objectives[28] to identify equity funds, and finally obtain

[27] For robustness, we will also select funds having at least 60 monthly return observations as our research fund sample in chapter of Robustness Tests. Finally, we find there is no material impact on our main results no matter which monthly return observation requirement is applied, 60 or 36 months.

[28] Such as ICDI objectives, strategic insight objectives, Wiesenberger fund type code, common stock policy in the CRSP-MF database, and investment objective codes in the TR-CDA database.

2543 distinct funds (including index funds, 4.53% of total sample) during the period 1984 to2003. For identifying equity funds, Cremers and Petajisto (2009) also look at investment objective codes from Wiesenberg, ICDI, and TR-CDA databases. Then they select funds whose average of percentage of stock-holdings are at least 80%, and require a fund's equity holdings to be greater than $10 million. Consequently, their sample consists of 2647 funds in the period 1980-2003. Barras et al. (2010) combine CRSP-MF with TR-CDA and select funds only having at least 60 monthly return observations. Their final sample has 2076 equity mutual funds during 1975 and 2006. In the latest research, the fund numbers of whole sample and the equity fund requirements are both very similar to that in our sample. It appears that our actively managed U.S. equity mutual fund sample is at least as inclusive as those in the existing literature (see Table 4.1).

Table 4.1

Comparison of Numbers and Requirements for Actively Managed Equity Funds

In this table, we compare the number of equity funds, research time period, and equity fund requirements in the latest research with our fund sample.

Authors	# Equity Funds	Time Period	Main Requirements
Ours (2010)	2417	1984-2008	IOC, % stock-holdings, # stock-holdings, # ret. obs.
Barras, Scaillet, and Wermers (2010)	2076	1975-2006	IOC, # ret. obs.
Cremers and Petajisto (2009)	2647	1980-2003	IOC, % stock-holdings, size of stock-holdings
Kacperczyk, Sialm, and Zheng (2008)	2543	1984-2003	IOC, % stock-holdings, # stock-holdings, fund scale
Jiang, Yao, and Yu (2007)	2294	1980-2002	IOC, # quarters of holding data, # ret. obs.
Kosowski, Timmermann, Wermers, and White (2006)	2118	1975-2002	IOC
Wermers (2000)	1788	1975-1994	IOC

Note: # equity funds - the number of equity funds;

IOC - various investment objective codes;

% stock-holdings - the percentage of stock-holdings;

stock-holdings - the number of stock-holdings;

ret. obs. - the number of return observations;

quarters of holding data - the number of quarters of stock-holdings.

In Table 4.2, we present summary statistics of fund characteristics of the 318378 fund-month observations (2417 unique equity mutual funds) in our entire sample. It reports the mean, standard deviation, lower quarter, median and upper quarter for fund return, fund size, percentage of stock-holdings, number of stock-holdings, various fund liquidity measures, as well as fund stock-holdings characteristics.

Table 4.2

Summary Statistics of Entire Actively Managed Equity Fund Sample

This table represents summary Statistics of the 318378 fund-month observations during the 25 year periods (1984-2008). It reports the mean, standard deviation, lower quarter (Q1), median, and upper quarter (Q3) respectively for fund return, fund size, percentage of stock-holdings, number of stock-holdings, diverse fund liquidity measures, and fund stock-holdings characteristics, including log cash flow (FLOW1), quantity of cash flow (FLOW2), Liu's trading discontinuity measure of liquidity (LM12), turnover ratio (TO12), Amihud's price impact ratio (RtoV12), Hasbrouck's effective cost (EC), stock-holdings' market capitalization (MV) and book-to-market ratio (B/M).

	Mean	Std Dev	Min	Q1	Median	Q3	Max
Fund Net Return (monthly)	0.617%	5.638%	-49.713%	-2.141%	1.012%	3.771%	101.619%
Total Net Assets ($ million)	1037.60	4299.38	0.00	44.00	166.90	616.30	202305.80
Pct. of Stock Holdings	85.60%	6.08%	70.00%	81.62%	86.49%	90.06%	99.81%
No. of Stock Holdings	95	129	12	48	67	100	2885
FLOW1	0.0053	0.0612	-2.5059	-0.0114	0.0025	0.0203	3.0333
FLOW2 ($ million)	4.40	265.52	-52629.70	-3.17	0.27	8.00	53090.21
Liu's LM12	0.4112	1.8626	0.0000	0.0000	0.0000	0.0709	48.9437
TO12	0.7496	0.4160	0.1151	0.4362	0.6457	0.9862	6.3016
Amihud's RtoV12 (10^6)	0.038474	0.193725	0.000004	0.000361	0.001825	0.012913	21.044170
Hasbrouck's EC	0.003714	0.001724	0.000572	0.002649	0.003340	0.004461	0.030514
MV ($ million)	31612.25	36288.24	41.43	3219.91	14172.64	53956.42	305896.10
B/M	0.3998	0.1929	0.0113	0.2681	0.3674	0.4883	7.3890

As a typical equity funds, its scale is $1037.60 millions, investing 85.60% of its assets in stocks and holding 95 stocks on average. Because the median and upper quarter of total net assets (TNA) are $166.90 million and $616.30 million respectively, both are considerably less than the mean of TNA ($1037.60 millions), it is reasonable to believe that there are some huge funds in our whole sample period.[29] For example, we find that the largest was the Growth Fund of America, whose TNA reached $202.31

[29] In our 2417 equity funds during the period of 1984-2008, there are two funds whose scales once were larger than $100 billion. They are Fidelity Magellan Fund and Growth Fund of America.

billion in October 2007. This reflects not just the bull capital market at that time[30], but also results from its owning 14 share-classes. Table 4.2 also summarizes fund liquidity measures and fund stock-holdings characteristics. We find that the log cash flow (FLOW1) is positive and quantity of cash flow (FLOW2) on average is $4.40 million. They both indicate net cash inflow, which is consistent with the boost of equity fund scale in recent decades. From the micro-level fund liquidity measures, we conclude that the equity funds favour the highly liquid stocks. More specifically, the stocks held by a typical equity fund, on average, have fewer no-trading days (0.4112 for Liu's LM12), higher trading turnover ratio (0.7496 for TO12), and lower price-impact ratio (0.038474 for Amihud's RtoV12) than the means of U.S. stock markets.[31] Moreover, this table shows that, on average, the stock-holdings' market capitalization (MV) is $31612.25 million and the book-to-market ratio (B/M) is 0.3998 only, which implies equity funds prefer to hold big companies and growth companies.

Over the whole time period of 1984-2008, Table 4.3 shows key characteristics, at four-year intervals, for all actively managed equity funds. Panel A presents fund number, return, size, stock-holdings' proportion and stock number in a fund. In an average year, there are 1129 equity funds with average TNA of $820.02 million, average proportion of stock-holdings of 84.53%, average number of stock-holdings of 88, and average net return of 0.821% per month (approximately 9.852% per year). Panel A also reports the evolution of equity mutual funds. The TNA of equity funds increases nearly sixfold during the 25-year period from $255.72 million in 1984 to $1379.26 million in 2008. At the same time, we find the equity funds invest in a broader spectrum of stock-holdings during the later years. The average fund held 66

[30] On 9th October 2007, the Dow Jones Industry Average (DJIA) closed at the record level of 14164.53. Two days later on 11th October 2007, the DJIA traded at its highest intra-day level ever at the 14198.10 mark.

[31] In Liu (2009), the means of LM12, TO12, and RtoV12 for NYSE/AMEX stocks over 1963-2005 are 10.2, 0.242, and 4.14 respectively.

stocks in 1984, nearly doubled to 104 stocks in 2008, but the proportion of stock-holdings is almost unchanged still around 85% over whole sample time period. Despite the rapid increase in number and size of equity funds, we do not find any significant evidence that active equity fund managers as a whole earned higher return than the aggregate market. The average net return of equity funds (0.821% per month, 9.85% yearly) is just a little higher than the average of market returns (0.757% per month, 9.08% yearly) during whole sample time. On average, a typical equity fund would have similar performance with the aggregate market index.

Panel B provides the diverse fund liquidity measures and fund stock-holdings characteristics. Since our interest lies in the impact of liquidity on fund performance, we take a look at the changing trends of fund liquidity measures (FLMs). From the viewpoint of macro-level FLMs, we find that the log cash flow (FLOW1) and quantity of cash flow (FLOW2) are positive during most years.[32] That indicates net cash inflow and is consistent with the boost of equity fund scale in recent decades. As to the micro-level FLMs, we discover that the equity funds increasingly favour the highly liquid stocks. More specifically, the stocks held by a typical equity fund have following trends on liquidity characteristics: fewer no-trading days (from 1.0933 in 1984 to only 0.0278 in 2008 for Liu's LM12), higher trading turnover ratio (from 0.2767 in 1984 to 1.2641 in 2008 for TO12), lower price-impact ratio (from 0.076992 in 1984 to only 0.010536 in 2008 for Amihud's RtoV12), and slightly lower effective cost of trading (from 0.002701 in 1984 to 0.002012 in 2006 for Hasbrouck's EC). Moreover, we notice that the MV of stock-holdings increases almost ninefold during the 25-year period from \$4.32 billion to \$37.65 billion, meanwhile the B/M falls

[32] Over all 25-year time period, the FLOW1 are positive for 21 years and negative for only 4 years (in 1990, 2002, 2007 and 2008). And the FLOW2 are positive for 20 years and negative for 5 years (in 1990, 2000, 2001, 2002 and 2008).

clearly from 0.7172 in 1984 to 0.5086 in 2008. The steep increase of MV and obvious drop of B/M indicates equity funds prefer to hold big companies and growth companies again. In short, a liquidity factor has been paid more and more attention by active equity fund managers and has become a determinant in their investment decisions.

Table 4.3

Characteristics of the U.S. Actively Managed Equity Funds

This table reports some key characteristics, at four-year intervals, for U.S. actively managed equity fund sample over the time period of 1984-2008. By averaging over the time series for whole sample, we obtain the following fund characteristics. Panel A presents fund number, scale, return and stock holding's statistics for entire fund dataset. Panel B provides the diverse fund liquidity measures and fund stock-holdings characteristics, including log cash flow (FLOW1), quantity of cash flow (FLOW2), Liu's trading discontinuity measure of liquidity (LM12), turnover ratio (TO12), Amihud's price impact ratio (RtoV12), Hasbrouck's effective cost (EC), market capitalization (MV), and book-to-market ratio (B/M).

	1984	1988	1992	1996	2000	2004	2008	Yearly Average
Panel A: Fund Summary Statistics								
No. of Equity Funds	257	402	658	1213	1749	1908	1567	1129
Fund Net Return (monthly)	0.697%	1.208%	0.824%	1.541%	0.150%	0.988%	-3.756%	0.821%
Market Return (monthly)	0.260%	1.357%	0.726%	1.611%	-0.973%	1.024%	-3.946%	0.757%
Total Net Assets ($ million)	255.72	315.97	488.02	815.86	1549.29	1106.62	1379.26	820.02
Pct. of Stock Holdings	81.98%	81.44%	82.28%	87.22%	88.53%	88.60%	79.72%	84.53%
No. of Stock Holdings	66	74	80	95	97	102	104	88
Panel B: Fund Liquidity Measures								
FLOW1	0.0035	0.0029	0.0125	0.0135	0.0049	0.0070	-0.0218	0.0063
FLOW2 ($ million)	2.41	1.81	9.95	18.62	-3.08	11.68	-62.61	5.36
Liu's LM12	1.0933	1.2606	1.1882	0.7004	0.2009	0.0689	0.0278	0.6763
Turnover Ratio, TO12	0.2767	0.4019	0.4174	0.5605	0.8605	0.8450	1.2641	0.6232
Amihud's RtoV12 (10^6)	0.076992	0.127779	0.087610	0.057140	0.022217	0.011965	0.010536	0.058651
Hasbrouck's EC	0.002701	0.004192	0.004045	0.003942	0.004552	0.002494	0.002012*	0.003734
MV ($ million)	4324.40	5175.13	8644.41	13717.67	59243.70	40191.87	37650.28	22832.64
B/M	0.7172	0.5838	0.4585	0.3557	0.2894	0.3699	0.5086	0.4457

* This figure of Hasbrouck's EC is for 2006, since the data are updated to 2006 only.

CHAPTER 5: METHODOLOGY

In the chapter, we will present and detail the evolution of main evaluation methods of mutual fund performance: from a simple time series regression, to constructing a portfolio of funds (POF), then to bootstrap simulation methods.

5.1. Models & Time Series Regression

Theoretically, fund abnormal performance is measured by alpha, which is defined as the intercept in a regression of a fund's excess returns on the returns of one or more benchmark assets (such as market portfolio, small-minus-big size portfolio, high-minus-low B/M portfolio, high-minus-low prior 1-year return portfolio, high-minus-low liquidity risk portfolio, and illiquid-minus-liquid portfolio). The general equation seems like as:

$$r_{i,t} = \alpha_i + \sum_{j=1}^{n} \beta_{i,j} r_{j,t} + \varepsilon_{i,t} ,$$

where $r_{i,t}$ is the excess return of fund i in period t, $r_{j,t}$ is the excess return of the benchmark assets j in period t, and α_i is just the fund's abnormal return. Our research estimates intercepts from five such regression models to obtain fund's abnormal performance. These five regression-based measures are base on CAPM, Fama-French three-factor model (FF3F), Carhart four-factor model (FF+Mom), Pastor-Stambaugh four-factor model (FF+PS), and Liu liquidity-augmented two-factor model (LCAPM).

The single-factor CAPM alpha is the intercept from the regression of portfolio excess return on the market portfolio excess returns:

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_i (R_{m,t} - R_{f,t}) + \varepsilon_{i,t} \text{, (CAPM)}$$

where $R_{i,t} - R_{f,t}$ is the excess return on fund i in period t, $R_{m,t} - R_{f,t}$ is the excess return on the market proxy portfolio in period t. $R_{i,t}$ is the return on fund i, $R_{f,t}$ is the risk-free rate (one month T-bill rate), $R_{m,t}$ is the return on market portfolio, which is the value-weighted return on all NYSE, AMEX, and NASDAQ stocks, and α_i and β_i are the regression's intercept and slope coefficient. As Jensen (1968) argues, if the fund manager has an ability to forecast security prices and earn abnormal return, α_i should be positive. The regression-based performance measures of other models (FF3F, FF+Mom, FF+PS, and LCAPM) are estimated respectively from expanded forms of CAPM:

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_{m,i}(R_{m,t} - R_{f,t}) + \beta_{s,i}SMB_t + \beta_{h,i}HML_t + \varepsilon_{i,t}\text{, (FF3F)}$$

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_{m,i}(R_{m,t} - R_{f,t}) + \beta_{s,i}SMB_t + \beta_{h,i}HML_t + \beta_{p,i}PR1YR_t + \varepsilon_{i,t}\text{, (FF+Mom)}$$

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_{m,i}(R_{m,t} - R_{f,t}) + \beta_{s,i}SMB_t + \beta_{h,i}HML_t + \beta_{l,i}LIQ\_V_t + \varepsilon_{i,t}\text{, (FF+PS)}$$

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_{m,i}(R_{m,t} - R_{f,t}) + \beta_{l,i}LIQ_t + \varepsilon_{i,t}\text{, (LCAPM)}$$

where SMB_t, HML_t, $PR1YR_t$, LIQ_V_t, and LIQ_t are the small-minus-big size portfolio return, high-minus-low B/M portfolio return, high-minus-low prior 1-year return portfolio return, high-minus-low value-weighted liquidity risk portfolio return, and illiquid-minus-liquid portfolio return in period t, respectively.[33]

Table 5.1 summarizes the properties of all factors of asset pricing models above. Over the whole sample period 1984 to 2008, LIQ has a mean of 0.699% per month and also is highly significant, which is more pronounced than for SMB, HML, and LIQ_V. SMB and HML have a mean of only 0.027% and 0.353% respectively, and SMB is insignificant (t-statistic of 0.14). This evidence suggests that explanatory power for asset returns using FF3F is limited. As can be seen from Panel B of Table 5.1, the

[33] These factors have been explained in details in the section of Asset Pricing Models in the Literature Review Chapter. The original papers are Fama and French (1993), Carhart (1997), Pastor and Stambaugh (2003), and Liu (2006).

correlation between LIQ and MKTRF is -0.792, which indicates that "the market is less liquid when it is in downturn states, and investors require higher returns to compensate them for the higher risks they bear in less liquid states" (Liu, 2006). In addition, the correlation between LIQ and HML is positive at 0.614, and HML is also negatively correlated with MKTRF at -0.451. Moreover, we also find the correlation coefficient between LIQ and SMB is -0.328, which means the least liquid stocks are not the smallest ones (or the most liquid stocks are not the largest ones).

Table 5.1

Properties of the Factors in Asset Pricing Models

This table reports the properties of the variant factors in asset pricing models. MKTRF is the excess return on the market proxy portfolio; SMB is the small-minus-big size portfolio return; HML is the high-minus-low book-to-market portfolio return, PR1YR is the high-minus-low prior 1-year return portfolio return, LIQ_V is the high-minus-low value-weighted liquidity risk portfolio return, and LIQ is the illiquid-minus-liquid portfolio return, respectively. Panel A presents the factors' basic statistics. Panel B shows the spearman correlation among these factors. All factors are monthly and available over the time period 1984 to 2008.

Panel A: Statistics Description of Factors (N=300)						
Variable	MKTRF	SMB	HML	PR1YR	LIQ_V	LIQ
Mean	0.456%	0.027%	0.353%	0.853%	0.499%	0.699%
Std Dev	4.474%	3.273%	3.075%	4.351%	3.496%	3.993%
t -statistic	1.77	0.14	1.99	3.40	2.47	3.03
Q1	-2.080%	-1.710%	-1.345%	-0.645%	-1.485%	-1.926%
Median	1.000%	-0.190%	0.295%	0.960%	0.533%	0.909%
Q3	3.480%	1.655%	1.760%	2.890%	2.631%	3.119%
Panel B: Spearman Correlation Coefficients (1984-2008)						
MKTRF	1					
SMB	0.188	1				
HML	-0.451	-0.232	1			
PR1YR	-0.086	-0.055	-0.048	1		
LIQ_V	0.032	-0.063	0.075	0.057	1	
LIQ	-0.792	-0.328	0.614	0.097	-0.007	1

Since we concentrate on the effect of liquidity on fund performance in this study, we emphasize the results obtained from the liquidity-based models (FF+PS and LCAPM). Pastor and Stambaugh (2003) define traded liquidity factor (LIQ_V) in their FF+PS as the value-weighted return on the 10-1 portfolio (i.e. high-liquidity-beta minus low-liquidity-beta portfolio) from a sort on historical liquidity betas. By adding LIQ_V into asset pricing models, they find a momentum strategy becomes less attractive from an investment perspective when portfolio spreads based on liquidity risk are also available for investment. However, their traded liquidity factor (LIQ_V) only grasps the liquidity risk and has less significance in our research. While, Liu LCAPM not only explains the size, book-to-market, and fundamental to price ratios, but also captures the liquidity level and liquidity risk, which are not properly explained by prior models. He suggests that liquidity factor (LIQ) is important for asset pricing and is an especially promising research direction. Additionally, his LIQ is highly significant in our research. Therefore, in this thesis, we attempt to reveal the relation between fund excess return and Liu's LIQ through the estimated coefficients on liquidity factor, $\beta_{l,i}$ (liquidity risk).

Using all sample data available for each fund, we present, in Table 5.2, an overview of the regression estimates of the parameters of these five regression models during 25-year from 1984 to 2008. For each fund, we conduct a time-series regression to obtain the estimated alpha and factor loadings using the various asset pricing models. Then we calculate the mean of these estimated alpha and factor loadings of all fund sample data for each model. Table 5.2 shows that the average monthly alphas are tiny, close to zero, negative for CAPM, FF3F, FF+Mom, and FF+PS (-0.0489%, -0.0811%, -0.0950%, and -0.0665% monthly) or positive for the Liu LCAPM (0.0861% per month).[34] That indicates that, on average, the active equity fund managers are not able to earn abnormal returns for investors; in other words, the actively managed equity

[34] The proportions of t-statistic of alphas of more then 1.96 or less than -1.96 are around only 14%-23% for the five models in our whole equity fund sample. For calculating annual return, we just simply multiple the monthly return by 12. The annual alphas for CAPM, FF3F, FF+Mom, FF+PS, and Liu LCAPM are -0.5873%, -0.9737%, -1.1396%, -0.7976%, and 1.0332%, respectively.

funds are insignificantly from the benchmarks. Moreover, the average loadings of market excess return (MKTRF) for all models are between 0.949 and 1.052. Thus, these equity funds, on average, tend to hold stocks with level similar risk to the market portfolio. In Panels B, C and D, the factor loadings of SMB, HML, and PR1YR are all positive, indicating that fund performance is positively impacted by small capitalization, high book-to-market, and high prior 1-year return.

Now we focus on the two liquidity-relative factors: LIQ_V in the FF+PS and LIQ in the Liu LCAPM. Panel D shows the estimated coefficient of traded liquidity factor (LIQ_V) is negative (-0.0263), indicating that fund managers prefer stocks with less liquidity risk; whilst Panel E reports that the estimated coefficient of liquidity factor (LIQ) is negative (-0.1373), which also means that fund managers are likely to hold more liquid stocks. To a large extent, these two factor loadings are consistent; the funds holding stocks with less liquidity risk or higher liquidity will earn lower excess returns. This supports one of our hypotheses, that the performances of actively managed equity funds are affected by their stock-holdings’ liquidity and, on average, the effect is adverse.

Table 5.2

Regression Estimates of Parameters of Asset Pricing Models

(Average of Time Series Regression)

This table reports an overview of the regression estimates of the parameters of various models for each fund during 25-year period from 1984 to 2008. β_mkt, β_smb, β_hml, β_pr1yr, β_liq_v, and β_liq, stand for the regression slopes of MKTRF, SMB, HML, PR1YR, LIQ_V, and LIQ, respectively. For each fund, we conduct a time-series regression to obtain the estimated factor loadings using various asset pricing models respectively. Then we calculate the mean of these estimated factor loadings of all fund sample data for each model. Panel A is for CAPM, Panel B is for Fama-French three-factor model (FF3F), Panel C is for Carhart four-factor model (FF+Mom), Panel D is for Pastor-Stambaugh four-factor model (FF+PS), and Panel E is for Liu liquidity-augmented two-factor model (LCAPM).

Panel A: CAPM	
alpha (monthly)	-0.0489%
β_mkt	1.0517
Panel B: Fama-French Three-Factor Model (FF3F)	
alpha (monthly)	-0.0811%
β_mkt	1.0143
β_smb	0.2075
β_hml	0.0053
Panel C: Carhart Four-Factor Model (FF+Mom)	
alpha (monthly)	-0.0950%
β_mkt	1.0225
β_smb	0.2042
β_hml	0.0049
β_pr1yr	0.0193
Panel D: Pastor-Stambaugh Four-Factor Model (FF+PS)	
alpha (monthly)	-0.0665%
β_mkt	1.0200
β_smb	0.2100
β_hml	0.0126
β_liq_v	-0.0263
Panel E: Liu Liquidity-Augmented Two-Factor Model (LCAPM)	
alpha (monthly)	0.0861%
β_mkt	0.9490
β_liq	-0.1373

5.2. Performance of Portfolio of Funds (POF)

In the previous sub-section, we presented a simple time-series regression for each fund to obtain the estimated alpha and factor loadings. However, one cannot assess the significance of the estimated alpha and factor loadings through averaging the t-statistics for all fund data. Additionally, funds have diverse survival time periods and different risk-taking preferences. Thus, we examine fund performance as a whole, by constructing a portfolio of funds (POF) in each month and run time-series regression for the cross-section of the fund portfolio's net returns.

Similar to the approach of Fama and French (2010), we first use two ways to construct portfolio of equity mutual funds. In the value-weighted portfolio of funds (hereafter, VWPOF), mutual funds are weighted by total net assets at the beginning of each month. In the equally-weighted portfolio of funds (hereafter, EWPOF), funds are weighted equally each month. Then we run time-series regression of asset pricing models above to estimate the performance (i.e. the intercepts in these models) of VWPOF and EWPOF, respectively.

The alphas of VWPOF tell us about the fate of aggregate wealth invested in funds (Fama and French, 2010). Whereas the EWPOF performance informs us whether funds on average produce returns different from those implied by their exposures to common factors (such as market, size, value, momentum, liquidity risk, and liquidity factors) in returns. To mass investors, it is of most concerned whether, on average, active fund managers have sufficient ability to create returns to cover the costs. As a result, we will primarily present the results of the intercepts in various model regressions for VWPOF at net return level, rather than at gross return level, which tests whether fund managers have any skills.[35]

If we assume the value-weighted aggregate of the U.S. equity portfolios of all investors is the market portfolio (passive investment portfolio), this is supposed to have a market (MKTRF) slope equal one, zero slopes on the other explanatory returns (such as SMB, HML, PR1YR, LIQ_V, and LIQ), and a zero intercept in these models. As Fama and French (2010) propose, we can simply account for these explanatory returns as diversified passive benchmark returns that capture patterns in average returns during our sample period, whatever the source of the average returns.

[35] The fund return values in the CRSP-MF database are based on net returns. It is known that fund gross returns pose more difficult measurement issues, so we leave it to the future work.

Abstracting from the variation in returns associated with MKTRF, SMB, HML, PR1YR, LIQ_V, and LIQ then allows us to focus better on the effects of active management (stock-picking ability), which should show up in the intercepts (alphas) of these models.

From an investment standpoint, the slopes on the explanatory returns (MKTRF, SMB, HML, PR1YR, LIQ_V, and LIQ) in these models describe a diversified portfolio of passive benchmarks that replicates the exposures of the fund on the left to common factor in returns. The regression intercept (alpha) then measures the average return provided by a fund in excess of the return on a comparable passive portfolio. Therefore, a positive expected intercept (+alpha) is interpreted as superior performance, and a negative expected intercept (−alpha) signals awful performance.

5.3. Bootstrap Simulation

More recently, some papers (such as Kosowski et al., 2006, Cuthbertson et al., 2008, Barras et al., 2010, and Fama and French, 2010) raise a new question: whether the superior performance of a few individual fund managers is credible evidence of genuine stock-picking ability, or simply comes from extraordinary luck. Earlier studies which use conventional statistical measures do not explicitly recognize and model the role of luck in fund performance. Now, through using the bootstrap method, we are able to separate skill from luck for individual funds and evaluate the fund performance from a new perspective.

Several studies have shown that mutual fund returns do not follow the normality assumption inherent in earlier academic research,[36] so normality may be a poor

[36] As Kosowski et al. (2006) describe, when they analyze the distribution of individual fund residuals, about 50% of the U.S. fund sample have alphas that are drawn from a distinctly non-normal distribution. And, Cuthbertson et al. (2008) report that around 64% of mutual funds in the U.K. reject normality in their regression residuals.

approximation in practice, even for a fairly large mutual fund sample. Violation of the normality assumption could induce a type I error (i.e. the error of rejecting a null hypothesis that should have been accepted), in the sense that empirical test reject evidence of no performance when performance patterns are actually absent. As Kosowski et al. (2006) assert, the cross-section of mutual fund alpha has a complex non-normal distribution because of heterogeneous risk-taking by funds and non-normalities in individual fund alpha distributions. Therefore, the bootstrap method provides improved inference in identifying funds with significant skills, in which most investors are primarily concerned.

5.3.1. Introduction to Bootstrap

The bootstrap method was introduced by Efron (1979) as a method to derive the estimate of standard error of arbitrary estimator. The use of the term “bootstrap” comes from the phrase “to pull oneself up by one’s bootstraps”[37], which generally interpreted as succeeding in spite of limited resource. Because of the power of this method, Efron (1979) once mentioned that he considered calling it “the shotgun” since it can “blow the head of any problem if the statistician can stand the resulting mess”. As we know, many conventional statistical methods of analysis make assumptions about normality, including correlation, regression, t tests, and analysis of variance. When these assumptions are violated, such methods may fail. In recent decades, with computer processors becoming more powerful, statistical inference based on data resampling has been paid a great deal of attention, and the bootstrap has become a very popular statistical technique.

The main idea in bootstrap resampling is not to assume much about the

[37] This phrase comes from The Adventures of Baron Munchausen by Raspe (1786). In one of Baron Munchausen’s adventures, he had fallen to the bottom of a lake and just as he was about to succumb to his fate he thought to pick himself up by his own bootstraps.

underlying population distribution but instead to attempt to gain the information about the population from the data. The method uses the relationship between the sample and resamples drawn from the sample, to approximate the relationship between the population and samples drawn from it. With the bootstrap method, the basic sample is treated as the population and a Monte Carlo style procedure is conducted on it. For instance, in the case of the sample mean, bootstrap will use the sample data as if they were the population and empirically build a picture of the sampling distribution of the sample mean. This is done by randomly drawing a large number of resamples of size B (e.g. B=100, 1000, or 10000) from this original sample with replacement. Relying on an analogy between the sample and the population from which the sample was drawn, Mooney and Duval (1993) claim that "the bootstrap may sometimes be better to draw conclusions about the characteristics of a population strictly from the sample at hand, rather than by making perhaps unrealistic assumptions about the population". When we turn to statistics and situations for which the sampling distribution is either unknown or intractable (for example an ordinary least squares, OLS, regression coefficient where the residuals are non-normal), bootstrap demonstrates its greatest practical importance.

In a formal definition, bootstrap is defined by Chernick (2008) as follows:

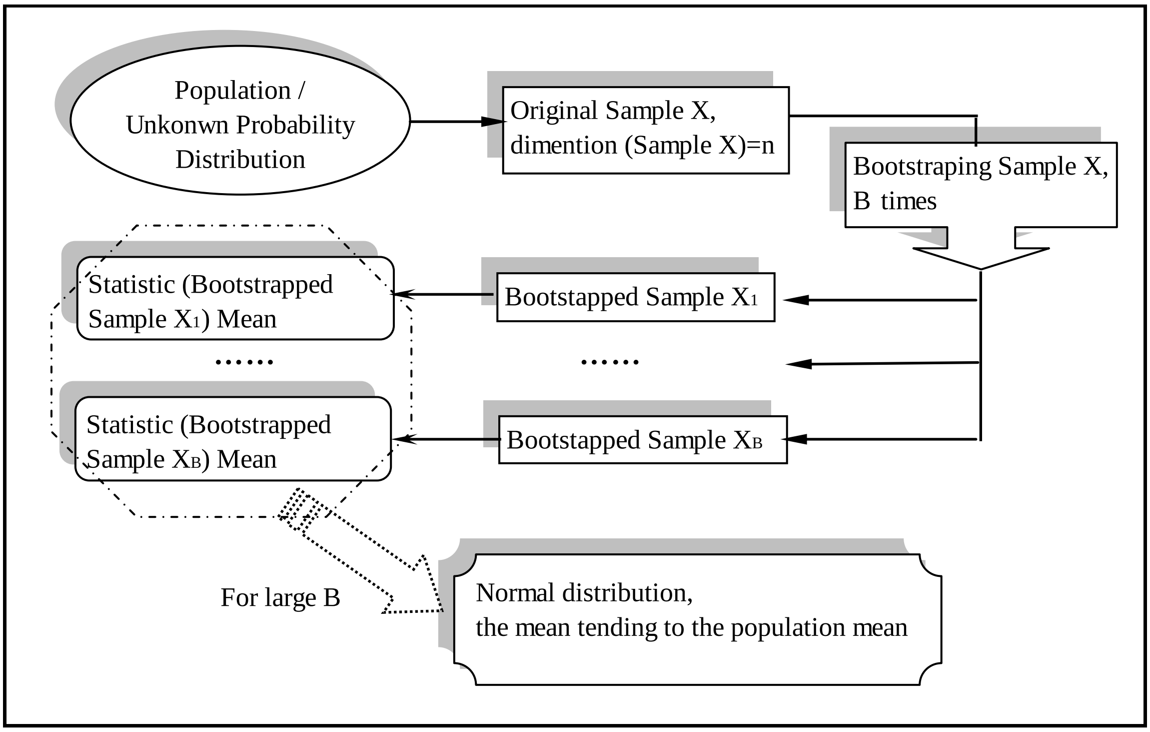
> "Given a sample of n independent identically distribution (iid) random vectors $X_1, X_2, ..., X_n$ and a real-valued estimator ($X_1, X_2, ..., X_n$) (denoted by $\hat{\theta}$) of the parameter, a procedure to assess the accuracy of $\hat{\theta}$ is defined in terms of the empirical distribution function F_n. This empirical distribution function assigns probability mass 1/n to each observed value of the random vector X_i for i=1, 2,…, n".

Specifically speaking, the empirical distribution function is the maximum likelihood estimator of the distribution for the observations when no parametric assumptions are made. The bootstrap distribution for $\hat{\theta}-\theta$ is the distribution obtained by generating $\hat{\theta}$'s by sampling independently with replacement from the empirical distribution F_n. The bootstrap estimate of the standard error of $\hat{\theta}$ is then the standard deviation of the bootstrap distribution for $\hat{\theta}-\theta$. By replicating B times bootstrap sampling, a Monte Carlo approximation to the distribution of θ^* is obtained. The standard deviation of this Monte Carlo distribution of θ^* is the Monte Carlo approximation to the bootstrap estimate of the standard error for $\hat{\theta}$. Often this estimate is simply referred to as the bootstrap estimate and for B very large (e.g. 1000) there is very little difference between the bootstrap estimator and this Monte Carlo approximation. As Chernick (2008) argues, "what we would like to know for inference is the distribution of $\hat{\theta}-\theta$, and what we have is a Monte Carlo approximation to the distribution of $\theta^*-\hat{\theta}$." It is apparent that the core thought of the bootstrap is that for n sufficiently large, we expect the two distributions to be nearly the identical. So the basic idea behind the bootstrap worth emphasizing here is that the variability of θ^* (based on F_n) around $\hat{\theta}$ will be similar to (or mimic) the variability of $\hat{\theta}$ (based on the true population distribution F) around the true parameter value θ. It is reasonable to believe that this will be true for large sample size, since as n gets larger and larger, F_n comes closer and closer to F and so sampling with replacement from F_n is almost like random sampling from F. In a word, the basic bootstrap approach is to treat the sample as if it were the population, and apply Monte Carlo sampling to generate an empirical estimate of the statistic's sampling distribution. The procedure is summarized in Figure 5.1 below.

Figure 5.1

The Algorithm for Bootstrap Method

1. An array of n data is considered Sample X=(X_1, X_2,…, X_n), representing the sample of n selections from the target population.
2. N random numbers are generated between 1 and n: i_1, i_2,…, i_n. These will be considered as indexes.
3. The array bootstrapped Sample X=(X_{i1}, X_{i2},… X_{in}) will be a new sample of pseudo-data obtained as repeated sampling with replacement from the original Sample X.
4. To the array bootstrapped Sample X, the statistic of interest, for example the mean, is applied.
5. The algorithm is taken over from the 2nd step. To be reliable, this algorithm must be taken over for a large number of times, B (e.g. 1000).



In a regression model, conventional parametric inference regarding coefficients is based on distribution conditions and assumptions that may or may not hold true for a given set of data (such as OLS estimators will be normally distributed if the model's error term is normally distributed). However, if the distribution conditions do not hold in a particular model and data, parametric inference about OLS estimators may be inaccurate. Thus it is the case such as this that a bootstrap may be useful in our research. Consider a standard linear regression model:

$$\mathrm{Y} = \mathrm{X}\beta + \varepsilon \, ,$$

where Y is an (n × 1) vector of response variables, X is an (n × k) matrix of explanatory variables (i.e. regressors), β is a (k × 1) vector of regression coefficients, and ε is an (n × 1) vector of error terms. This regression model can be bootstrapped via two methods. The most straightforward method is simply to resample entire cases of data, that is, resample rows in the data matrix. In this way, B resamples of size n would be generated, and the regression model estimated for each resample. This would yield a (B × k) matrix of bootstrapped regression coefficients, each column of which would contain B $\hat{\beta}_{\mathrm{k}}^{*}$'s. And these $\hat{\beta}_{\mathrm{k}}^{*}$ can be converted into an estimate of the sampling distribution of $\hat{\beta}_{\mathrm{k}}$ in the usual way, by placing a probability of 1/B at each value of $\hat{\beta}_{\mathrm{k}}^{*}$. However, this approach has a problem: it ignores the error structure of the regression model. The classic regression model holds that the regressors are fixed constants and the response variable is a function of these fixed constants, plus a random error term. Since the only random aspect of the process is the error term, ε, it is this quantity that should be resampled in bootstrap. In contrast to the resampling entire cases, the second method, bootstrapping an estimated regression coefficient by resampling the error terms (i.e. residuals), is somewhat more complicated. First of all, we estimate β using the OLS method. Using this estimate, $\hat{\beta}$, and the values of the observed variables, we calculate the residuals:

$$\hat{\varepsilon}_{\mathrm{i}} = \mathrm{Y}_{\mathrm{i}} - \hat{\mathrm{Y}}_{\mathrm{i}},$$

where $\hat{\mathrm{Y}} = \mathrm{X}\hat{\beta}$. Then a resample of these residuals is drawn randomly with replacement. So we generate a bootstrapped vector of the response variables for this resample, by adding the resampled vector of residuals ($\hat{\varepsilon}_{\mathrm{b}}^{*}$) to the vector of fitted response values from the sample:

$$\mathrm{Y}_{\mathrm{b}}^{*} = \hat{\mathrm{Y}} + \hat{\varepsilon}_{\mathrm{b}}^{*}.$$

These bootstrapped responses, Y_b^*, are then regressed casewise on the fixed explanatory variables to estimate a bootstrapped vector of estimated coefficients, $\hat{\beta}_b^*$, for this resample:

$$Y_b^* = X\hat{\beta}_b^* + \hat{\varepsilon} \ .$$

This procedure, from residual resample to the estimation of $\hat{\beta}_b^*$, is repeated B times.

So far, we have noticed an interesting fact: there are two different ways of bootstrapping a regression model: resampling the entire cases and resampling the residuals. Which bootstrap method is better? Mooney and Duval (1993) claim that researchers need to consider the stochastic component of the model in choosing between these two bootstrap methods. Generally, it is theoretically most justifiable to resample this portion of the model. Therefore, most theoretical statisticians suggest the resampling of residuals. As Efron and Tibshirani (1993) argue, although the two approaches are asymptotically equivalent for the given model, the first method, resampling the entire cases, is less sensitive to model misspecification, that is, it provides better estimates of the variability in the regression parameters when the model is not correct. It also appears that if we do not bootstrap the residuals, the resampling the entire cases may be less sensitive to the assumptions concerning independence or exchangeability of the error terms. Thus, Chernick (2008) concludes that "the resampling the entire cases is over resampling the residuals when (i) there is heteroscedasticity in the residual variance, (ii) there is correlation structure in the residuals, or (iii) there may be other important parameters missing from the model".

When using bootstrap tests for a regression model, a p-value is supposed to be calculated and compared with the desired significance level. There are differences in opinion about how the bootstrapped p-value should be calculated and two methods are both quite popular. The first method, described in Davison and Hinkley (1997), is based on applying a Monte Carlo p-value formula to estimate the p-value of an observed test statistic $\hat{t}$. Thus, in this method, the bootstrapped p-value of $\hat{t}$ is computed using:

$$\bar{p} = \frac{\#\{t_b^* \geq \hat{t}\} + 1}{B + 1},$$

where the terms t_b^*, b=1, 2,…, B, are the bootstrap realizations of the test statistic. The second one, given in Efron and Tibshirani (1993), does not use the same formula as a Monte Carlo test and estimated bootstrapped p-values are instead obtained using:

$$\hat{p} = \frac{\#\{t_b^* \geq \hat{t}\}}{B}.$$

Godfrey (2009) asserts that “in the bootstrap tests based on comparing $\hat{t}$ with t_b^*, b=1, 2,…, B, an artificial bootstrap world is constructed, conditional on the observed data, in order to approximate the finite sample null distribution of test statistics that are only asymptotically pivotal”. The use of $\hat{p}$ in the second method reflects the conditioning on the observed test statistic, with the B bootstrap statistics being used to obtain the classical sample proportion estimator, under the bootstrap law, which provides the approximation to the true p-value. Given that, in empirical applications, B is likely to be 1000 or 2000, and that

$$0 \leq \bar{p} - \hat{p} \leq \frac{1}{B+1},$$

it seems difficult to disagree with the second method. Therefore, it is immaterial whether one uses $\hat{p}$ or $\bar{p}$.

5.3.2. Bootstrap Application in our Research

In this research, we perform successively these two cross-section bootstrap simulation methods (residual-only resampling and entire cases resampling) to evaluate the individual fund performance and separate the skilled funds from lucky funds, even when idiosyncratic risks are highly non-normal.

In the first bootstrap method, residual-only resampling, the basic idea of our procedure is to construct zero true-alpha funds. Consider an estimated model of equilibrium returns of the form (standard model)[38]:

$$r_{i,t} = \alpha_i + \beta_i X_t + \varepsilon_{i,t},$$

where $r_{i,t}$ is the excess return of fund i, X_t is the matrix of explanatory factors returns, and $\varepsilon_{i,t}$ is the residuals. We also let T_i be the number of observations (i.e. time length) of fund i. Our residual-only resampling bootstrap procedure involves five steps as follows. (i) For each fund, we compute OLS-estimated funds' alphas, factor loadings and residual returns using the standard model. For fund i, we save the coefficient estimates $\left\{\hat{\alpha}_i, \hat{\beta}_i\right\}$, the time series of estimated residuals $\left\{\hat{\varepsilon}_{i,t}\right\}$, and the t-statistic of alpha ($\hat{t}_{\hat{\alpha}i}$). (ii) For each fund i, we draw a random sample with replacement of length T_i from the residuals $\left\{\hat{\varepsilon}_{i,t}\right\}$, and create a pseudo-time series of resampled residuals $\left\{\hat{\varepsilon}^b_{i,t}\right\}$. In such way, the ordering of original sample of residuals is adjusted, and the resampled residuals are reordered. Meanwhile, the original chronological ordering of the factor returns X_t is unaltered (retaining the original chronological ordering). (iii) We use these resampled residuals $\left\{\hat{\varepsilon}^b_{i,t}\right\}$ to generate a simulated excess return series $\left\{r^b_{i,t}\right\}$ for fund i, under the null hypothesis of zero true performance (α_i =0),

$$r^b_{i,t} = \hat{\beta}_i X_t + \hat{\varepsilon}^b_{i,t} \ .$$

As the equation above indicates, this sequence of artificial returns has a true alpha that

[38] This standard model is the origin of various asset pricing models and to be used to explain the bootstrap procedure, for brevity.

is zero by construction. (iv) Using the simulated excess return series $\left\{r_{i,t}^{b}\right\}$, the standard model is estimated again and the resulting estimate of alpha, bootstrapped alpha $\hat{\alpha}_{i}^{b}$, for each fund is obtained.[39] Since the bootstrap procedure may have drawn an abnormally high number of positive residuals, a positive bootstrapped alpha may result or, conversely, a negative alpha may result if an abnormally high number of negative residuals are drawn. The bootstrapped alpha for each fund represents sampling variation around a true alpha of zero, totally due to luck. (v) Repeating the steps above, for all bootstrap iterations B=1, 2,…, 1000, across all funds i=1, 2,…, N, we arrive at a draw from the cross section of bootstrapped alphas. Then we build the distribution of these cross-sectional draws of alphas, $f(\hat{\alpha}_{i}^{b})$, that result purely from sampling variation while imposing the null of a true alpha equals to zero. The main difference between bootstrap simulation and earlier conventional studies is that, under the null of no outperformance, it does not assume that the distribution of alpha of each fund is normal and each fund's alpha can follow any distribution.

So far, we are able to compare any ex-post $\hat{\alpha}_{i}$ with its appropriate luck distribution $f(\hat{\alpha}_{i}^{b})$. For instance, if we are interested in whether the performance of the best fund (the maximum of $\hat{\alpha}_{i}$, i.e. $\hat{\alpha}_{max}$) is due to skill or luck. If the $\hat{\alpha}_{max}$ is greater than the 10% upper tail cut off point from $f(\hat{\alpha}_{max}^{b})$, we reject the null that its performance is due to luck at 90% confidence level and infer that the best fund has skill. This can be repeated for any other point in the performance distribution, right down to the performance of the worst fund in our fund sample. Here, we have to stress that the null hypothesis is different for the top performing funds and the bottom performing funds. For the former, the null hypothesis is $H_0 : \alpha_i \leq 0, H_A : \alpha_i > 0$, and

[39] At the same time, we also get the bootstrapped t-statistics of alpha for each fund.

for the latter, the null hypothesis is $H_0 : \alpha_i \geq 0, H_A : \alpha_i < 0$. Except for the estimated alpha $\hat{\alpha}$, we are more concerned another test statistics, the estimated t-statistics of alpha:

$$\hat{t}_{\hat{\alpha}} = \frac{\hat{\alpha}_i}{s/\sqrt{n}},$$

where s is the standard deviation of alpha, and n is observations of fund. As Kosowski et al. (2006) argue, "the $\hat{\alpha}$ measures the economic size of abnormal performance, but suffers from a potential lack of precision in the construction of confidence interval, whereas the $\hat{t}_{\hat{\alpha}}$ is a pivotal statistic with better sampling properties". For example, a fund that has a short life or engages in high risk-taking will have a high variance-estimated alpha distribution, thus alpha for this fund will tend to show as spurious outliers in the cross section. Nevertheless, the t-statistic provides a correction for these spurious outliers by normalizing the estimated alpha by the estimated variance of the alpha estimate. Moreover, the cross-sectional distribution of standard deviation has better properties than the cross section of alphas, in the presence of heterogeneous fund volatilities due to differing fund risk levels or life spans. Since the t-statistic has these attractive statistical properties, we use $\hat{t}_{\hat{\alpha}}$ rather than $\hat{\alpha}$ as performance statistic in our implementation. Similar to $\hat{\alpha}$, we also can compare any ex-post $\hat{t}_{\hat{\alpha}i}$ with its appropriate luck distribution $f(\hat{t}^b_{\hat{\alpha}i})$. In practice, besides $\hat{t}_{\hat{\alpha}i}$, we need to present the p-values of the t-statistics based on standard critical values. For comparison, we calculate the cross-sectional bootstrapped p-values (p^b_i) of the t-statistics as well. According to Godfrey (2009), the bootstrapped p-value formula is

$$p^b_i = \frac{\#\{t^b_i \geq \hat{t}_i\}}{B},$$

where t^b_i is the bootstrapped t-statistics, $\hat{t}_i$ is the estimated t-statistics, and B is number of bootstrap iterations. Let us present an example to illustrate the bootstrapped p-value. For example, a fund which is in top performing funds has t-statistic=2.5, but its bootstrapped p-value is 0.150. The bootstrapped p-value indicates that among the 1000 bootstrap simulations, under the null hypothesis of zero abnormal performance, 15% of the bootstrapped t-statistic for this fund are greater than its estimate t-statistic=2.5. Thus using a 10% upper tail cut off point (90% confidence level), we cannot reject the hypothesis that this fund's actual t-statistic=2.5 may be explained by luck alone. Whilst the conventional t-statistics of this fund indicates skill, the non-parametric bootstrap indicates good luck. So if we observe the funds in the extreme tails, the conventional test statistics may give misleading inference. This apparent contradiction is primarily due to the highly non-normal distribution of idiosyncratic risk of this fund.

Following Fama and French (2010), our second bootstrap simulation (entire cases resampling, or called as joint resampling) is to jointly resample fund and explanatory returns. Although there is some difference between joint resampling and residual-only resampling, the aim remains to construct zero true-alpha funds. This time, to set alpha to zero, we subtract a fund's alpha estimate from its monthly returns. For example, we still consider an estimated benchmark model of the form (the standard model):

$$R_{i,t} - R_{f,t} = r_{i,t} = \alpha_i + \beta_i X_t + \varepsilon_{i,t},$$

where $R_{i,t}$ is the monthly return of fund i, $R_{f,t}$ is the risk-free rate, $r_{i,t}$ is the excess return of fund i, X_t is the matrix of explanatory factors returns, and $\varepsilon_{i,t}$ is the residuals. After computing OLS-estimated funds' alphas for each fund, we subtract the fund's alpha estimate from its monthly returns:

$$R_{i,t} - \hat{\alpha}_i - R_{f,t} = r_{i,t} - \hat{\alpha}_i = \beta_i X_t .$$

Accordingly, we obtain the benchmark-adjusted (zero true alpha) returns for each fund.

Then a random sample with replacement is implemented for the calendar months of January 1984 to December 2008. Each simulation run has 300 months. For each fund, we estimate the benchmark model on the simulation draw on months of benchmark-adjusted returns. Each run thus produces cross-sections of estimates alpha $\hat{\alpha}$ (or t-statistics of alpha, $\hat{t}_{\hat{\alpha}}$) using the same random sample of months from adjusted fund returns. We run 1000 simulation to produce distribution of $\hat{\alpha}$ (or $\hat{t}_{\hat{\alpha}}$) for a world in which true alpha is zero. As with the residual-only resampling, we are also more concerned with the estimated t-statistics of alpha, $\hat{t}_{\hat{\alpha}}$ than the estimated alpha $\hat{\alpha}$.

This time, we jointly resample fund and explanatory returns, whereas the first bootstrap simulation (residual-only resampling) performs independent simulations for each fund. Although residual-only resampling has the benefit that the number of months a fund is in a simulation run always matches the fund’s actual number of months of returns, its simulation takes no account of the correlation of alpha estimates for different funds that arises because a benchmark model does not capture all common variation in fund returns. Also, it never jointly resamples fund returns and explanatory returns, which means it misses any effects of correlated movement in the volatilities of explanatory returns and residuals, as Fama and French (2010) assert. Meanwhile, the method of entire cases resampling has the following benefits: it captures the cross-correlation of fund returns and its effects on the distribution of estimated t-statistics of alpha, because a simulation run is the same random sample of months for all funds. Additional, it captures any correlated heteroscedasticity of the explanatory returns and disturbances of a benchmark model because of joint resampling fund and explanatory returns.

CHAPTER 6: FUND LIQUIDITY PREMIUM

Liquidity premium at stock level has been widely proven by earlier research. Liu (2006), for example, shows that the least liquid decile stocks significantly outperform the most liquid decile stocks by, on average, 0.682% per month over a 12-month holding period, after sorting stocks into ten equally-weighted portfolios based on their liquidity measure (LM12). However, the liquidity premium at fund level, i.e. fund liquidity premium, has received little considered in academia. It appears that the existence of a liquidity premium at fund level deserves further study.

6.1. Fund Liquidity Construction

Before verifying whether there is liquidity premium at fund level, we need to introduce our basic thoughts of construction of fund liquidity measures. In addition, the study of the effect of liquidity on fund performance is the most essential part in our research. Hence it remains necessary to explain specifically the design and process of fund liquidity construction in this section.

6.1.1. Individual Stock Liquidity

Liquidity is a complex concept, and is hard to capture in a single dimension. Liu (2006) defines liquidity as “the ability to trade large quantities quickly at low cost with little price impact”. In this context, liquidity includes at least four dimensions: trading speed, trading quantity, price impact, and trading cost. So far, in academia, there has been little consensus on which measures are better and little evidence that any of the proposed measures are related to investor experience. Thus, in this thesis, we primarily exploit four individual stock liquidity measures to represent these dimensions: LM12, RtoV12, TO12, and EC. We will next explain each of them in turn.

(1) LM12, trading discontinuity measure of liquidity, captures multiple dimensions of liquidity, especially emphasis on the trading speed (Liu, 2006). It is defined at the end of each month as the standardized turnover-adjusted number of zero daily trading volumes over the prior 12 months:

$$\text{LM12} = [\text{No. of zero daily volumes in prior 12 months} + \frac{1/(\text{12-month turnover})}{\text{Deflator}}] \times \frac{21 \times 12}{\text{NoTD}},$$

where 12-month turnover is the sum of daily turnover over the prior 12 months, daily turnover is the ratio of the number of shares traded on a day to the number of shares outstanding at the end of the day; NoTD is the total number of trading days over the prior 12 months; and the Deflator is chosen such that

$$0 < \frac{1/(\text{12-month turnover})}{\text{Deflator}} < 1,$$

for all sample stocks.[40] The factor 21 $\times$12/NoTD standardizes the number of 12 month trading days in the market to 252 (i.e. 21$\times$12). The number of zero daily trading volumes over the prior 12 months captures the discontinuity of trading; that is the absence of trade indicates a security's degree of illiquidity. Thus, it relates to the trading speed dimension. Then the turnover adjustment reflects the dimension of trading quantity. Furthermore, Liu's LM12 also captures the trading cost dimension, because the number of zero returns (close link to no trade) is a good proxy for transaction costs (Lesmond et al., 1999).

(2) TO12, the turnover measure (in percentage), is defined at the end of each month as the average daily turnover over the prior 12 months, where daily turnover is the ratio of the number of shares traded on a day to the number of shares outstanding on that day:

[40] Liu (2006) uses a deflator of 11000 in constructing LM12 in his study.

$$\text{Turnover}_t = \frac{\text{Trading Volume}_t}{\text{Shares Outstanding}_t}.$$

Datar et al. (1998) apply the turnover rate as a proxy for liquidity. By examining the influence of liquidity as measured by the turnover rate on the cross-section of stock returns, they find that turnover rate is significantly negatively related to stock returns. Also, the TO12 captures one dimension of liquidity, the trading quantity.

(3) RtoV12, Amihud (2002) price impact measure, is defined at the end of each month as the daily absolute-return-to-dollar-volume ratio averaged over the prior 12 months:

$$\text{RtoV}_{iy} = \frac{1}{D_{iy}} \sum_{t=1}^{Diy} \frac{|R_{iyd}|}{\text{VOLD}_{iyd}},$$

where $D_{i,y}$ is the number of days for stock i in year y, R_{iyd} is the return on stock i on day d of year y, and VOLD_{iyd} is daily dollar volume. Intuitively, if a stock's price moves a lot in response to little volume, the stock is illiquid, i.e. has a high value of RtoV12. This measure is interpreted as the price reaction to trading volume. Amihud (2002) tests the effect of illiquidity over time and finds that "expected market illiquidity has a positive and significant effect on ex ante stock excess return and unexpected illiquidity has a negative and significant effect on contemporaneous stock return".

(4) EC, Hasbrouck (2009) effective cost, is defined as Gibbs estimate of cost from Basic Market-Adjusted model:

$$\Delta p_t = c\Delta q_t + \beta_m r_m + u_t,$$

where p_t is the log trade price, q_t is the direction indicator, which takes the value +1 (for a buy) or -1 (for a sale) with equal probability, c is viewed as the effective cost, and r_m is the excess market return on day t. As Hasbrouck (2009) emphasizes, "when c is large relative to the efficient price increments (Δp_t), the price path appears distinctly spikey, as a consequence of the large bid-ask bounce." Thus EC, as a trading cost measure of liquidity, implies a diversification of bid-ask spread.

Besides these four liquidity measures, we also employ two individual stock characteristics: MV (the market capitalization measured in millions of dollars) and B/M (the book-to-market-value ratio). In Liu (2009), the MV and B/M are indicated high correlation with some liquidity measures (such as LM12, TO12, and RtoV12).

6.1.2. Fund Liquidity Measures (FLMs)

According to micro-level fund liquidity concept, we construct all our liquidity measures at fund level. Our fund liquidity measures (FLM_t) is based on the value-weighted average of the liquidity measure ($\mathrm{LM}_{i,t}$) of individual stocks held by a fund:

$$\mathrm{FLM}_t = \sum_{i=1}^{n_{jt}} \omega_{i,t} \mathrm{LM}_{i,t},$$

where $\omega_{i,t} = \frac{N_{i,t} P_{i,t}}{V_t}$ is the value-weight, $N_{i,t}$ is the number of shares of stock i that the fund holds at time t, $P_{i,t}$ is the price of stock i, and $V_t = \sum_i N_{i,t} P_{i,t}$ is the market value of the stock-holdings.

Although the definition of fund liquidity looks natural, two remarks are in order. First, the equation above is in the absence of short positions. In contrast with hedge funds, mutual funds are subject to strict limitations on short-selling and the use of leverage in order to comply with the Investment Company Act of 1940. Thus, we need not consider the liquidity of a fund with short positions. Second, the equation above is a function only of a fund stock-holdings' weights and not of the dollar value of the fund, so the FLM is not a function of fund size to some degree (called as scale-independence by Lo et al., 2003)[41]. To explain fund liquidity is scale independent, let us consider a case. There are two funds A and B both holding 20% of their assets in stock X and 80% of assets in stock Y. These two stocks' LM12 are 0.1 and 0.2, respectively. According to the fund liquidity measure equation above, the FLM of fund A and FLM of fund B both equal to 0.18[42], no matter how much their total net assets are.

With the equation above, the liquidity measure conversion from individual stock level to unique fund level comes true. Hence, these four stock liquidity measures have become FLMs. At the same time, the two individual stock characteristics (MV and B/M) are also converted to fund level using the same micro-level concept as FLMs (i.e. value-weighted average of the stock characteristics of individual stocks held by a fund). Hereafter, LM12, TO12, RtoV12, and EC represent fund liquidity measures; and MV and B/M represent fund stock-holdings characteristics. Moreover, they are all at the micro-level; that is, fund liquidity comes from the liquidity of stock-holdings of a fund. To some extent, they are able to tell us the liquidity preference of fund managers, as well as how easily they can be managed. However, some other factors, such as cash inflow (investors' purchase) and outflow (investors' redemption) of a fund due to market expectation, cannot be reflected by these micro-level FLMs. Thus, we also construct two cash flow variables to indicate fund macro-level liquidity. First, we use the log of the cash flow into a fund (FLOW1), which is similar to the concept of log flow in Pollet and Wilson (2008). It is defined as the change in log TNA not attributable to the portfolio return. Then, we calculate another similar cash flow (FLOW2), the difference between current TNA and previous TNA with current

[41] As a matter of fact, Lo et al. (2003) affirm that except for liquidity measure of price impact (such as Amihud's RtoV12) other fund liquidity measures all are scale independent.

[42] Based on our fund liquidity measure equation, 20%*0.1+80%*0.2=0.18.

portfolio return. The equations of them are as following:

$$FLOW1 = \log \frac{TNA_{i,t}}{TNA_{i,t-1}(1+R_{i,t})},$$

$$FLOW2 = TNA_{i,t} - TNA_{i,t-1}(1+R_{i,t}),$$

where $TNA_{i,t}$ is the total net assets of fund i at the end of month t, and $R_{i,t}$ is the total net return of fund i during month t. If they are positive, that means net cash inflow, while negative represents net cash outflow. FLOW1 focuses on the direction only, whereas FLOW2 can tell us the quantity change of fund assets. It is easy, therefore, to recognize whether the fund scale increase (decrease) comes from good performance (bad performance) or cash inflow (outflow).

Table 6.1 represents the Spearman rank correlation among these FLMs. As we know, liquidity measures might change over time. Thus we not only report the total correlations among FLMs for whole sample observations in Panel A, but also show the time-series average of yearly Spearman correlation in Panel B. Since Panel B more accurately displays the correlation among the FLMs, we concentrate on the results from there. In Panel B, the correlation between FLOW1 and FLOW2 (the two macro-level FLMs) is very high at 0.845, whereas they are not highly correlated with other micro-level FLMs. This low correlation between macro and micro-level fund liquidity indeed implies that fund managers control well the micro-level liquidity under their management and, as to investors' cash flow, they seem to be incompetent. Among these micro-level FLMs, the LM12 (the trading discontinuity) is highly correlated with the RtoV12 (the price impact) at 0.574, while this correlation in Liu (2006) is at 0.665.[43] To some extent, LM12 captures some of the price impact of

[43] Although, our liquidity measures are at fund level, whereas the liquidity measures in Liu (2006) are at stock level, it remains reasonable to compare them due to our micro-level FLMs are constructed by stock-holdings' liquidity measures. .

liquidity. LM12 is inversely correlated with MV (the market capitalization of stock-holdings) at -0.359, also similar to -0.514 in Liu (2006). It translates as these funds holding small companies being less liquid. As expected, the RtoV12 is highly correlated with EC (the trading cost) at 0.789, which means price impact brings out the increase of trading cost. Moreover, the correlation is -0.820 between RtoV12 and MV, somewhat is constant with -0.944 of Liu (2006), which is practically negatively correlated. Apparently, LM12 and RtoV12, among all FLMs, are the most representative proxies for fund liquidity. Also, MV could be a reasonable liquidity proxy to a large extent.

Table 6.1

Spearman Correlation Coefficients of Fund Liquidity Measures

This table reports the Spearman rank correlations for the fund liquidity measures and fund stock-holdings characteristics in our study. FLOW1 is the log cash flow; FLOW2 is the quantity of cash flow; LM12 is Liu's discontinuity measure of liquidity; TO12 (%) is the average daily turnover over the prior 12 months; RtoV12 (in millions) is Amihud's liquidity measure on price impact; EC is Hasbrouck's effective cost; MV is market capitalization measured in millions of dollars; and B/M is the book-to-market-value ratio. Panel A stands for the Spearman rank correlations among FLMs for all observations in entire sample. Since FLMs change over time, we also calculate the correlation coefficients among them year by year, and then average the yearly correlation coefficients. Panel B represents the time-series average of yearly Spearman correlation coefficient of FLMs.

Panel A. Spearman Correlation Coefficients (Total Sample)								
	FLOW1	FLOW2	LM12	TO12	RTOV12	EC	MV	BM
FLOW1	1.000							
FLOW2	0.867	1.000						
LM12	0.124	0.099	1.000					
TO12	-0.080	-0.073	-0.542	1.000				
RTOV12	0.101	0.063	0.670	-0.168	1.000			
EC	0.034	-0.009	0.379	0.227	0.592	1.000		
MV	-0.059	-0.032	-0.380	-0.055	-0.822	-0.475	1.000	
BM	-0.067	-0.055	0.192	-0.375	0.272	-0.078	-0.298	1.000
Panel B. Spearman Correlation Coefficients (Yearly Average)								
FLOW1	1.000							
FLOW2	0.845	1.000						
LM12	0.023	0.007	1.000					
TO12	0.014	0.004	-0.149	1.000				
RTOV12	0.031	0.001	0.574	0.282	1.000			
EC	0.025	-0.012	0.396	0.543	0.789	1.000		
MV	-0.021	0.006	-0.359	-0.383	-0.820	-0.778	1.000	
BM	-0.038	-0.029	0.117	-0.444	0.103	-0.103	-0.096	1.000

6.2. Absence of Fund Liquidity Premium

Here, to verify the existence of fund liquidity premium, we sort funds into ten portfolios based on trading discontinuity measure (Liu's LM12) and price impact measure (Amihud's RtoV12).[44] If the least liquid portfolio consistently outperforms the most liquid portfolio, this is evidence of the presence of liquidity premium at fund level, and vice versa.

6.2.1. LM12-Sorted Fund Portfolios

At the beginning of each month, all eligible equity funds in our sample are sorted in ascending order according to their LM12. Based on this sort, funds are grouped into ten equally weighted portfolios (deciles). We then calculate the mean of each characteristic of equity funds in each decile. We report results of basic characteristics in Table 6.2 for all fund portfolios during the 25-year period. Decile 1 (H) contains the most liquid funds and the least liquid funds are in Decile 10 (L). Additionally, we form a zero-investment portfolio L-H consisting of long positions in the least liquid funds (Decile 10, L) and short positions in the most liquid funds (Decile 1, H).

Sorting by LM12, Panel A reports the fund's size, the proportion and number of stock-holdings in each decile. We find a salient phenomenon that the least liquid portfolio (Decile 10) is the smallest fund portfolio ($385.51 million)[45] with the highest number of stock-holdings (153 stocks). It makes sense that the small funds need to hold many more stocks than large funds due to the illiquidity of their stock-holdings. Since share redemption by investors might be precipitate and unexpected sometimes, the small funds have to depend on increasing the number of stock-holdings to deal

[44] In the previous section, we have concluded that LM12 and RtoV12, among all FLMs, are the most representative proxies for fund liquidity.

[45] It is consistent with the findings of previous research, such as Keim (1999), Shawky and Tian (2010). Shawky and Tian (2010) conclude that the better performance of small-cap equity funds is because they tend to buy less liquid stocks and sell more liquid stocks, which provides liquidity services to the market.

with the redemption, so that their liquidity requirement is not threatened. Panel B presents the liquidity measures and stock-holdings characteristics of each decile. As can be seen, the fund portfolio with the least liquid stock-holdings (Decile 10) has the biggest log cash inflow (FLOW1), the second lowest turnover ratio (TO12), the highest Amihud's price impact ratio (RtoV12), the highest Hasbrouck's effective cost (EC), the smallest capitalization of stock-holdings (MV), and the highest B/M ratio (relatively, the value companies). As to the most liquid portfolio (Decile 1), though it has the highest turnover (TO12), the third lowest price impact ratio (RtoV12), and the lowest B/M ratio, other characteristics' rankings are not as notable as Decile 10. In general, LM12 captures the fund liquidity well, and is able to represent fund liquidity. Panel C shows the holding period returns for 1 month (HPR1M) and for 12 months (HPR12M) of each decile, and reveals that there is no significant liquidity premium over the 1-month or 12-month holding periods. In moving from the most liquid decile (Decile 1) to the least liquid decile (Decile 10), the portfolio holding period returns for 1 month and 12 month both increase gradually and monotonically. Although the portfolio L-H discloses liquidity premium 0.211% for HPR1M and 3.437% for HPR12M, both are not significant (their t-statistics are only 1.04 and 1.19, respectively). Consistent with our expectation, liquidity premium at fund level does not exist, because almost all mutual funds (at least actively managed equity funds) pay a great deal of attention to liquidity. Therefore, it is impossible to find significant liquidity premium within liquid portfolios.

Table 6.2

Characteristics of the LM12-Sorted Fund Portfolios

The table reports the characteristics of fund portfolios sorted by the LM12 in our sample. At the beginning of each month, eligible equity funds are sorted in ascending order based on their LM12. Based on this sort, funds are grouped into ten equally weighted portfolios. 1 (H) denotes the lowest LM12 decile portfolio, i.e. the most liquid decile. 10 (L) denotes the highest LM12 decile portfolio, i.e. the least liquid decile. L-H denotes a zero-investment portfolio consisting of long positions in the least liquid funds (Decile 10, L) and short positions in the most liquid funds (Decile 1, H). HPR1M shows the mean return of a fund portfolio over one month holding period, and similarly for HPR12M. Panel A shows the characteristics of fund size and stock-holdings for each fund portfolio. Panel B stands for the results of fund liquidity measures and fund stock-holdings characteristics. Panel C represents the performance of the LM12-sorted fund portfolios.

	1 (H)	2	3	4	5	6	7	8	9	10 (L)	L-H
Panel A: Fund Size and Stock Holdings											
TNA	541.85	713.98	799.42	1011.88	1178.79	1023.84	994.39	965.94	620.56	385.51	-156.34
STKPCT	83.99%	85.21%	85.12%	84.85%	84.86%	85.00%	84.74%	84.73%	84.11%	82.81%	-1.19%
STKNUM	59	69	78	81	81	82	87	91	100	153	94
Panel B: Liquidity Measures											
FLOW1	0.00484	0.00593	0.00645	0.00512	0.00535	0.00605	0.00606	0.00769	0.00718	0.00894	0.00413
FLOW2	3.5197	7.5855	6.2533	9.5542	6.1922	6.7892	2.4809	4.7514	3.3461	3.4135	-0.0875
LM12	0.0000	0.0007	0.0053	0.0186	0.0495	0.1159	0.2446	0.4928	1.0437	4.7204	4.7204
TO12	0.9315	0.6617	0.5815	0.5745	0.5801	0.5707	0.5581	0.5946	0.6358	0.5662	-0.3653
RTOV12	0.00436	0.00309	0.00396	0.00592	0.01032	0.01762	0.03012	0.05310	0.09192	0.36192	0.35756
EC	0.00355	0.00307	0.00297	0.00304	0.00318	0.00332	0.00355	0.00399	0.00463	0.00615	0.00260
MV	14294.2	17755.8	21931.8	25992.4	30205.0	33976.1	34585.4	29807.2	16803.1	4172.1	-10122.0
B/M	0.3941	0.4471	0.4692	0.4539	0.4310	0.4156	0.4200	0.4168	0.4409	0.5500	0.1560
Panel C: Holding Period Returns											
HPR1M	0.708%	0.781%	0.781%	0.789%	0.793%	0.809%	0.844%	0.919%	0.924%	0.919%	0.211%
t-statistics	1.90	2.77	3.05	3.01	3.01	3.02	3.15	3.24	3.20	3.34	1.04
HPR12M	9.004%	10.182%	10.958%	10.313%	10.716%	10.992%	11.290%	11.285%	11.579%	12.440%	3.437%
t-statistics	1.85	2.60	2.96	2.79	2.93	2.98	3.04	2.93	3.02	3.26	1.19

We also test fund liquidity premium by controlling for risk using various regression models mentioned before. If the risk-adjusted performance in the least liquid portfolio is significantly better than that in the most liquid portfolio, that still will be a strong evidence of the presence of fund liquidity premium. This time, we sort all equity funds in each month on the decile rankings of their LM12 of the previous month. Then we track these ten portfolios for one month and use the entire time series of their monthly net returns to calculate the alpha and betas to the various factors for each of these ten portfolios. To be specific, for each month we run a time-series regression of excess portfolio returns on the excess market return (MKTRF), size factor (SMB), value factor (HML), momentum factor (PR1YR), liquidity risk factor (LIQ_V), and liquidity factor (LIQ) respectively in various models. At the same time, we also calculate the alpha and betas to the various factors for the zero-investment portfolio L-H.

Table 6.3 reports the risk-adjusted performance in various asset pricing models for fund portfolios classified by LM12. Panels A to E present parameter estimates of the CAPM, FF3F, FF+Mom, FF+PS, and LCAPM, respectively. Results here all show that fund liquidity premium is little to none after controlling for risks. The CAPM performance is not enough good with respect to the less liquid portfolios (such as 0.034% in Decile 9 and 0.063% in Decile 10), resulting in a liquidity premium of 0.357% per month, compared to the unadjusted value of 0.211%. However, its t-statistic is only 1.90, which indicates the liquidity premium is not significant. There is a similar story (insignificant liquidity premium) with the FF3F, FF+Mom, and FF+PS. As to the risk-adjusted performance of Liu LCAPM, the performance of the least liquid portfolio (Decile 10) is even worse than the performance of the most liquid portfolio (Decile 1), which results in a negative liquidity premium. The absence of fund liquidity premium is confirmed by the risk-adjusted performance.

Table 6.3

Risk-Adjusted Performance of the LM12-Sorted Fund Portfolios

The table reports the risk-adjusted performance in various asset pricing models for fund portfolios classified by LM12. In each month, all eligible equity funds are sorted in ascending order based on their LM12 of the previous month. Based on this sort, funds are grouped into equally weighted decile portfolio. 1 (H) denotes the lowest LM12 decile portfolio, i.e. the most liquid decile. 10 (L) denotes the highest LM12 decile portfolio, i.e. the least liquid decile. L-H denotes a zero-investment portfolio consisting of long positions in the least liquid funds (Decile 10, L) and short positions in the most liquid funds (Decile 1, H). Panel A presents parameter estimate of the CAPM:

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_{m,i}(R_{m,t} - R_{f,t}) + \varepsilon_{i,t},$$

Panel B reports parameter estimates of the Fama-French three-factor model (FF3F):

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_{m,i}(R_{m,t} - R_{f,t}) + \beta_{s,i} SMB_t + \beta_{h,i} HML_t + \varepsilon_{i,t},$$

Panel C shows parameter estimates of the Carhart four-factor model (FF+Mom):

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_{m,i}(R_{m,t} - R_{f,t}) + \beta_{s,i} SMB_t + \beta_{h,i} HML_t + \beta_{p,i} PR1YR_t + \varepsilon_{i,t},$$

Panel D stands for parameter estimates of the Pastor-Stambaugh four-factor model (FF+PS):

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_{m,i}(R_{m,t} - R_{f,t}) + \beta_{s,i} SMB_t + \beta_{h,i} HML_t + \beta_{l,i} LIQ\_V_t + \varepsilon_{i,t},$$

Panel E reports parameter estimates of the Liu liquidity-augmented two-factor model (LCAPM):

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_{m,i}(R_{m,t} - R_{f,t}) + \beta_{l,i} LIQ_t + \varepsilon_{i,t},$$

where $R_{i,t} - R_{f,t}$ is the excess return on fund i in period t, $R_{m,t} - R_{f,t}$ is the excess return on the market proxy portfolio in period t ($R_{i,t}$ is the return on fund i, $R_{f,t}$ is the risk-free rate, in this research we define it as one month T-bill rate, $R_{m,t}$ is the return on market portfolio, which is the value-weighted return on all NYSE, AMEX, and NASDAQ stocks); SMB, HML, PR1YR, LIQ_V, and LIQ are the small-minus-big size portfolio return, high-minus-low book-to-market portfolio return, high-minus-low prior 1-year return portfolio return, high-minus-low value-weighted liquidity risk portfolio return, and illiquid-minus-liquid portfolio return in period t, respectively; and α_i and β_i are the regression's intercept and slope coefficients for explanatory factors.

Table 6.3 - Continued

	1 (H)	2	3	4	5	6	7	8	9	10 (L)	L-H
Panel A: CAPM-adjusted performance											
α	-0.294%	-0.107%	-0.071%	-0.077%	-0.071%	-0.057%	-0.017%	0.031%	0.034%	0.063%	0.357%
t (α)	-1.71	-1.33	-1.45	-1.81	-1.34	-0.80	-0.21	0.35	0.34	0.57	1.90
β_mkt	1.274	1.037	0.961	0.990	0.988	0.991	0.981	1.036	1.041	0.970	-0.304
t (β_mkt)	33.44	58.04	88.24	105.23	83.39	62.65	55.42	54.03	47.42	39.45	-7.30
R^2	0.791	0.919	0.963	0.974	0.959	0.930	0.912	0.908	0.884	0.840	0.150
Panel B: FF3F-adjusted performance											
α	-0.074%	-0.067%	-0.092%	-0.101%	-0.094%	-0.080%	-0.051%	0.093%	0.050%	-0.055%	0.018%
t (α)	-0.62	-0.93	-1.89	-2.39	-1.76	-1.11	-0.64	1.44	0.83	-0.90	0.12
β_mkt	1.080	0.989	0.969	1.005	1.005	1.011	1.006	0.964	0.979	0.982	-0.097
t (β_mkt)	37.07	56.82	81.40	97.69	77.39	58.06	51.71	61.43	66.34	65.63	-2.64
β_smb	0.428	0.178	0.049	0.006	-0.022	-0.038	-0.024	0.264	0.418	0.520	0.092
t (β_smb)	11.00	7.65	3.10	0.42	-1.24	-1.61	-0.91	12.58	21.20	25.99	1.87
β_hml	-0.444	-0.072	0.049	0.054	0.048	0.046	0.071	-0.115	-0.003	0.298	0.742
t (β_hml)	-9.74	-2.65	2.65	3.34	2.34	1.68	2.35	-4.68	-0.12	12.72	12.88
R^2	0.9010	0.9379	0.9646	0.9748	0.9603	0.9313	0.9141	0.9502	0.9574	0.9520	0.4630
Panel C: FF+Mom-adjusted performance											
α	-0.128%	-0.129%	-0.099%	-0.102%	-0.071%	-0.054%	-0.015%	0.034%	0.018%	-0.014%	0.115%
t (α)	-1.05	-1.79	-1.97	-2.33	-1.30	-0.74	-0.18	0.52	0.30	-0.22	0.74
β_mkt	1.091	1.002	0.970	1.005	1.001	1.005	0.998	0.976	0.985	0.974	-0.117
t (β_mkt)	36.92	57.70	79.91	95.71	75.89	56.81	50.61	62.56	65.95	64.64	-3.14
β_smb	0.424	0.173	0.049	0.006	-0.020	-0.036	-0.021	0.259	0.416	0.523	0.099
t (β_smb)	10.93	7.60	3.06	0.41	-1.14	-1.53	-0.81	12.66	21.18	26.43	2.03
β_hml	-0.432	-0.059	0.051	0.054	0.043	0.041	0.064	-0.102	0.004	0.289	0.721
t (β_hml)	-9.44	-2.19	2.71	3.31	2.09	1.48	2.08	-4.22	0.18	12.38	12.55
β_pr1yr	0.053	0.060	0.007	0.000	-0.022	-0.024	-0.035	0.058	0.031	-0.040	-0.093
t (β_pr1yr)	1.93	3.73	0.61	0.03	-1.81	-1.48	-1.92	3.98	2.21	-2.87	-2.70
R^2	0.9019	0.9405	0.9645	0.9747	0.9606	0.9316	0.9149	0.9526	0.9580	0.9532	0.4743
Panel D: FF+PS-adjusted performance											
α	-0.108%	-0.092%	-0.113%	-0.094%	-0.077%	-0.046%	-0.018%	0.123%	0.086%	-0.037%	0.071%
t (α)	-0.90	-1.30	-2.35	-2.21	-1.46	-0.66	-0.23	1.96	1.48	-0.61	0.47
β_mkt	1.070	0.982	0.963	1.008	1.010	1.020	1.015	0.972	0.989	0.988	-0.082
t (β_mkt)	36.81	56.91	82.23	97.36	78.13	59.96	53.03	63.42	70.00	66.19	-2.25
β_smb	0.430	0.180	0.051	0.005	-0.023	-0.040	-0.026	0.262	0.416	0.519	0.089
t (β_smb)	11.17	7.85	3.26	0.38	-1.32	-1.76	-1.02	12.88	22.19	26.23	1.83
β_hml	-0.457	-0.082	0.041	0.057	0.054	0.059	0.085	-0.103	0.012	0.305	0.763
t (β_hml)	-10.08	-3.06	2.25	3.51	2.69	2.23	2.83	-4.29	0.53	13.10	13.38
β_liq_v	0.090	0.067	0.054	-0.019	-0.044	-0.087	-0.087	-0.079	-0.094	-0.048	-0.138
t (β_liq_v)	2.66	3.36	3.97	-1.61	-2.94	-4.43	-3.92	-4.46	-5.73	-2.79	-3.26
R^2	0.9030	0.9400	0.9663	0.9749	0.9613	0.9354	0.9181	0.9532	0.9616	0.9531	0.4801
Panel E: LCAPM-adjusted performance											
α	0.239%	0.047%	-0.021%	-0.050%	-0.055%	-0.047%	-0.019%	0.220%	0.248%	0.100%	-0.138%
t (α)	1.50	0.57	-0.40	-1.12	-0.96	-0.62	-0.22	2.55	2.50	0.85	-0.76
β_mkt	0.920	0.935	0.928	0.973	0.977	0.985	0.982	0.910	0.899	0.945	0.025
t (β_mkt)	18.58	36.81	57.88	69.66	55.37	41.75	37.21	33.94	29.22	25.82	0.45
β_liq	-0.535	-0.154	-0.051	-0.026	-0.017	-0.010	0.002	-0.191	-0.215	-0.037	0.498
t (β_liq)	-9.66	-5.42	-2.84	-1.69	-0.84	-0.36	0.06	-6.35	-6.25	-0.91	7.88
R^2	0.8405	0.9263	0.9642	0.9741	0.9591	0.9296	0.9118	0.9187	0.8969	0.8400	0.2961

6.2.2. RtoV12-Sorted Fund Portfolios

Along with Liu's trading discontinuity measure (LM12), Amihud's price impact ratio (RtoV12) is one of the most significant proxies for liquidity, among all FLMs. For robustness, it remains possible to examine the fund liquidity premium again after sorting funds based on their RtoV12.

Similar to sorting funds into decile based on LM12, we sort all equity funds into ten portfolios (deciles) by RtoV12 for each month. At the same time, we also construct a zero-investment portfolio L-H consisting of long positions in the least liquid funds and short positions in the most liquid funds. We report results of basic characteristics in Table 6.4 for RtoV12-sorted fund portfolios. Panel A presents the fund's size, the proportion and number of stock-holdings of fund in each decile. Similar to sorting by LM12, we also find that the least liquid portfolio is the smallest fund portfolio ($294.61 million) with the highest number of stock-holdings (141 stocks). It is reasonable that the small funds hold many more stocks than large funds due to the illiquidity of their stock-holdings. In Panel B, it can be seen that the fund portfolio with the least liquid stock-holdings has the biggest log cash inflow (FLOW1), the highest Liu's trading discontinuity (LM12), the highest Hasbrouck's effective cost (EC), the smallest capitalization of stock-holdings (MV), and the highest B/M ratio. In a word, RtoV12, as LM12, also captures the fund liquidity well. Panel C discloses that there is no significant fund liquidity premium. Although the portfolio L-H demonstrates liquidity premium 0.174% for HPR1M and 2.851% for HPR12M, both are not significant (their t-statistics are only 1.10 and 1.02, respectively). This result is consistent with our expectation and confirms the result of sorting by LM12.

Table 6.4

Characteristics of the RtoV12-Sorted Fund Portfolios

The table reports the characteristics of fund portfolios sorted by the RtoV12 in our sample. At the beginning of each month, eligible equity funds are sorted in ascending order based on their RtoV12. Based on this sort, funds are grouped into ten equally weighted portfolios. 1 (H) denotes the lowest RtoV12 decile portfolio, i.e. the most liquid decile. 10 (L) denotes the highest RtoV12 decile portfolio, i.e. the least liquid decile. L-H denotes a zero-investment portfolio consisting of long positions in the least liquid funds (Decile 10, L) and short positions in the most liquid funds (Decile 1, H). HPR1M shows the mean return of a fund portfolio over one month holding period, and similarly for HPR12M. Panel A shows the characteristics of fund size and stock-holdings for each fund portfolio. Panel B stands for the results of fund liquidity measures and fund stock-holdings characteristics. Panel C represents the performance of the RtoV12-sorted fund portfolios.

	1 (H)	2	3	4	5	6	7	8	9	10 (L)	L-H
Panel A: Fund Size and Stock Holdings											
TNA	1495.26	1320.09	1116.11	1169.12	896.36	695.12	525.55	396.58	330.98	294.61	-1200.65
STKPCT	87.18%	85.77%	85.27%	84.93%	84.24%	84.10%	83.66%	83.98%	83.47%	82.82%	-4.36%
STKNUM	65	77	80	81	78	80	80	91	108	141	76
Panel B: Liquidity Measures											
FLOW1	0.00541	0.00526	0.00522	0.00507	0.00537	0.00625	0.00696	0.00765	0.00714	0.00930	0.00391
FLOW2	8.5375	3.2452	5.6403	6.4473	8.6672	7.2570	4.4985	3.6253	3.1302	2.8875	-5.5606
LM12	0.0082	0.0108	0.0182	0.0373	0.0803	0.1697	0.3135	0.5981	1.1046	4.3556	4.3474
TO12	0.4878	0.5188	0.5238	0.5547	0.6541	0.7099	0.7243	0.7634	0.7055	0.6109	0.1231
RTOV12	0.00081	0.00166	0.00274	0.00438	0.00775	0.01399	0.02444	0.04428	0.08644	0.39546	0.39464
EC	0.00258	0.00274	0.00282	0.00297	0.00322	0.00351	0.00382	0.00432	0.00484	0.00663	0.00405
MV	54416.7	43545.6	37957.2	31700.8	20626.3	14135.4	12388.4	7165.0	4633.9	3061.0	-51355.7
B/M	0.4152	0.4266	0.4510	0.4525	0.4436	0.4239	0.4208	0.4143	0.4536	0.5375	0.1223
Panel C: Holding Period Returns											
HPR1M	0.734%	0.725%	0.734%	0.746%	0.831%	0.859%	0.915%	0.903%	0.910%	0.908%	0.174%
t-statistics	2.89	2.83	2.92	2.94	3.05	3.04	3.12	2.89	2.96	3.09	1.10
HPR12M	9.462%	9.230%	9.784%	10.374%	11.018%	11.207%	11.709%	11.922%	11.751%	12.313%	2.851%
t-statistics	2.40	2.45	2.62	2.86	2.82	2.93	2.93	2.87	2.99	3.06	1.02

Furthermore, we also test fund liquidity premium through risk-adjusted performance. Similar to the procedure of sorting by LM12, we sort all equity funds in each month on the decile rankings of their RtoV12 of the previous month. In addition, we also form a zero-investment portfolio L-H and then calculate the alpha and betas to the various factors for this zero-investment portfolio. Results from Panels A to E in Table 6.5 again reveal that fund liquidity premium does not exist after controlling for risks. In fact, the FF3F and FF+PS performance of the least liquid portfolio are even worse than the performance of the most liquid portfolio, which leads to the negative liquidity premium. The FF+Mom performance is poor at each decile; all are negative.

The liquidity premiums of CAPM and Liu LCAPM are positive at 0.140% and 0.167% per month, but their t-statistics are only 0.88 and 0.99, which indicates that the liquidity premium is insignificant. The absence of fund liquidity premium is proved again by sorting funds based on RtoV12.

Table 6.5

Risk-Adjusted Performance of the RtoV12-Sorted Fund Portfolios

The table reports the risk-adjusted performance in various asset pricing models for fund portfolios classified by RtoV12. In each month, all eligible equity funds are sorted in ascending order based on their RtoV12 of the previous month. Based on this sort, funds are grouped into equally weighted decile portfolio. 1 (H) denotes the lowest RtoV12 decile portfolio, i.e. the most liquid decile. 10 (L) denotes the highest RtoV12 decile portfolio, i.e. the least liquid decile. L-H denotes a zero-investment portfolio consisting of long positions in the least liquid funds (Decile 10, L) and short positions in the most liquid funds (Decile 1, H). Panel A presents parameter estimate of the CAPM:

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_{m,i}(R_{m,t} - R_{f,t}) + \varepsilon_{i,t},$$

Panel B reports parameter estimates of the Fama-French three-factor model (FF3F):

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_{m,i}(R_{m,t} - R_{f,t}) + \beta_{s,i}SMB_t + \beta_{h,i}HML_t + \varepsilon_{i,t},$$

Panel C shows parameter estimates of the Carhart four-factor model (FF+Mom):

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_{m,i}(R_{m,t} - R_{f,t}) + \beta_{s,i}SMB_t + \beta_{h,i}HML_t + \beta_{p,i}PR1YR_t + \varepsilon_{i,t},$$

Panel D stands for parameter estimates of the Pastor-Stambaugh four-factor model (FF+PS):

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_{m,i}(R_{m,t} - R_{f,t}) + \beta_{s,i}SMB_t + \beta_{h,i}HML_t + \beta_{l,i}LIQ\_V_t + \varepsilon_{i,t},$$

Panel E reports parameter estimates of the Liu liquidity-augmented two-factor model (LCAPM):

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_{m,i}(R_{m,t} - R_{f,t}) + \beta_{l,i}LIQ_t + \varepsilon_{i,t},$$

where $R_{i,t} - R_{f,t}$ is the excess return on fund i in period t, $R_{m,t} - R_{f,t}$ is the excess return on the market proxy portfolio in period t ($R_{i,t}$ is the return on fund i, $R_{f,t}$ is the risk-free rate, in this research we define it as one month T-bill rate, $R_{m,t}$ is the return on market portfolio, which is the value-weighted return on all NYSE, AMEX, and NASDAQ stocks); SMB, HML, PR1YR, LIQ_V, and LIQ are the small-minus-big size portfolio return, high-minus-low book-to-market portfolio return, high-minus-low prior 1-year return portfolio return, high-minus-low value-weighted liquidity risk portfolio return, and illiquid-minus-liquid portfolio return in period t, respectively; and α_i and β_i are the regression's intercept and slope coefficients for explanatory factors.

Table 6.5 - Continued

	1 (H)	2	3	4	5	6	7	8	9	10 (L)	L-H
Panel A: CAPM-adjusted performance											
α	-0.115%	-0.133%	-0.115%	-0.108%	-0.053%	-0.039%	0.004%	-0.026%	-0.011%	0.025%	0.140%
$t(\alpha)$	-2.40	-4.07	-4.07	-3.39	-1.12	-0.60	0.05	-0.24	-0.10	0.20	0.88
β_{mkt}	0.955	0.974	0.956	0.965	1.028	1.057	1.084	1.121	1.105	1.026	0.072
$t(\beta_{mkt})$	89.84	133.92	152.44	136.59	97.57	73.52	62.45	45.77	45.14	37.24	2.04
R^2	0.965	0.984	0.987	0.984	0.970	0.948	0.929	0.876	0.873	0.824	0.011
Panel B: FF3F-adjusted performance											
α	-0.037%	-0.095%	-0.114%	-0.112%	-0.041%	-0.026%	0.019%	0.024%	-0.021%	-0.070%	-0.033%
$t(\alpha)$	-1.05	-3.42	-4.54	-3.54	-0.94	-0.48	0.32	0.38	-0.36	-1.07	-0.38
β_{mkt}	0.923	0.961	0.964	0.972	1.008	1.026	1.041	1.032	1.048	1.014	0.091
$t(\beta_{mkt})$	106.46	142.69	157.55	125.85	93.79	76.67	71.00	68.23	74.19	63.31	4.32
β_{smb}	-0.150	-0.092	-0.074	-0.031	0.095	0.185	0.267	0.463	0.517	0.600	0.750
$t(\beta_{smb})$	-12.94	-10.17	-9.10	-3.04	6.62	10.37	13.63	22.91	27.39	28.05	26.78
β_{hml}	-0.180	-0.091	-0.007	0.007	-0.018	-0.012	-0.012	-0.071	0.062	0.253	0.433
$t(\beta_{hml})$	-13.25	-8.61	-0.77	0.57	-1.08	-0.58	-0.53	-3.00	2.82	10.11	13.20
R^2	0.9809	0.9887	0.9903	0.9849	0.9746	0.9636	0.9592	0.9618	0.9658	0.9519	0.7157
Panel C: FF+Mom-adjusted performance											
α	-0.038%	-0.096%	-0.101%	-0.104%	-0.050%	-0.049%	-0.013%	-0.047%	-0.044%	-0.021%	0.017%
$t(\alpha)$	-1.04	-3.37	-3.93	-3.19	-1.10	-0.87	-0.22	-0.77	-0.73	-0.32	0.19
β_{mkt}	0.923	0.961	0.962	0.970	1.010	1.031	1.047	1.047	1.053	1.004	0.081
$t(\beta_{mkt})$	104.31	139.84	155.25	123.32	92.15	75.84	70.62	70.57	73.33	62.47	3.80
β_{smb}	-0.150	-0.092	-0.073	-0.031	0.094	0.184	0.265	0.458	0.515	0.604	0.754
$t(\beta_{smb})$	-12.91	-10.15	-9.02	-2.98	6.56	10.30	13.59	23.51	27.34	28.62	27.10
β_{hml}	-0.180	-0.090	-0.010	0.005	-0.016	-0.007	-0.005	-0.056	0.067	0.243	0.422
$t(\beta_{hml})$	-13.10	-8.49	-1.06	0.42	-0.96	-0.34	-0.23	-2.43	3.02	9.75	12.87
β_{pr1yr}	0.001	0.001	-0.013	-0.008	0.008	0.022	0.031	0.068	0.022	-0.047	-0.048
$t(\beta_{pr1yr})$	0.10	0.21	-2.25	-1.07	0.83	1.74	2.29	4.97	1.65	-3.18	-2.45
R^2	0.9809	0.9887	0.9904	0.9849	0.9745	0.9638	0.9598	0.9646	0.9660	0.9534	0.7205
Panel D: FF+PS-adjusted performance											
α	-0.033%	-0.093%	-0.110%	-0.108%	-0.041%	-0.019%	0.031%	0.038%	0.001%	-0.046%	-0.013%
$t(\alpha)$	-0.92	-3.35	-4.35	-3.39	-0.93	-0.34	0.52	0.60	0.02	-0.71	-0.15
β_{mkt}	0.924	0.961	0.966	0.973	1.008	1.028	1.044	1.037	1.054	1.021	0.096
$t(\beta_{mkt})$	105.82	141.40	156.97	125.05	92.86	76.29	70.97	68.34	75.51	64.39	4.58
β_{smb}	-0.150	-0.092	-0.075	-0.032	0.095	0.185	0.266	0.462	0.516	0.599	0.749
$t(\beta_{smb})$	-12.98	-10.17	-9.16	-3.07	6.60	10.35	13.65	22.99	27.86	28.49	26.88
β_{hml}	-0.178	-0.090	-0.005	0.009	-0.018	-0.009	-0.007	-0.065	0.071	0.263	0.441
$t(\beta_{hml})$	-13.04	-8.49	-0.57	0.70	-1.08	-0.43	-0.32	-2.76	3.26	10.62	13.43
β_{liq_v}	-0.012	-0.004	-0.012	-0.011	0.000	-0.020	-0.032	-0.037	-0.058	-0.063	-0.051
$t(\beta_{liq\_v})$	-1.20	-0.48	-1.69	-1.18	0.01	-1.27	-1.88	-2.10	-3.58	-3.46	-2.11
R^2	0.9810	0.9887	0.9904	0.9849	0.9745	0.9637	0.9596	0.9622	0.9671	0.9537	0.7190
Panel E: LCAPM-adjusted performance											
α	-0.045%	-0.096%	-0.104%	-0.077%	0.060%	0.116%	0.193%	0.271%	0.218%	0.122%	0.167%
$t(\alpha)$	-0.90	-2.80	-3.45	-2.31	1.27	1.82	2.51	2.54	1.96	0.93	0.99
β_{mkt}	0.908	0.950	0.948	0.945	0.953	0.954	0.958	0.924	0.953	0.962	0.054
$t(\beta_{mkt})$	58.91	88.97	101.64	90.72	65.47	48.07	40.07	27.95	27.63	23.58	1.02
β_{liq}	-0.071	-0.037	-0.011	-0.031	-0.114	-0.156	-0.190	-0.298	-0.230	-0.098	-0.027
$t(\beta_{liq})$	-4.09	-3.10	-1.07	-2.63	-6.97	-7.01	-7.11	-8.06	-5.96	-2.14	-0.47
R^2	0.9664	0.9842	0.9874	0.9847	0.9740	0.9553	0.9396	0.8982	0.8864	0.8261	0.0079

In summary, fund liquidity premium is a different story with stock liquidity premium. There is an absence of liquidity premium at fund level, no matter which FLMs are used for sorting (Liu's trading discontinuity measure, LM12 or Amihud's price impact ratio, RtoV12), and no matter which fund performance are examined (holding period returns or risk-adjusted performance). The truth behind the phenomenon appears to be that almost all actively managed equity funds in effect pay much attention to liquidity and, thus, it might not be feasible to find significant liquidity premium within these highly liquid fund portfolios.

CHAPTER 7: FUND PERFORMANCE

7.1. Performance of Portfolio of Funds

As described in the Methodology Chapter, we have conducted a simple time series regression for each fund to obtain the estimated alpha and factor loadings for various asset pricing models (including conventional models and liquidity-based models). Then we calculated the mean of these estimated alpha and factor loadings of the fund sample for each model. However, this is unable to achieve the significance of the estimated alpha and factor loadings through averaging the t-statistics for all fund data. In addition, funds have diverse survival time period and different risk-taking preference. Thus, we examine fund performance as a whole, by constructing a portfolio of funds in each month and run time-series regression for the cross-section of the fund portfolio's net returns.

We use two methods (value weighting and equal weighting) to construct a portfolio of equity mutual funds in each month. In the value-weighted portfolio of funds (VWPOF), all eligible equity funds are weighted by fund scale (total net assets, TNA) at the beginning of each month. In the equally-weighted portfolio of funds (EWPOF), equity funds are weighted equally each month. After constructing these two kinds of portfolio of funds, we run time-series regression of various asset pricing models to estimate the performance (i.e. the intercepts in these models, or monthly alphas) of VWPOF and EWPOF, respectively. In addition, we provide and analyze the results from the conventional models (CAPM, Fama-French three-factor model - FF3F, and Carhart four-factor model - FF+Mom) and liquidity-based models (Pastor-Stambaugh four-factor model - FF+PS, and Liu liquidity-augmented two-factor model - LCAPM):

$$r_{i,t} = \alpha_i + \beta_i MKTRF_t + \varepsilon_{i,t}, \text{ (CAPM)}$$

$$r_{i,t} = \alpha_i + \beta_{m,i} MKTRF_t + \beta_{s,i} SMB_t + \beta_{h,i} HML_t + \varepsilon_{i,t}, \text{ (FF3F)}$$

$$r_{i,t} = \alpha_i + \beta_{m,i} MKTRF_t + \beta_{s,i} SMB_t + \beta_{h,i} HML_t + \beta_{p,i} PR1YR_t + \varepsilon_{i,t}, \text{ (FF+Mom)}$$

$$r_{i,t} = \alpha_i + \beta_{m,i} MKTRF_t + \beta_{s,i} SMB_t + \beta_{h,i} HML_t + \beta_{l,i} LIQ\_V_t + \varepsilon_{i,t}, \text{ (FF+PS)}$$

$$r_{i,t} = \alpha_i + \beta_{m,i} MKTRF_t + \beta_{l,i} LIQ_t + \varepsilon_{i,t}. \text{ (LCAPM)}$$

In this research, we prefer the results from the net returns of VWPOF, because the performance of VWPOF informs us whether the aggregate wealth invested in funds can add value, which is of most concern to mass investors. Hence, we primarily report the results of the intercepts in various model regressions for VWPOF at net return level.

Table 7.1 presents the annualized intercepts[46], t-statistics, and p-values for the intercepts for various models estimated on value-weighted (VW) and equally-weighted (EW) net returns on the portfolio of actively managed equity funds. Also, this table shows the regression slopes (β_mkt, β_smb, β_hml, β_pr1yr, β_liq_v, and β_liq, for MKTRF, SMB, HML, PR1YR, LIQ_V, and LIQ factor, respectively), t-statistics, and p-values for the slopes, and the regression R^2.

In Panel A of Table 7.1, the intercepts summarize the performance of aggregate wealth invested in funds (VWPOF) relative to passive benchmarks. At first glance, the fund performance is poor. The annualized intercepts of the first four models are all negative, ranging from -0.721% to -1.057% per year, with t-statistics from -2.37 to -3.23. These results are in line with pervious work[47] and are especially consistent with the results of Fama and French (2010). These significant negative alphas tell us that,

[46] The annualized intercepts are approximately obtained by multiplying monthly alpha (i.e. the original intercept) by 12.

[47] Such as Jensen (1968), Malkiel (1995), and Gruber (1996).

on average, actively managed equity funds do not have the ability to generate sufficient returns to cover the costs and expenses. However, the result from Liu LCAPM is a different story. Not only is the model's intercept negative nearly zero (-0.116% per year), but also its t-statistic is insignificant (only -0.34). The fund performance being insignificantly different from zero indicates that the aggregate portfolio of funds mimics the performance of benchmarks. Furthermore, for EWPOF (in Panel B), the annualized intercepts of conventional models are still negative, but the LCAPM's yearly alpha becomes positive at 0.768% with t-statistic of 1.35.

The market slopes (β_mkt) in Table 7.1 are close to 1.0, ranging from 0.942 to 1.023. That is not surprising since our sample is actively managed equity funds that invest primarily in U.S. stocks. The SMB slopes (β_smb) for VWPOF are around at 0.06, which is smaller than that in EWPOF (around 0.18). Fama and French (2010) also discover a similar phenomenon. It can be inferred that the smaller funds show more tilt toward small stocks, but total dollars invested in actively managed equity funds (i.e. captured by returns of VWPOF) have little tilt to small stocks. In Panel A, the slopes of HML and PR1YR are significant negative and positive, respectively, which indicates that actively managed equity funds prefer to invest in growth stocks and prior 1-year winner stocks. As to the liquidity risk factor (LIQ_V in FF+PS) and liquidity factor (LIQ in the LCAPM), the slope of liquidity risk (β_liq_v) is negative at -0.011 insignificantly, whereas the slope of liquidity factor (β_liq) is also negative at -0.079, but with significant (t-statistic is -7.93). Apparently, actively managed equity funds are likely to invest in stocks with less liquid risk, as well as more liquid stocks. Furthermore, we discover that Liu's liquidity factor (LIQ) not only grasps the liquidity risk but also has much significant than liquidity risk factor (LIQ_V). Therefore, in this thesis, we focus the relation between fund excess return and Liu's liquidity factors

(LIQ) through the estimated coefficients on liquidity factor.

All facts above tell us two different stories. The first is, based on the first four models, actively managed equity funds as a whole underperforms the benchmarks. In contrast, based on the Liu LCAPM, equity funds in aggregate hold a portfolio mimics the performance of benchmarks. These results echo our expectations. The underperformance of funds in the first story is, we suggest, due to the liquidity factor not having been properly considered in the earlier models.[48] In contrast, the funds' mimicking the performance of benchmarks in the second story is attributed to having considered the fund liquidity requirements in Liu LCAPM.

Earlier academic research based on conventional asset pricing models gave less consideration to the impact of a liquidity factor on fund performance. In research on mutual funds, we have to accept that fund managers need to hold a large quantity of highly liquid stocks for providing liquidity to investors and handling possible share redemptions. We have revealed that the estimated coefficients on liquidity risk factor in FF+PS and liquidity factor in Liu LCAPM are both negative. Thus, the less liquidity risk or the more liquid for a portfolio of funds, the less excess returns. To a large extent, the fund performance is affected adversely by fund liquidity requirements.

[48] Although the Pastor-Stambaugh four-factor model (FF+PS) considers the liquidity risk factor, the effect of liquidity risk is much weak. Its slope is only -0.011 with t-statistics -1.57 in our research.

Table 7.1

Intercepts and Slopes in Asset Pricing Models for Portfolio of Funds

The table reports the annualized intercepts (monthly alpha×12), t-statistics and p-values for the intercepts for various models (CAPM, Fama-French three-factor model - FF3F, Carhart four-factor model - FF+Mom, Pastor-Stambaugh four-factor model - FF+PS, and Liu liquidity-augmented two-factor model - LCAPM) estimated on value-weighted (VW) and equally-weighted (EW) net returns on the portfolios of actively managed equity funds in our sample. Also this table shows the regression slopes (β_mkt, β_smb, β_hml, β_ pr1yr, β_liq_v, and β_liq, for MKTRF, SMB, HML, PR1YR, LIQ_V, and LIQ, respectively), t-statistics and p-value for the slopes, and the regression R^2. Panel A presents the intercepts and slopes in various asset pricing models for value-weighted portfolio of actively managed equity funds. Panel B shows the intercepts and slopes in various asset pricing models for equally-weighted portfolios of actively managed equity funds.

Model		α (yearly)	β_mkt	β_smb	β_hml	β_pr1yr	β_liq_v	β_liq	R^2
Panel A: Value-Weigted Portfolios of Funds (VWPOF)									
CAPM	coef	-1.057%	0.997						0.987
	t-statistic	-2.98	152.07						
	p-value	0.0031	<0.0001						
Fama-French three-factor model (FF3F)	coef	-0.773%	0.974	0.062	-0.047				0.991
	t-statistic	-2.54	158.2	7.54	-4.83				
	p-value	0.0115	<0.0001	<0.0001	<0.0001				
Carhart four-factor model (FF+Mom)	coef	-0.995%	0.978	0.061	-0.043	0.018			0.991
	t-statistic	-3.23	158.14	7.47	-4.44	3.12			
	p-value	0.0014	<0.0001	<0.0001	<0.0001	0.002			
Pastor-Stambaugh four-factor model (FF+PS)	coef	-0.721%	0.976	0.062	-0.045		-0.011		0.991
	t-statistic	-2.37	157.51	7.53	-4.63		-1.57		
	p-value	0.0186	<0.0001	<0.0001	<0.0001		0.1167		
Liu liquidity-augmented two-factor model (LCAPM)	coef	-0.116%	0.945					-0.079	0.990
	t-statistic	-0.34	106.49					-7.93	
	p-value	0.7362	<0.0001					<0.0001	
Panel B: Equal-Weigted Portfolios of Funds (EWPOF)									
CAPM	coef	-0.694%	1.023						0.969
	t-statistic	-1.2	95.34						
	p-value	0.2324	<0.0001						
Fama-French three-factor model (FF3F)	coef	-0.580%	0.995	0.179	-0.006				0.984
	t-statistic	-1.38	117.13	15.75	-0.48				
	p-value	0.1673	<0.0001	<0.0001	0.6291				
Carhart four-factor model (FF+Mom)	coef	-0.697%	0.997	0.178	-0.004	0.009			0.984
	t-statistic	-1.62	115.24	15.67	-0.32	1.17			
	p-value	0.1065	<0.0001	<0.0001	0.746	0.2414			
Pastor-Stambaugh four-factor model (FF+PS)	coef	-0.471%	0.997	0.178	-0.003		-0.024		0.984
	t-statistic	-1.13	117.45	15.82	-0.21		-2.43		
	p-value	0.2605	<0.0001	<0.0001	0.8353		0.0155		
Liu liquidity-augmented two-factor model (LCAPM)	coef	0.768%	0.942					-0.122	0.973
	t-statistic	1.35	64.2					-7.45	
	p-value	0.1768	<0.0001					<0.0001	

7.2. Bootstrap Evaluation of Fund Performance

7.2.1. Normality of Individual Funds

Before conducting our bootstrap evaluation, we analyze the distribution of individual funds residuals generated by the five asset pricing models (CAPM, FF3F, FF+Mom, FF+PS, and LCAPM) respectively:

$$r_{i,t} = \alpha_i + \beta_i MKTRF_t + \varepsilon_{i,t}\text{, (CAPM)}$$

$$r_{i,t} = \alpha_i + \beta_{m,i} MKTRF_t + \beta_{s,i} SMB_t + \beta_{h,i} HML_t + \varepsilon_{i,t}\text{, (FF3F)}$$

$$r_{i,t} = \alpha_i + \beta_{m,i} MKTRF_t + \beta_{s,i} SMB_t + \beta_{h,i} HML_t + \beta_{p,i} PR1YR_t + \varepsilon_{i,t}\text{, (FF+Mom)}$$

$$r_{i,t} = \alpha_i + \beta_{m,i} MKTRF_t + \beta_{s,i} SMB_t + \beta_{h,i} HML_t + \beta_{l,i} LIQ\_V_t + \varepsilon_{i,t}\text{, (FF+PS)}$$

$$r_{i,t} = \alpha_i + \beta_{m,i} MKTRF_t + \beta_{l,i} LIQ_t + \varepsilon_{i,t}\text{. (LCAPM)}$$

In the Shapiro-Wilk W test for normality,[49] the p-value of W test is based on the assumption that the distribution is normal. In this study, if the p-value is less than 0.05 (i.e. at 5% significance level), we reject the null hypothesis that the residual is normally distributed. Kosowski et al. (2006) find that normality is rejected for 48% of funds when using Carhart four-factor model. In our tests, the normality is rejected for 59.3%, 48.7%, 43.5%, 47.6%, and 55.4% of funds when using five models above, respectively.

Also we find that residuals from funds in the extreme tails (best funds and worst funds) tend to exhibit higher variance and a greater degree of non-normality than residuals from funds closer to the centre of the performance distribution. This is exceptionally evident in Figures 7.1 to 7.5 which show the bootstrap histograms and kernel density estimate of t-statistics of alpha, t(alpha), at selected points of the performance distribution. These figures vividly illustrates that, although funds in the

[49] Although Kolmogorov-Smirnov, Cramer-von Mises, and Anderson-Darling tests are provided, Shapiro-Wilk W test will be appropriate for our research, since the number of observations of each fund at most is 300, which is considerably less than 2000.

centre (top or bottom 10% and 20% funds) of the performance distribution may exhibit near normal idiosyncratic risks, those in each of the tails (top or bottom 1, 1%, and 5% funds) are not normally distributed. This strong finding of non-normal residuals (i.e. roughly half of funds have alphas are drawn from a distinctly non-normal distribution) challenges the validity of earlier research that relies on normality assumptions. Accordingly, this phenomenon strongly indicates the need to bootstrap simulation, especially in the tails, to determine whether significant performance is due to fund manager's ability or to luck alone.

7.2.2. Bootstrap 1 – Residual-Only Resampling

By applying the residual-only resampling method, we analyze the significance of actively managed equity fund performance, especially the t-statistics of alpha, t(alpha). We rank all equity funds in our sample on their ex-post t(alpha), and report the main findings through a residual-only resampling bootstrap evaluation procedure. Panels A to E of Table 7.2 show the results for actively managed equity funds for each of these five asset pricing models. The first row in each panel reports the ex-post, actual, t(alpha) for various points and percentiles of performance distribution, ranking from worst fund (bottom) to best fund (top). The second row presents the associated alpha for these t-statistics. Row three and row four report the parametric (standard) p-values and bootstrapped p-values of the t-statistics based on 1000 bootstrap resamples.

It is important to note that our bootstrap results reported in Table 7.2 are based on the t-statistic of the estimated alpha, which is a measure of fund performance better than the estimated alpha itself. The t-statistic can scale alpha by its standard error, which tends to be larger for shorter-lived funds and for funds that take higher levels of risk. Hence, the distribution of bootstrapped t-statistics in the tails is likely to reveal better properties than the distribution of bootstrapped alpha. Moreover, for each ranked fund we compare bootstrapped p-values (p-boot) with parametric standard p-values (p-value) that correspond to the t-statistics of these individual ranked funds.

Overall, the results in Panel A of Table 7.2 show that funds with t(alpha) ranked in the top 10^{th} percentile and above generally exhibit significant bootstrapped p-values using CAPM. For FF3F, FF+Mom, and FF+PS (in Panels B, C, and D), only the top 5^{th} percentile and above present significant outperformance. Once again, the Liu LCAPM provides a contrast: in Panel E, using LCAPM, the funds with significant outperformance are extended to top 20^{th} percentile and above. In this study, whether a fund achieves significant performance is estimated at a 10% significance level. That indicates the funds with bootstrapped p-values less than 0.100 have significant outperformance in right tails. Since these funds' bootstrapped p-values are so small that the null hypothesis (underperform the benchmarks) is rejected, we can conclude these fund managers achieve outperformance through true stock-picking skill, rather than luck alone.

Another important point is that the inference from our cross-section bootstrap (bootstrapped p-value) differs from the standard normal assumption (parametric standard p-value). Our top funds have bootstrapped p-values that are lower than their parametric p-values for all five models. Let us use the top 20^{th} percentile fund in the LCAPM as an example, at a 10% significance level, using parametric standard p-value (of 0.163) we cannot reject the null hypothesis for this fund, whereas we can reject it if using bootstrapped p-value (of 0.082). Apparently, under the earlier method, this fund underperforms the benchmark, whilst it does possess stock-picking skill under bootstrap analysis.

When examining funds below the median, using a null hypothesis that these funds do not underperform their benchmarks,[50] we do not find all bootstrapped p-values strongly reject this null as Kosowski et al. (2006) claim. As can be seen in Panel A of Table 7.2, using the LCAPM, no funds between the top 30th and bottom 30th percentiles exhibit t-statistics sufficient to beat their benchmark, and bottom 20th percentile and below have significantly negative t-statistics, which indicates that these funds may very well be inferior to their benchmark. Using the other models, we obtain the similar results, that is, around bottom 30th or 20th percentile and below are truly unskilled, which means these funds' inferior performance is not due to the bad luck.

Although the results of these asset pricing models are similar in left tails (bottom funds), the results in right tails (top funds) differ markedly and deserve further discussion. When using the FF3F and FF+Mom, only top 5th percentile and above exhibit outperformance, which is similar to the findings of Kosowski et al. (2006). However, using the LCAPM, the top 20th percentile and above exhibit significant outperformance. Roughly, 15% of sample funds, around 360 funds, move to skilled from lucky if we use the LCAPM instead of FF3F or FF+Mom. Apparently, after considering the liquidity factor, the performances of equity funds are improved markedly. That echoes our expectation again. For whatever reason, fund managers holding a great amount of highly liquid stocks will adversely impact fund performance. Therefore, it is safe to conclude that liquidity is an important and non-negligible determinant in the evaluation of fund performance.

[50] The null hypothesis is different for the top funds and the bottom funds. For the former, the null hypothesis is $\mathrm{H_0}: \alpha_i \le 0, \mathrm{H_A}: \alpha_i > 0$; and for the latter, the null hypothesis is $\mathrm{H_0}: \alpha_i \ge 0, \mathrm{H_A}: \alpha_i < 0$.

Table 7.2

Residual-Only Resampling Bootstrap Results of Entire Actively Managed Equity Fund Sample

The table reports the statistics for actively managed equity funds during 1984 to 2008 for various asset pricing models. Panels A, B, C, D, and E show statistics from the CAPM, Fama-French three-factor model (FF3F), Carhart four-factor model (FF+Mom), Pastor-Stambaugh four-factor model (FF+PS), and Liu liquidity-augmented two-factor model (LCAPM), respectively. The first row in each panel reports the ex-post t-statistics of alpha, t(alpha), for various points and percentiles of performance distribution, ranking from worst fund (bottom) to best fund (top). The second row presents the associated alpha for these t-statistics. The third and fourth rows report the parametric (standard) p-values and bootstrapped p-values of the t-statistics based on 1000 bootstrap residual-only resamples.

	bottom	3	5	1%	3%	5%	10%	20%	30%	40%	mdian	40%	30%	20%	10%	5%	3%	1%	5	3	top
Panel A: CAPM																					
t (alpha)	-6.424	-4.364	-4.264	-3.656	-3.009	-2.536	-2.015	-1.365	-0.946	-0.568	-0.219	0.137	0.446	0.786	1.297	1.776	2.110	2.705	3.865	3.969	6.289
alpha	-0.04%	-0.64%	-1.44%	-1.96%	-0.27%	-0.27%	-1.11%	-0.16%	-0.17%	-0.09%	-0.07%	0.05%	0.11%	0.64%	0.28%	0.44%	0.23%	0.48%	1.45%	0.63%	4.36%
p-value	0.000	0.000	0.000	0.001	0.005	0.013	0.048	0.176	0.345	0.573	0.827	0.892	0.656	0.435	0.197	0.078	0.038	0.010	0.000	0.000	0.000
p- boot	0.000	0.000	0.000	0.000	0.003	0.005	0.016	0.092	0.197	0.276	0.412	0.438	0.350	0.217	0.083	0.039	0.018	0.003	0.000	0.000	0.000
Panel B: Fama-French three-factor Model (FF3F)																					
t (alpha)	-6.269	-4.719	-4.464	-3.684	-3.031	-2.798	-2.205	-1.650	-1.225	-0.882	-0.561	-0.215	0.117	0.557	1.058	1.597	1.923	2.564	3.775	3.980	7.035
alpha	-0.04%	-0.31%	-0.75%	-0.40%	-0.60%	-1.15%	-0.31%	-0.33%	-0.19%	-0.18%	-0.08%	-0.04%	0.02%	0.09%	0.33%	0.26%	0.09%	0.54%	0.60%	2.41%	4.04%
p-value	0.000	0.000	0.000	0.001	0.003	0.008	0.029	0.101	0.225	0.379	0.575	0.830	0.907	0.578	0.292	0.112	0.055	0.011	0.000	0.000	0.000
p- boot	0.001	0.000	0.000	0.000	0.000	0.003	0.016	0.047	0.099	0.178	0.314	0.417	0.432	0.278	0.138	0.062	0.033	0.006	0.000	0.001	0.000
Panel C: Carhart four-factor Model (FF+Mom)																					
t (alpha)	-6.181	-4.596	-4.318	-3.489	-2.925	-2.715	-2.167	-1.630	-1.240	-0.914	-0.608	-0.297	0.065	0.457	1.035	1.514	1.823	2.504	3.369	3.508	6.746
alpha	-0.04%	-0.89%	-0.35%	-0.64%	-1.24%	-0.24%	-0.68%	-0.47%	-0.09%	-0.23%	-0.21%	-0.12%	0.01%	0.15%	0.67%	0.17%	0.47%	0.20%	0.71%	3.38%	3.91%
p-value	0.000	0.000	0.000	0.001	0.005	0.007	0.032	0.113	0.216	0.364	0.546	0.767	0.948	0.649	0.304	0.134	0.071	0.013	0.001	0.001	0.000
p- boot	0.000	0.000	0.000	0.000	0.002	0.003	0.013	0.054	0.094	0.187	0.286	0.408	0.471	0.295	0.124	0.065	0.024	0.010	0.000	0.000	0.000
Panel D: Pastor-Stambaugh four-factor Model (FF+PS)																					
t (alpha)	-5.894	-4.523	-4.434	-3.591	-2.947	-2.693	-2.142	-1.593	-1.173	-0.828	-0.498	-0.185	0.179	0.569	1.178	1.697	1.995	2.675	3.700	4.306	7.257
alpha	-0.04%	-0.30%	-0.19%	-0.29%	-0.60%	-0.52%	-0.55%	-0.36%	-0.07%	-0.60%	-0.26%	-0.05%	0.09%	0.11%	0.28%	0.34%	0.66%	0.38%	3.76%	2.61%	4.28%
p-value	0.000	0.000	0.000	0.000	0.004	0.007	0.035	0.118	0.242	0.413	0.621	0.853	0.859	0.571	0.241	0.093	0.048	0.008	0.001	0.000	0.000
p- boot	0.001	0.000	0.000	0.000	0.000	0.005	0.014	0.056	0.108	0.237	0.300	0.396	0.447	0.282	0.100	0.047	0.020	0.002	0.000	0.000	0.000
Panel E: Liu liquidity-augmented two-factor Model (LCAPM)																					
t (alpha)	-6.649	-4.617	-4.280	-3.507	-2.928	-2.605	-2.095	-1.440	-0.924	-0.441	0.029	0.452	0.905	1.400	2.034	2.517	2.840	3.483	4.317	4.425	6.190
alpha	-0.04%	-0.29%	-0.56%	-0.48%	-0.55%	-0.51%	-0.30%	-0.81%	-0.13%	-0.11%	0.01%	0.42%	0.75%	0.42%	0.56%	0.63%	1.09%	0.46%	1.17%	1.13%	4.50%
p-value	0.000	0.000	0.000	0.001	0.004	0.011	0.040	0.159	0.357	0.661	0.977	0.654	0.369	0.163	0.044	0.013	0.005	0.001	0.000	0.000	0.000
p- boot	0.000	0.000	0.000	0.000	0.001	0.012	0.019	0.074	0.185	0.327	0.482	0.308	0.180	0.082	0.024	0.007	0.002	0.001	0.000	0.000	0.000

Figure 7.1

Estimated t vs. Boostrapped t Distributions using CAPM

This figure plots histograms and kernel density estimates of the bootstrapped t-statistics of alpha (under H_0: alpha=0) at various points in the upper end (Panels A1 - A4) and lower end (Panels B1 - B4) of the performance distribution using CAPM. The x-axis shows the t-statistics of alpha, and the y-axis shows the frequency of histogram. The ex-post (actual) t-statistics are indicated by the black solid vertical line (the number is in parentheses), and the kernel density estimate is indicated by the red curve line. Panels A1 - A4 show marginal fund in the right tail of the distribution. Panels B1 - B4 show marginal funds in the left tail of the distribution.

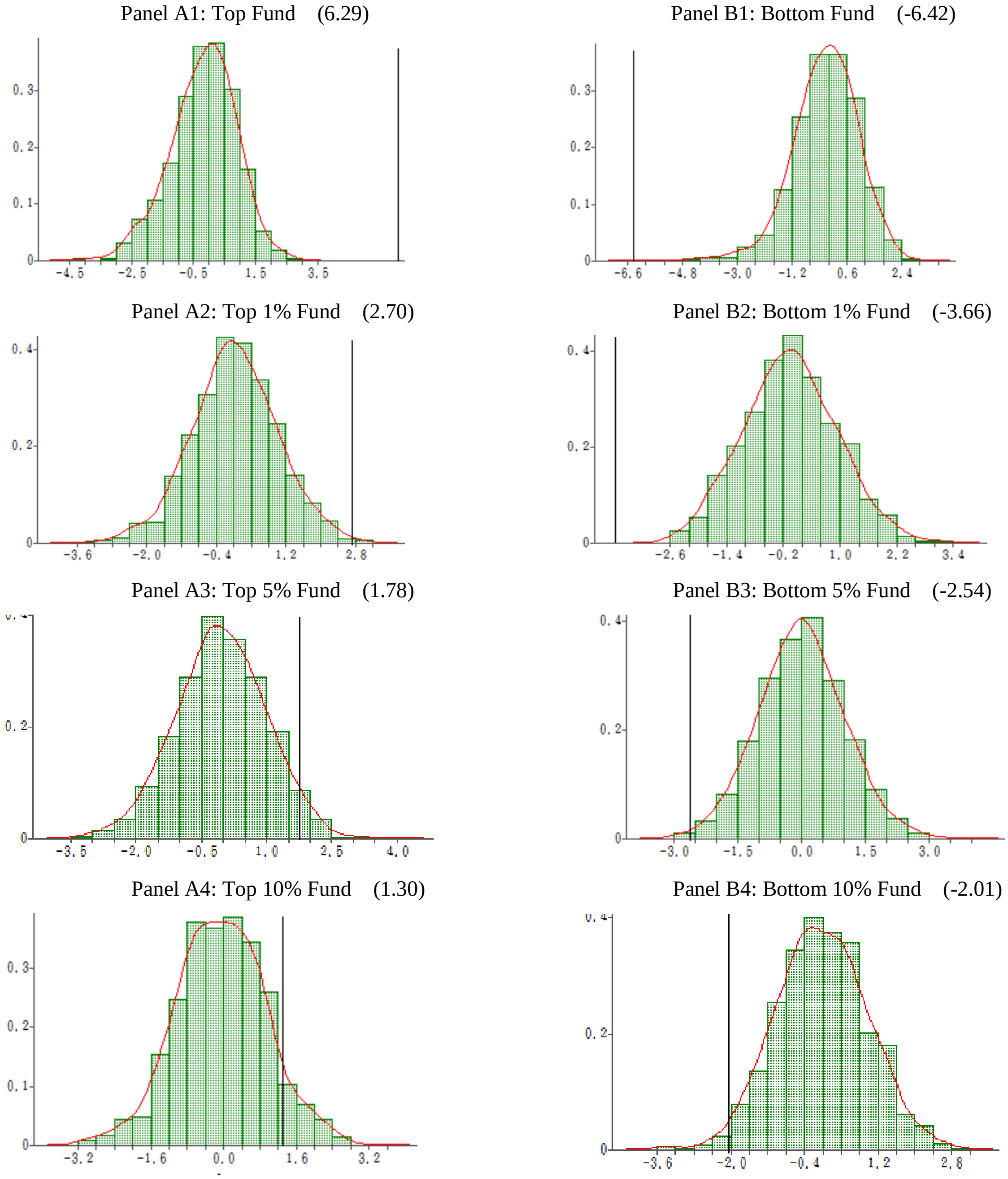
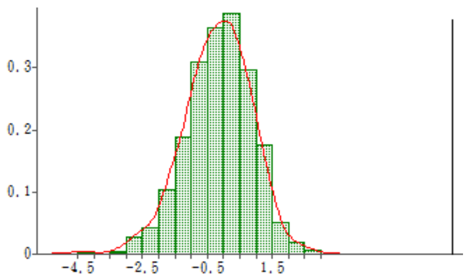


Figure 7.2

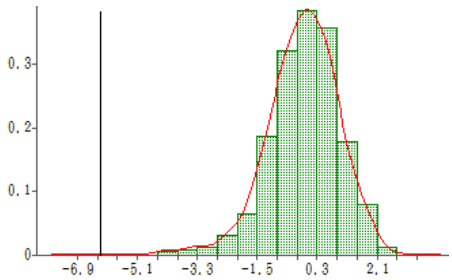
Estimated t vs. Boostrapped t Distributions using FF3F

This figure plots histograms and kernel density estimates of the bootstrapped t-statistics of alpha (under H_0: alpha=0) at various points in the upper end (Panels A1 - A4) and lower end (Panels B1 - B4) of the performance distribution using Fama-French three-factor model (FF3F). The x-axis shows the t-statistics of alpha, and the y-axis shows the frequency of histogram. The ex-post (actual) t-statistics are indicated by the black solid vertical line (the number is in parentheses), and the kernel density estimate is indicated by the red curve line. Panels A1 - A4 show marginal fund in the right tail of the distribution. Panels B1 - B4 show marginal funds in the left tail of the distribution.

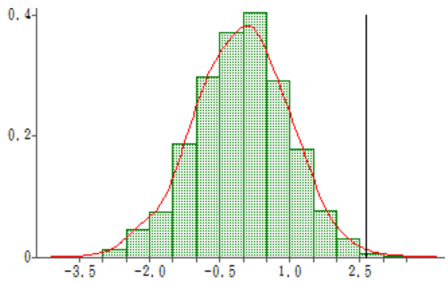
Panel A1: Top Fund (7.04)



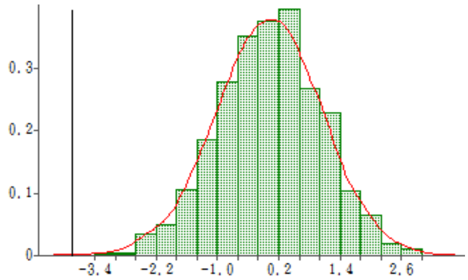
Panel B1: Bottom Fund (-6.27)



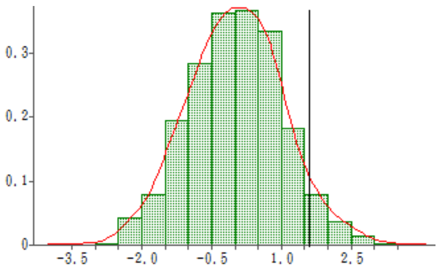
Panel A2: Top 1% Fund (2.56)



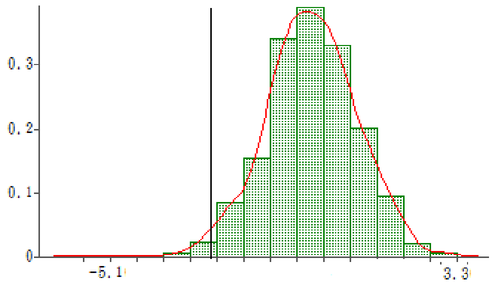
Panel B2: Bottom 1% Fund (-3.68)



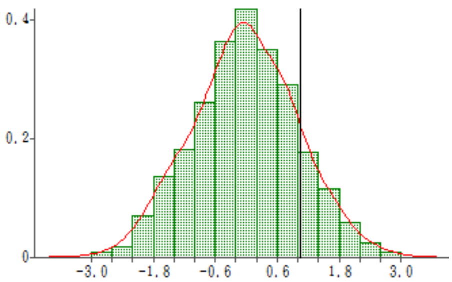
Panel A3: Top 5% Fund (1.60)



Panel B3: Bottom 5% Fund (-2.80)



Panel A4: Top 10% Fund (1.06)



Panel B4: Bottom 10% Fund (-2.21)

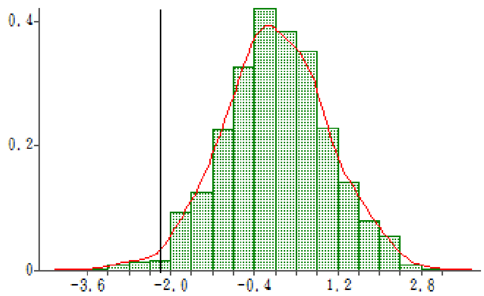


Figure 7.3

Estimated t vs. Boostrapped t Distributions using FF+Mom

This figure plots histograms and kernel density estimates of the bootstrapped t-statistics of alpha (under H0: alpha=0) at various points in the upper end (Panels A1 - A4) and lower end (Panels B1 - B4) of the performance distribution using Carhart four-factor model (FF+Mom). The x-axis shows the t-statistics of alpha, and the y-axis shows the frequency of histogram. The ex-post (actual) t-statistics are indicated by the vertical black solid vertical line (the number is in parentheses), and the kernel density estimate is indicated by the red curve line. Panels A1 - A4 show marginal fund in the right tail of the distribution. Panels B1 - B4 show marginal funds in the left tail of the distribution.

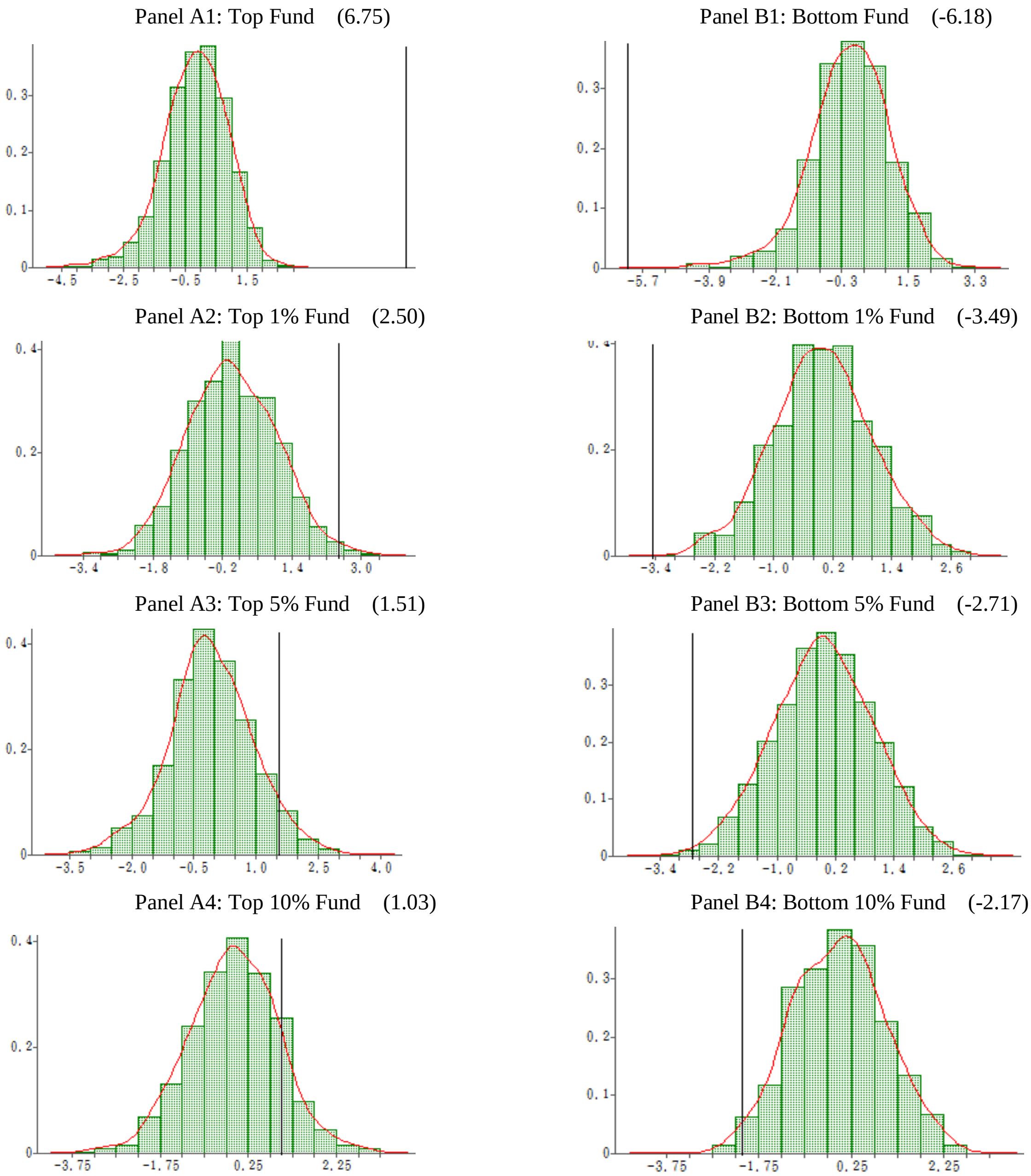
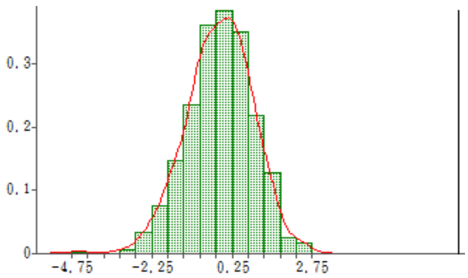


Figure 7.4

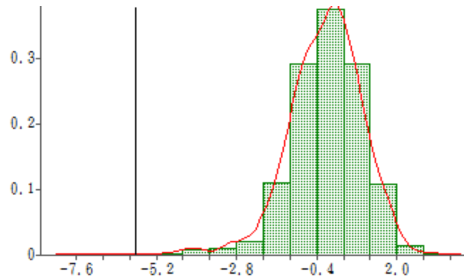
Estimated t vs. Boostrapped t Distributions using FF+PS

This figure plots histograms and kernel density estimates of the bootstrapped t-statistics of alpha (under H_0: alpha=0) at various points in the upper end (Panels A1 - A4) and lower end (Panels B1 - B4) of the performance distribution using Pastor-Stambaugh four-factor model (FF+PS). The x-axis shows the t-statistics of alpha, and the y-axis shows the frequency of histogram. The ex-post (actual) t-statistics are indicated by the black solid vertical line (the number is in parentheses), and the kernel density estimate is indicated by the red curve line. Panels A1 - A4 show marginal fund in the right tail of the distribution. Panels B1 - B4 show marginal funds in the left tail of the distribution.

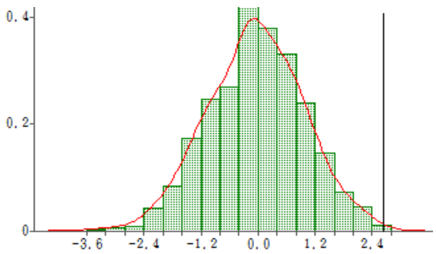
Panel A1: Top Fund (7.26)



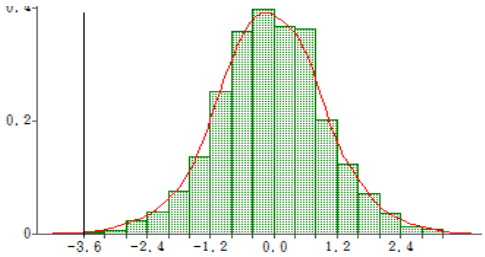
Panel B1: Bottom Fund (-5.89)



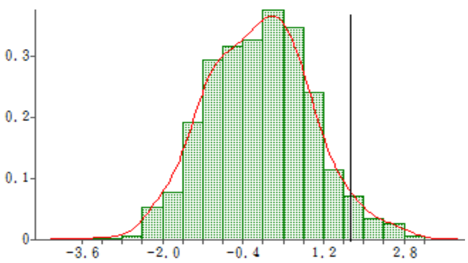
Panel A2: Top 1% Fund (2.67)



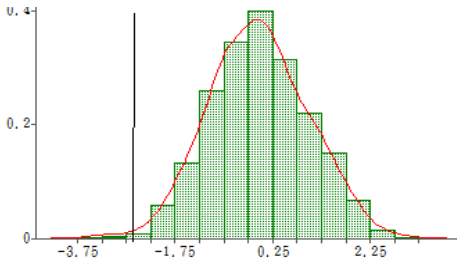
Panel B2: Bottom 1% Fund (-3.59)



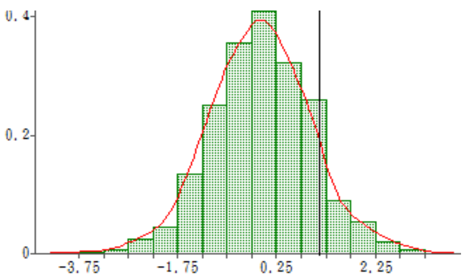
Panel A3: Top 5% Fund (1.70)



Panel B3: Bottom 5% Fund (-2.69)



Panel A4: Top 10% Fund (1.18)



Panel B4: Bottom 10% Fund (-2.14)

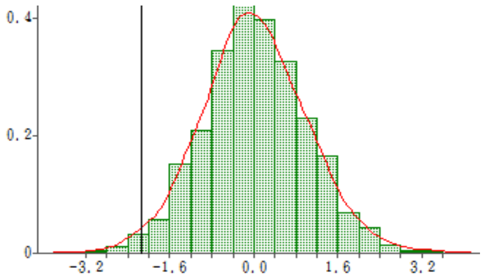
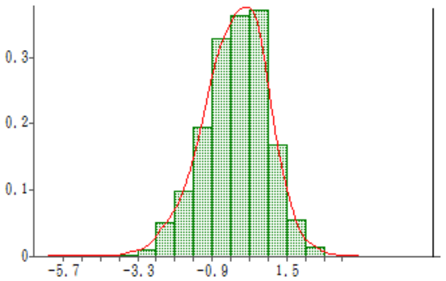


Figure 7.5

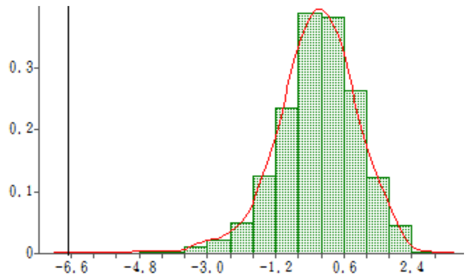
Estimated t vs. Boostrapped t Distributions using LCAPM

This figure plots histograms and kernel density estimates of the bootstrapped t-statistics of alpha (under H_0: alpha=0) at various points in the upper end (Panels A1 - A4) and lower end (Panels B1 - B4) of the performance distribution using Liu liquidity-augmented two-factor model (LCAPM). The x-axis shows the t-statistics of alpha, and the y-axis shows the frequency of histogram. The ex-post (actual) t-statistics are indicated by the black solid vertical line (the number is in parentheses), and the kernel density estimate is indicated by the red curve line. Panels A1 - A4 show marginal fund in the right tail of the distribution. Panels B1 - B4 show marginal funds in the left tail of the distribution.

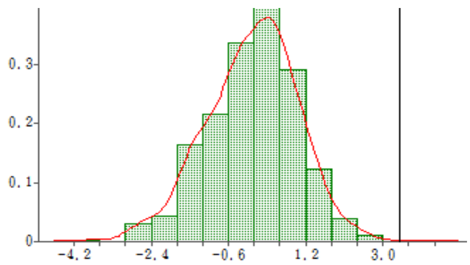
Panel A1: Top Fund (6.19)



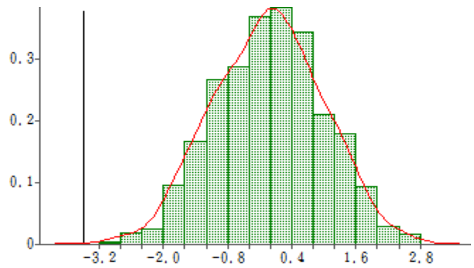
Panel B1: Bottom Fund (-6.65)



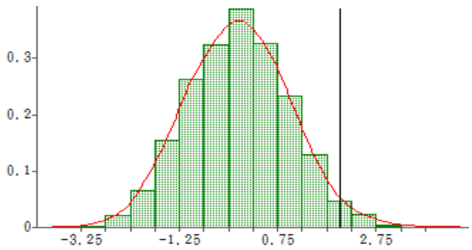
Panel A2: Top 1% Fund (3.48)



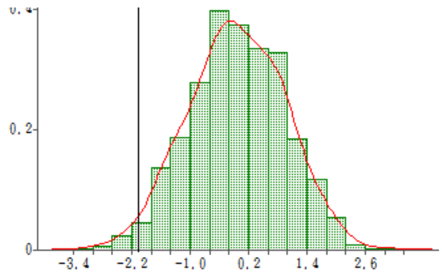
Panel B2: Bottom 1% Fund (-3.51)



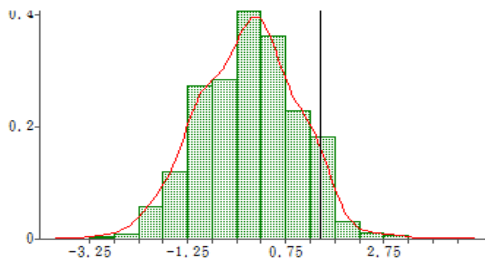
Panel A3: Top 10% Fund (2.03)



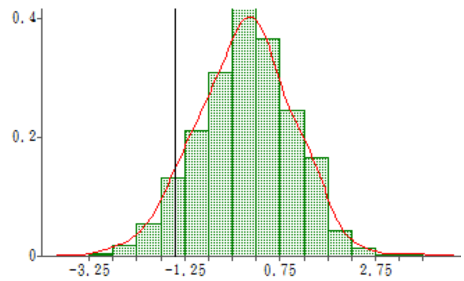
Panel B3: Bottom 10% Fund (-2.09)



Panel A4: Top 20% Fund (1.40)



Panel B4: Bottom 20% Fund (-1.44)



7.2.3. Bootstrap 2 – Entire Cases Resampling

In the context of model misspecification, the entire cases resampling (joint resampling) bootstrap method provides better estimates of the variability in the regression parameters. To develop perspective on the joint resampling, we follow the methods of Fama and French (2010): (i) compare the percentiles of the cross-section of t(alpha) estimates from actual fund returns and the average values of the percentiles from the simulations; (ii) turn to likelihood statements about whether the cross-section of t(alpha) estimates for actual fund returns points to the existence of skill.

After estimating a benchmark model on the net returns of each fund, we attain a cross-section of t(alpha) estimates that can be ordered into a cumulative distribution function (CDF) of t(alpha) estimates for actual fund returns. A joint resampling bootstrap simulation run for the same benchmark model also produce a cross-section of t(alpha) estimates and its CDF for a world where true alpha is zero. In our initial examination of the simulations, we compare the value t(alpha) at selected percentiles of the CDF of the t(alpha) estimates from actual fund returns and the averages across the 1000 simulations runs of the t(alpha) estimates at the same percentiles. To be specific, taking the 1st percentile, bottom 1%, in CAPM (Panel A of Table 7.3) as an example, the 1st percentile of the CAPM t(alpha) estimates for actual net returns is -3.66 (ACT). Whereas, the average 1st percentile from the 1000 simulation runs is -2.37 (SIM), after ranking funds by their simulated t(alpha) in each simulation run.

Table 7.3 reports the CDF of t(alpha) at selected percentiles (PCT) of the distribution of t(alpha) estimates for actual (ACT) net fund returns and the average of the 1000 simulation CDFs (SIM). It can be seen that the average simulation CDFs are similar for various models (SIM are around -2.37 to -2.59 for 1st percentile and around 2.33 to 2.55 for 99th percentile in various models). This is not surprising, since true alpha is set to zero in the simulations. Moreover, the left tail percentile of the t(alpha) estimates from actual net fund returns are far below the corresponding average values from the simulations. For instance, the 10^{th} percentiles of the actual t(alpha) estimates, -2.01, -2.21, -2.17, -2.14, and -2.09 for various models, are much more extreme than the average estimates from the simulation, -1.29, -1.30, -1.31, -1.30, and -1.38, whereas the right tails of the t(alpha) suggest the presence of skill sufficient to cover costs. In the tests that use the CAPM, the t(alpha) estimates from the actual net returns are above the average values from the simulations for all above 90^{th} percentile. Using the FF3F, FF+Mom, and FF+PS, only the 97^{th}, 99^{th} and 95^{th} percentiles for actual net returns are above (slightly) the average simulation 97^{th}, 99^{th}, and 95^{th} percentiles in each model. The evidence for skill sufficient to cover costs is even weaker with an adjustment for momentum exposure. In the tests that use FF+Mom, the percentiles of the t(alpha) estimates for actual net returns are nearly below the average values from the simulations. In other words, the averages of the percentile values of FF+Mom t(alpha) from the simulations of net returns, to a large extent, beat the corresponding percentiles of t(alpha) for the actual net returns. However, when we use the LCAPM, there is a glimmer of hope for investors in the tests on the net returns. The results from this model suggest widespread skill sufficient to cover costs after considering the adjustment for liquidity exposure. In the Panel E of Table 7.3, the 50^{th} percentile for actual net return is above the average simulation 50^{th} percentile. This indicates that half of fund managers have enough skill to produce expected benchmark adjusted net returns that cover costs if the liquidity factor is taken into account.

Figure 7.6 plots kernel density estimate of the cumulative density function (CDF) of the distribution for these models. Red line and black line represent the actual and simulated cross-sectional distribution of the t-statistic of mutual fund alpha respectively. In Panels B, C, and D, the percentiles of FF3F t(alpha), FF+Mom t(alpha), and FF+PS t(alpha) for actual net fund returns (red line) are almost all below the averages from the simulations (black line). However, in Panel E, only half of the percentiles of LCAPM t(alpha) for actual net fund returns are below the averages from the simulation, and the other half of the percentiles of LCAPM t(alpha) for actual net fund returns are above the averages from the simulation. The pictures of the actual and average simulated CDFs do confirm that almost half of mutual fund managers have genuine skill rather than luck if the liquidity factor is considered.

Comparing the percentiles of t(alpha) estimates for actual fund returns with the simulation averages gives hints about whether fund manager skill affects expected returns in qualitative terms. In Table 7.3, we also offer likelihoods (%<ACT), that is specifically, the proportions of the 1000 simulation runs that produce lower values of t(alpha) than actual fund returns at selected percentiles. Fama and French (2010) claim that these likelihoods can judge more properly "whether the tails of the cross-section of t(alpha) estimates for actual fund returns are extreme relative to what they observe when true alpha is zero".

The basic logic is that we can infer that some fund managers do lack skill sufficient to cover costs if a low proportion of the simulation runs produce left tail percentiles of t(alpha) below those from actual net fund returns. Similarly, we also infer that some fund managers do possess selection skill to yield benchmark-adjusted expected returns beyond costs if a large proportion of the simulation runs produce right tail percentiles of t(alpha) below those from actual fund returns. Nevertheless, there are two problems in drawing inferences from the likelihood: multiple comparisons issues and correlated likelihood for different percentiles. One approach to these problems is to focus on a given percentile of each tail of t(alpha), thus we focus on the extreme tails, where performance is most likely to be identified.

The likelihoods (%<ACT) in Panels A to D of Table 7.3 confirm that skill is rare in the right tail. Taking the FF3F as an example, the 90th percentile of the cross-section of t(alpha) estimates is 1.05, and the likelihood is 0.00%. That indicates nil of the 1000 simulation runs for the 90th percentile t(alpha) estimates below 1.05. For the other three models: CAPM, FF+Mom, and FF+PS, the likelihood results are similar to those with the FF3F. Therefore, it seems safe to conclude that most fund managers do not have sufficient skill to produce benchmark-adjusted net returns to cover costs if assessed in this way. The likelihoods for the most extreme right tail percentiles for these four models also confirm our earlier result that a few managers do have sufficient skill to cover costs. The 90th, 97th, 98th, and 95th percentiles of the cross section of t(alpha) estimates from actual net returns for these models are close to or above the average values of t(alpha) estimates from the simulations. In addition, 54.4% to 80.9% of the t(alpha) estimates from the 1000 simulation runs are below those from the actual net returns. However, the likelihoods (%<ACT) in Panel E provide us with a different result. Using the Liu LCAPM, the 50th percentile of the cross-section of t(alpha) estimates is 0.03, and the likelihood is 80.9%. This means almost four-fifths of the 1000 simulation runs for the 50th percentile t(alpha) estimates below 0.03. Obviously, after considering the liquidity factor, we can conclude that roughly half of fund managers do have enough skill to produce benchmark-adjusted net returns to cover costs. The 90th percentile of the cross section of t(alpha) estimates from actual net returns is 2.03, which is far above the average values of t(alpha) estimates from the simulations 1.39. And 100% of the t(alpha) estimates from the 1000 simulation runs are below those from the actual net returns.

The entire cases resampling (joint resampling) bootstrap simulation not only relieves some problems of residual-only resampling,[51] but also re-confirms the effect of a liquidity factor on fund performance. All in all, no matter which bootstrap simulation method is used, we find that few funds have enough skill to cover costs before the liquidity factor is taken into account, and the proportion of skilled funds increases strikingly after considering the liquidity exposure. Therefore, when evaluating the mutual fund performance, we propose that a liquidity-based model (such as LCAPM) could be used.

[51] Such as: the residual-only resampling simulation takes no account of the correlation of alpha estimates for different funds that arises because a benchmark model does not capture all common variation in fund returns. Also, it misses any effects of correlated movement in the volatilities of factor explanatory returns and residuals, as Fama and French (2010) declare.

Table 7.3

Joint Resampling Bootstrap Results of Entire Actively Managed Equity Fund Sample

The table reports the values of t(alpha) at selected percentiles (PCT) of the distribution of t(alpha) estimates for actual (ACT) net fund returns. The table also shows the percent of the 1000 simulation runs that produce lower values of t(alpha) at the selected percentiles than those observed for actual fund returns (%<ACT). SIM is the average value of t(alpha) at the selected percentiles from the simulation after ranking the funds by their simulated t(alpha) in each run. The time period is January 1984 to December 2008, and Panels A, B, C, D, and E show results for the CAPM, Fama-French three-factor model (FF3F), Carhart four-factor model (FF+Mom), Pastor-Stambaugh four-factor model (FF+PS), and Liu liquidity-augmented two-factor model (LCAPM), respectively.

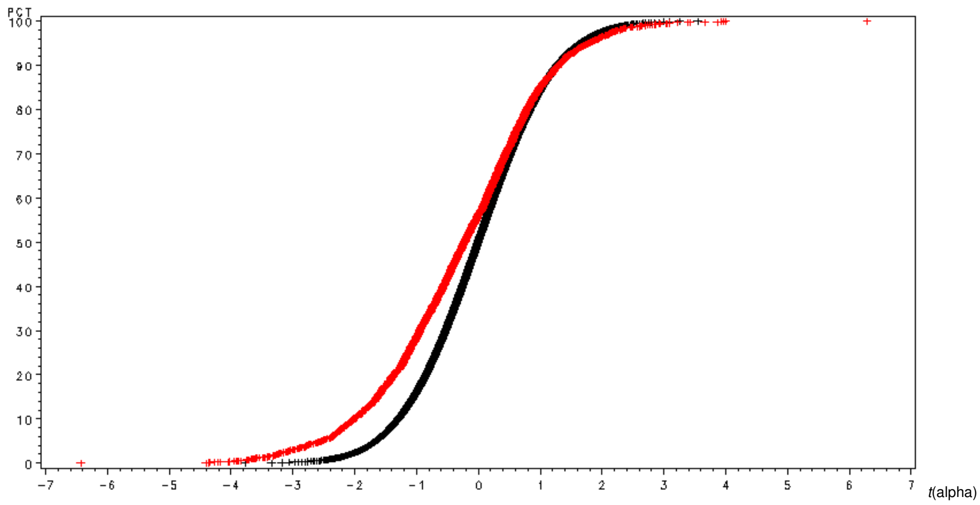
	bottom 1%					bottom 10%					median					top 10%					top 1%
PCT	1%	2%	3%	4%	5%	10%	15%	20%	30%	40%	50%	60%	70%	80%	85%	90%	95%	96%	97%	98%	99%
Panel A: CAPM																					
SIM	-2.37	-2.09	-1.90	-1.77	-1.66	-1.29	-1.04	-0.85	-0.53	-0.26	0.00	0.25	0.52	0.84	1.03	1.27	1.64	1.74	1.87	2.05	2.33
ACT	-3.66	-3.26	-3.01	-2.78	-2.54	-2.01	-1.63	-1.36	-0.95	-0.57	-0.22	0.13	0.44	0.79	0.99	1.30	1.77	1.93	2.10	2.26	2.65
%<ACT	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.10	4.20	13.70	72.70	99.90	100.00	100.00	99.90	100.00
Panel B: Fama-French three-factor model (FF3F)																					
SIM	-2.40	-2.11	-1.92	-1.78	-1.67	-1.30	-1.05	-0.85	-0.53	-0.26	-0.01	0.25	0.52	0.84	1.03	1.28	1.65	1.76	1.89	2.08	2.36
ACT	-3.68	-3.29	-3.03	-2.91	-2.80	-2.21	-1.91	-1.65	-1.23	-0.88	-0.56	-0.22	0.11	0.56	0.78	1.05	1.59	1.73	1.92	2.12	2.50
%<ACT	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	10.10	26.70	66.30	76.80	95.40
Panel C: Carhart four-factor model (FF+Mom)																					
SIM	-2.44	-2.14	-1.94	-1.81	-1.69	-1.31	-1.06	-0.86	-0.53	-0.26	0.00	0.26	0.54	0.87	1.06	1.31	1.69	1.80	1.94	2.13	2.42
ACT	-3.49	-3.23	-2.93	-2.82	-2.71	-2.17	-1.88	-1.63	-1.24	-0.91	-0.61	-0.30	0.06	0.46	0.68	1.03	1.50	1.66	1.82	2.13	2.48
%<ACT	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.10	1.00	54.40	78.70
Panel D: Pastor-Stambaugh four-factor model (FF+PS)																					
SIM	-2.41	-2.11	-1.92	-1.79	-1.68	-1.30	-1.05	-0.86	-0.53	-0.26	0.00	0.25	0.52	0.85	1.04	1.28	1.66	1.76	1.90	2.08	2.37
ACT	-3.59	-3.18	-2.95	-2.80	-2.69	-2.14	-1.82	-1.59	-1.17	-0.83	-0.50	-0.19	0.18	0.57	0.85	1.18	1.70	1.84	1.99	2.20	2.66
%<ACT	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.30	80.90	95.20	96.10	97.60	100.00
Panel E: Liu liquidity-augmented two-factor model (LCAPM)																					
SIM	-2.59	-2.26	-2.06	-1.91	-1.79	-1.38	-1.11	-0.90	-0.56	-0.27	0.01	0.28	0.57	0.91	1.12	1.39	1.79	1.90	2.05	2.24	2.55
ACT	-3.51	-3.12	-2.93	-2.73	-2.60	-2.09	-1.71	-1.44	-0.92	-0.44	0.03	0.45	0.90	1.41	1.64	2.03	2.52	2.66	2.82	3.05	3.46
%<ACT	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	80.90	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00

Figure 7.6

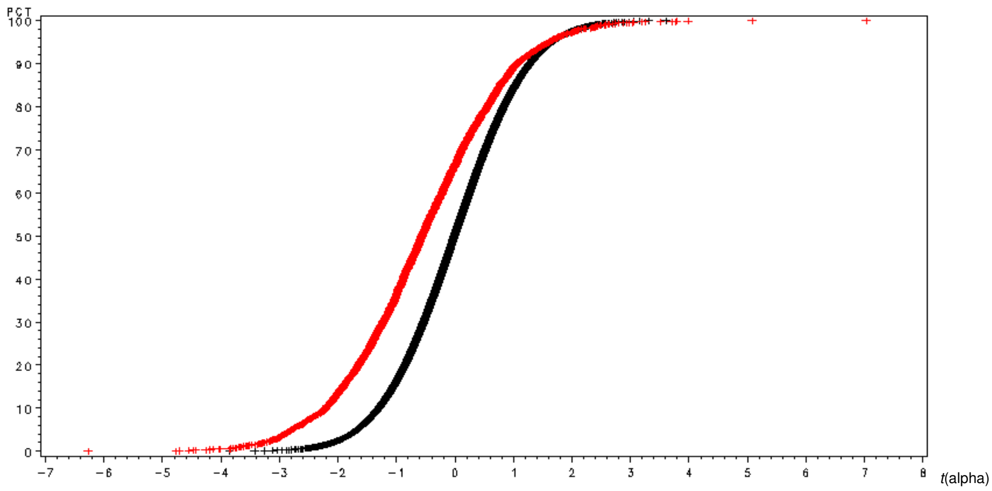
Simulated and Actual Cumulative Density Function of t(alpha)

The figure plots kernel density estimate of the cumulative density function (CDF) of the distribution. Red line and black line show the actual and simulated cross-sectional distributions of the t-statistic of mutual fund alphas respectively. The alpha estimates are based on the CAPM, Fama-French three-factor model (FF3F), Carhart four-factor model (FF+Mom), Pastor-Stambaugh four-factor model (FF+PS) and Liu liquidity-augmented two-factor model (LCAPM) respectively, applied to the U.S. actively managed equity funds during 1984 to 2008 period.

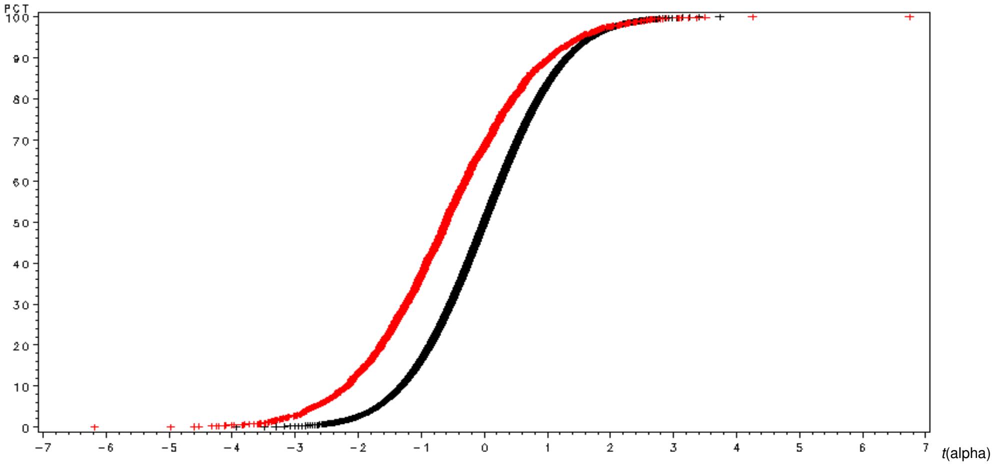
Panel A: CAPM



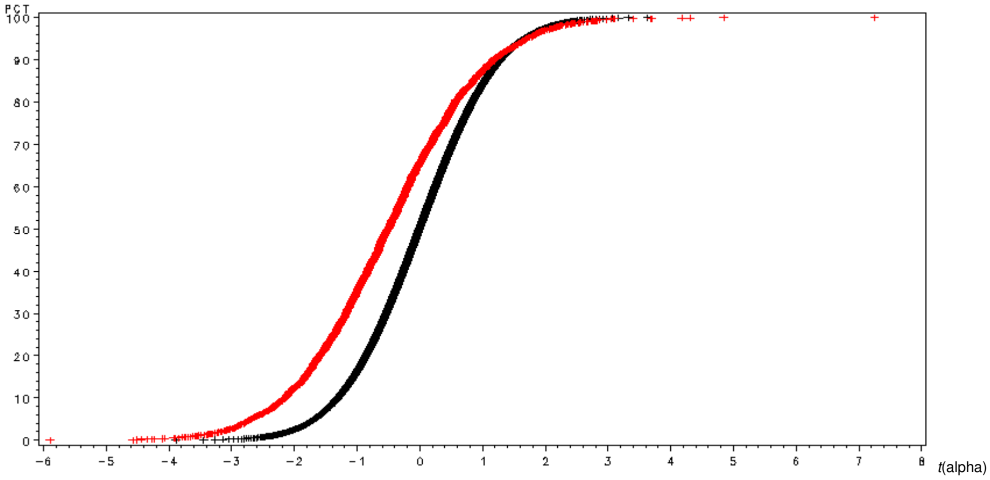
Panel B: FF3F



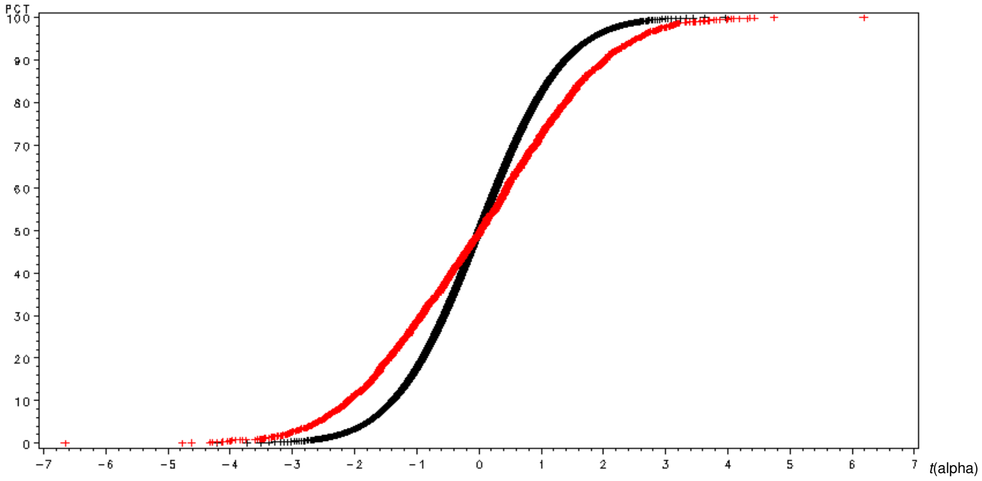
Panel C: FF+Mom



Panel D: FF+PS



Panel E: LCAPM



CHAPTER 8: ROBUSTNESS TESTS

In this chapter, we report a series of sensitivity analyses to test whether our results are robust to changes of mutual fund sample (such as limiting funds that reach a given number $million in assets in order to lessen the effect of incubation, or changing a minimum fund return requirement from 36 to 60 months), or to the subperiods of research time period (such as separating the 25-year time period into two subperiods). In general, we demonstrate that our main findings in pervious chapters are robust to these changes in fund sample.

8.1. Subsample Analysis

8.1.1 Fund Size Filter

Commonly, fund management companies provide seed money to new funds to develop a return history. As Fama and French (2010) claim, the incubation bias arises because funds typically open to the public only if the returns turn out to be attractive, so that their pre-release returns are included in mutual fund databases. To alleviate the incubation bias, Fama and French (2010) limit their tests to funds that reach $5 million in assets, since the total net asset (TNA) is likely to be low during the pre-release period. Evans (2010) also applies a fund size filter to lessen the effects of incubation bias. He proposes filtering out incubated funds through removing funds below a certain size (typically $25 million), because the TNA filter of $25 million can remove nearly half of incubated funds. Thus, in this robustness test, we also require funds that reach $25 million in TNA. That is, a fund is included in all subsequent tests once it passes the TNA minimum ($25 million). This change provides us with a smaller sample of 2175 funds (as opposed to 2417 funds for original fund sample).

Accordingly, our new sample is the 2175 actively managed U.S. equity mutual funds with at least $25 million in assets between 1984 and 2008 (hereafter, subsample 1).

First of all, we examine the existence of liquidity premium at fund level in this subsample. Same as baseline tests, we sort funds into ten portfolios based on their FLMs (Liu's LM12 or Amihud's RtoV12). At the same time, we form a zero-investment portfolio L-H, consisting of long positions in the least liquid funds (Decile 10, L) and short positions in the most liquid funds (Decile 1, H). Panel A1 and Panel B1 of Table 8.1 reveal that there are not significant fund liquidity premium over the 1-month or 12-month holding periods, no matter fund portfolios are sorted by LM12 or RtoV12. As can be seen in Panel A1 (sorted by LM12), although the portfolio L-H discloses liquidity premium 0.179% per month for HPR1M and 3.003% per year for HPR12M, both are not significant (their t-statistics are only 0.91 and 1.08, respectively). The same results are shown in Panel B1 (sorted by RtoV12). Moreover, we also test fund liquidity premium by controlling for risk using various asset pricing models. Using the fund portfolios sorted by LM12 as an example, results in Panels A2 to A6 of Table 8.1 all reveal that the liquidity premium at fund level is little to none after controlling for risks. As we can see, only the CAPM, FF+Mom, and FF+PS result in a liquidity premium (positive alpha for L-H). However, their t-statistics are very low, which indicates the liquidity premium is not significant. There are even negative alpha for portfolio L-H in the FF3F and LCAPM, which means no liquidity premium at all. Therefore, consistent with our previous baseline results, in this subsample, there is an absence of liquidity premium at fund level, no matter what fund liquidity measures are used for sorting, no matter what fund performances are examined (holding period returns or risk-adjusted performance). Our results for fund liquidity premium are robust to the change of mutual fund sample.

Second, we test the performance of portfolio of funds in the subsample 1. Here we only use value weighting to construct portfolio of equity mutual funds in each month, because the performance of value-weighed portfolio informs us whether the aggregate wealth invested in funds can add value. Table 8.2 presents the annualized intercepts, t-statistics, and p-values for the intercepts for various models estimated on value-weighted net returns on the portfolio of equity funds in this subsample. The intercepts (yearly alpha) in Table 8.2 summarize the performance of aggregate wealth invested in funds (value-weighed returns of portfolio of funds) relative to passive benchmarks. From the angle of the CAPM, FF3F, FF+Mom, and FF+PS, we find fund performance is poor. These models' annualized intercepts are negative, ranging from -0.722% to -1.058% per year, with t-statistics from -2.37 to -3.24. These significant negative alphas tell us on average actively managed equity funds have not the ability to generate sufficient returns to cover the costs and expenses. However the result from the LCAPM is totally different. Although the model's annualized intercept is negative at -0.118% per year, its t-statistic is only -0.34. That means the fund performance is insignificantly different with zero. In other words, the aggregate portfolio of funds is close to the benchmarks. Looking at the liquidity factors (LIQ in LCAPM), its slope (β_liq) is negative at -0.0788 with significant (t-statistic is -7.93). It is apparent that actively managed equity funds would like to invest in stocks with more liquidity. These results from our new subsample are almost identical to our previous findings. Thus, our results about performance of portfolio of funds are robust to the change of mutual fund sample.

Third, by applying the residual-only resampling bootstrap method, we analyze the significance of actively managed equity fund performance (especially the t-statistics of alpha). In this subsample, we rank them on their ex-post t-statistics of alpha, and report the main findings through residual-only resampling bootstrap evaluation procedure. Table 8.3 shows the results for actively managed equity funds in this subsample for each of three typical asset pricing models.[52] Since top funds' bootstrapped p-values are so small as to reject the null hypothesis (do not outperform the benchmarks), we can conclude these fund managers achieve outperformance through true stock-picking skill, rather than luck alone. Moreover, the results in Panels A and B show that funds with t-statistic of alpha ranked in the top 5^{th} percentile and above generally exhibit significant bootstrapped p-values using FF3F and FF+Mom. Using the LCAPM (in Panel C), the funds with significant outperformance are extended to top 20^{th} percentile and above. Obviously, the results in right tails (top funds) still are much different for different models, which deserve further discussion. Approximately, there are 15% of sample funds move to skilled from lucky if we use LCAPM instead of FF3F and FF+Mom. Apparently, after considering liquidity factor, the performances of equity funds are improved markedly. These results also are identical to our baseline results.

Finally, we evaluate the fund performance through resampling entire cases (joint resampling) in this subsample. Table 8.4 reports the CDF of t(alpha) at selected percentiles (PCT) of the distribution of t(alpha) estimates for actual (ACT) net fund returns and the average of the 1000 simulation CDF (SIM). In the tests that use the FF3F (in Panel A), the t(alpha) estimates from the actual net returns are above the average values from the simulations for only above 99^{th} percentile. Using the FF+Mom (in Panel B), the percentile of the t(alpha) estimates for actual net fund returns are always below the average values from the simulations. In other words, the average of the percentile values of FF+Mom t(alpha) from the simulations always beats the corresponding percentiles of t(alpha) for actual. Thus, the evidence of skill sufficient to

[52] In this section, we just use the Fama-French three-factor model (FF3F), Carhart four-factor model (FF+Mom), and Liu liquidity-augmented two-factor model (LCAPM) as typical models, for brevity.

cover costs is even weaker with an adjustment for momentum exposure. However, the results with the LCAPM suggest widespread skill sufficient to cover costs after considering the adjustment for liquidity exposure. In Panel C of Table 8.4, the 50th percentile for actual net return is above the average simulation 50th percentile. This indicates that half of fund managers have enough skill to produce expected benchmark adjusted net returns that cover costs if the liquidity factor is considered. Lastly, comparing the percentiles of t(alpha) estimates for actual fund returns with the simulation averages gives hints about whether fund manager skill affects expected returns in qualitative terms. In Table 8.4, the %<ACT of the FF3F and FF+Mom confirm that skill is rare in the right tail, because only the %<ACT of the 99th percentile of the cross-section of t(alpha) estimates in Panel A is more than 50%. It seems safe to conclude that the majority of fund managers do not have enough skill to produce returns to cover costs. However, in Panel C, using the LCAPM, the %<ACT is 53.10% for the 50th percentile of the cross-section of t(alpha) estimates. This means more than half of the 1000 simulation runs for the 50th percentile t(alpha) estimates below the actual fund returns. Obviously, after considering the liquidity factor, it seems reasonable to conclude that roughly half of fund managers do have enough skill to produce benchmark-adjusted net returns to cover costs. Using this joint resampling bootstrap in this subsample, the result is also same to our previous baseline findings.

For this subsample, we examine the existence of fund liquidity premium and test the performance of portfolio of funds. To sum up, the results for fund liquidity premium and fund performance of the subsample are almost identical to our baseline results. It is demonstrated that our main findings are robust to the change of the fund size requirement.

Table 8.1

Liquidity Premium of Fund Portfolios Sorted by LM12 (RtoV12) in the Subsample 1

The table reports the results for our 2175 actively managed U.S. equity funds with at least $25 million during the period 1984 to 2008. Panel A shows the holding period returns and risk-adjusted performance of the LM12-sorted fund portfolios; Panel B represents the holding period returns and risk-adjusted performance of the RtoV12-sorted fund portfolios. 1 (H) denotes the lowest LM12 (RtoV12) decile portfolio, i.e. the most liquid decile. 10 (L) denotes the highest LM12 (RtoV12) decile portfolio, i.e. the least liquid decile. L-H denotes the difference between L and H deciles.

	1 (H)	2	3	4	5	6	7	8	9	10 (L)	L-H
Panel A: Sorted by LM12	Panel A1: Holding Period Returns										
HPR1M	0.704%	0.787%	0.787%	0.782%	0.786%	0.808%	0.806%	0.889%	0.923%	0.882%	0.179%
t-statistics	1.88	2.77	3.05	2.99	2.99	3.00	3.03	3.15	3.14	3.19	0.91
HPR12M	8.755%	10.379%	10.964%	10.425%	10.587%	10.847%	11.162%	10.818%	11.411%	11.759%	3.003%
t-statistics	1.82	2.62	2.95	2.79	2.93	2.95	3.01	2.89	3.00	3.13	1.08
Panel A2: CAPM-adjusted performance											
α	-0.299%	-0.104%	-0.069%	-0.084%	-0.078%	-0.060%	-0.053%	0.002%	0.025%	0.023%	0.322%
t-statistics	-1.74	-1.27	-1.42	-2.00	-1.46	-0.85	-0.68	0.03	0.24	0.21	1.77
Panel A3: FF3F-adjusted performance											
α	-0.082%	-0.063%	-0.087%	-0.112%	-0.102%	-0.082%	-0.088%	0.063%	0.059%	-0.085%	-0.003%
t-statistics	-0.68	-0.87	-1.80	-2.71	-1.91	-1.16	-1.13	0.99	0.95	-1.44	-0.02
Panel A4: FF+Mom-adjusted performance											
α	-0.142%	-0.135%	-0.099%	-0.115%	-0.084%	-0.061%	-0.045%	0.009%	0.009%	-0.050%	0.092%
t-statistics	-1.15	-1.85	-1.99	-2.68	-1.53	-0.83	-0.56	0.15	0.14	-0.83	0.61
Panel A5: FF+PS-adjusted performance											
α	-0.115%	-0.090%	-0.105%	-0.104%	-0.083%	-0.050%	-0.058%	0.092%	0.095%	-0.069%	0.046%
t-statistics	-0.96	-1.25	-2.19	-2.51	-1.58	-0.72	-0.75	1.49	1.59	-1.17	0.31
Panel A6: LCAPM-adjusted performance											
α	0.222%	0.052%	-0.019%	-0.066%	-0.068%	-0.053%	-0.059%	0.186%	0.258%	0.076%	-0.146%
t-statistics	1.38	0.62	-0.37	-1.49	-1.19	-0.71	-0.71	2.24	2.50	0.65	-0.82
Panel B: Sorted by RtoV12	Panel B1: Holding Period Returns										
HPR1M	0.745%	0.731%	0.754%	0.737%	0.805%	0.863%	0.872%	0.892%	0.870%	0.885%	0.141%
t-statistics	2.92	2.84	3.00	2.90	2.96	3.04	2.98	2.84	2.81	2.98	0.88
HPR12M	9.586%	9.321%	9.791%	10.295%	10.893%	11.222%	11.079%	11.862%	11.224%	11.784%	2.198%
t-statistics	2.43	2.46	2.62	2.85	2.80	2.96	2.81	2.91	2.88	2.99	0.80
Panel B2: CAPM-adjusted performance											
α	-0.105%	-0.129%	-0.095%	-0.117%	-0.080%	-0.036%	-0.038%	-0.040%	-0.054%	-0.002%	0.103%
t-statistics	-2.20	-3.88	-3.26	-3.74	-1.79	-0.55	-0.50	-0.36	-0.49	-0.02	0.65
Panel B3: FF3F-adjusted performance											
α	-0.027%	-0.091%	-0.097%	-0.126%	-0.072%	-0.019%	-0.021%	0.011%	-0.051%	-0.088%	-0.061%
t-statistics	-0.78	-3.29	-3.69	-4.09	-1.66	-0.35	-0.35	0.17	-0.86	-1.41	-0.73
Panel B4: FF+Mom-adjusted performance											
α	-0.032%	-0.090%	-0.087%	-0.114%	-0.082%	-0.047%	-0.057%	-0.067%	-0.077%	-0.055%	-0.023%
t-statistics	-0.90	-3.17	-3.24	-3.61	-1.85	-0.84	-0.95	-1.08	-1.28	-0.87	-0.27
Panel B5: FF+PS-adjusted performance											
α	-0.023%	-0.088%	-0.092%	-0.121%	-0.069%	-0.012%	-0.008%	0.023%	-0.030%	-0.067%	-0.044%
t-statistics	-0.66	-3.15	-3.50	-3.91	-1.59	-0.22	-0.14	0.36	-0.51	-1.08	-0.53
Panel B6: LCAPM-adjusted performance											
α	-0.036%	-0.096%	-0.091%	-0.101%	0.014%	0.122%	0.152%	0.256%	0.197%	0.111%	0.147%
t-statistics	-0.73	-2.73	-2.92	-3.04	0.30	1.89	2.02	2.37	1.78	0.84	0.87

Table 8.2

Performance of Portfolio of Funds in the Subsample 1

The table reports the annualized intercepts (monthly alpha×12), t-statistics and p-values for the intercepts for a series of models estimated on value-weighted (VW) net returns on the portfolios in the subsample (actively managed U.S. equity funds with at least $25 million during the period 1984 to 2008).

Model		α (yearly)	β_mkt	β_smb	β_hml	β_pr1yr	β_liq_v	β_liq	R^2
CAPM	coef	-1.058%	0.9928						0.987
	t -statistic	-2.99	152.17						
	p-value	0.003	<0.0001						
Fama-French three-factor model (FF3F)	coef	-0.773%	0.9744	0.0618	-0.0465				0.991
	t -statistic	-2.54	158.17	7.51	-4.83				
	p-value	0.0115	<0.0001	<0.0001	<0.0001				
Carhart four-factor model (FF+Mom)	coef	-0.996%	0.9781	0.0604	-0.0426	0.0179			0.991
	t -statistic	-3.24	158.12	7.44	-4.44	3.13			
	p-value	0.0014	<0.0001	<0.0001	<0.0001	0.002			
Pastor-Stambaugh four-factor model (FF+PS)	coef	-0.722%	0.9756	0.0615	-0.0448		-0.0112		0.991
	t -statistic	-2.37	157.47	7.49	-4.63		-1.57		
	p-value	0.0185	<0.0001	<0.0001	<0.0001		0.1186		
Liu liquidity-augmented two-factor model (LCAPM)	coef	-0.118%	0.9452					-0.0788	0.990
	t -statistic	-0.34	106.56					-7.93	
	p-value	0.7319	<0.0001					<0.0001	

Table 8.3

Residual-Only Resampling Bootstrap Results of the Subsample 1

The table reports the statistics for actively managed equity mutual funds with at least $25 million in assets during 1984 to 2008 for each of three typical asset pricing models. Panels A, B, and C show statistics from the Fama-French three-factor model (FF3F), Carhart four-factor model (FF+Mom), and Liu liquidity-augmented two-factor model (LCAPM), respectively. The first row in each panel reports the ex-post t-statistics of alpha for various points and percentiles of performance distribution, ranking from worst fund (bottom) to best fund (top). The second row presents the associated alpha for these t-statistics. The third and fourth rows report the parametric (standard) p-values and bootstrapped p-values of the t-statistics based on 1000 bootstrap residual-only resamples.

	bottom	3	5	1%	3%	5%	10%	20%	30%	40%	mdian	40%	30%	20%	10%	5%	3%	1%	5	3	top
Panel A: FF3F																					
t-stat	-4.915	-4.464	-4.211	-3.667	-3.079	-2.782	-2.205	-1.628	-1.218	-0.867	-0.539	-0.222	0.112	0.539	1.009	1.542	1.768	2.474	3.623	3.775	4.658
alpha	-0.20%	-0.75%	-1.09%	-0.36%	-0.94%	-0.74%	-0.31%	-0.26%	-0.21%	-0.15%	-0.09%	-0.18%	0.02%	0.11%	0.16%	0.32%	0.20%	0.43%	1.85%	0.60%	2.48%
p-value	0.000	0.000	0.000	0.000	0.003	0.006	0.029	0.108	0.224	0.388	0.592	0.828	0.911	0.591	0.315	0.124	0.081	0.015	0.001	0.000	0.000
p-boot	0.000	0.000	0.000	0.001	0.004	0.003	0.019	0.040	0.113	0.215	0.308	0.449	0.441	0.294	0.174	0.058	0.042	0.005	0.000	0.000	0.000
Panel B: FF+Mom																					
t-stat	-4.944	-4.587	-4.246	-3.545	-2.955	-2.676	-2.194	-1.630	-1.233	-0.913	-0.613	-0.299	0.055	0.414	0.984	1.452	1.751	2.310	3.006	3.369	4.537
alpha	-0.20%	-1.08%	-1.88%	-0.19%	-0.52%	-0.46%	-0.24%	-0.13%	-0.19%	-0.26%	-0.17%	-0.15%	0.01%	0.07%	0.21%	0.29%	0.55%	1.14%	0.82%	0.71%	3.81%
p-value	0.000	0.000	0.000	0.001	0.004	0.008	0.029	0.104	0.219	0.366	0.543	0.766	0.956	0.681	0.328	0.150	0.081	0.037	0.003	0.001	0.000
p-boot	0.000	0.000	0.000	0.001	0.001	0.003	0.016	0.040	0.103	0.174	0.268	0.388	0.463	0.343	0.187	0.065	0.046	0.013	0.000	0.000	0.000
Panel C: LCAPM																					
t-stat	-4.765	-4.320	-4.143	-3.457	-2.941	-2.625	-2.092	-1.445	-0.927	-0.486	0.006	0.425	0.817	1.312	1.985	2.460	2.753	3.301	4.352	4.747	12.065
alpha	-0.38%	-0.79%	-0.35%	-0.45%	-0.71%	-1.10%	-0.20%	-0.16%	-0.41%	-0.10%	0.00%	0.07%	0.36%	0.39%	0.59%	0.58%	0.44%	1.08%	0.83%	1.07%	5.71%
p-value	0.000	0.000	0.000	0.001	0.004	0.011	0.037	0.151	0.363	0.628	0.995	0.672	0.415	0.193	0.050	0.015	0.007	0.001	0.000	0.000	0.053
p-boot	0.000	0.000	0.000	0.000	0.001	0.005	0.022	0.089	0.167	0.295	0.503	0.340	0.208	0.087	0.022	0.005	0.003	0.000	0.000	0.000	0.008

Table 8.4

Joint Resampling Bootstrap Results of the Subsample 1

The table reports the values of t(alpha) at selected percentiles (PCT) of the distribution of t(alpha) estimates for actual (ACT) net fund returns. The table also shows the percent of the 1000 simulation runs that produce lower values of t(alpha) at the selected percentiles than those observed for actual fund returns (%<ACT). SIM is the average value of t(alpha) at the selected percentiles from the simulation after ranking the funds by their simulated t(alpha) in each run. Panels A, B, and C show results for the Fama-French three-factor model (FF3F), Carhart four-factor model (FF+Mom), and Liu liquidity-augmented two-factor model (LCAPM), respectively. The subsample 1 is these 2175 actively managed equity mutual funds with at least $25 million in assets during January 1984 to December 2008.

	bottom 1%					bottom 10%					median					top 10%					top 1%
PCT	1%	2%	3%	4%	5%	10%	15%	20%	30%	40%	50%	60%	70%	80%	85%	90%	95%	96%	97%	98%	99%
Panel A: FF3F																					
SIM	-2.43	-2.12	-1.93	-1.79	-1.68	-1.30	-1.05	-0.85	-0.53	-0.26	-0.01	0.24	0.52	0.84	1.03	1.28	1.65	1.76	1.90	2.08	2.35
ACT	-3.67	-3.28	-3.08	-2.93	-2.78	-2.20	-1.89	-1.63	-1.22	-0.87	-0.54	-0.22	0.11	0.54	0.76	1.03	1.54	1.65	1.79	2.03	2.49
%<ACT	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	1.20	2.40	23.00	95.70
Panel B: FF+Mom																					
SIM	-2.51	-2.17	-1.97	-1.83	-1.71	-1.32	-1.06	-0.86	-0.54	-0.26	0.00	0.26	0.53	0.86	1.06	1.31	1.69	1.80	1.94	2.13	2.41
ACT	-3.56	-3.23	-2.96	-2.82	-2.68	-2.19	-1.88	-1.63	-1.23	-0.91	-0.61	-0.29	0.06	0.42	0.69	0.99	1.46	1.62	1.77	1.97	2.37
%<ACT	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.60	34.10
Panel C: LCAPM																					
SIM	-2.48	-2.15	-1.96	-1.81	-1.70	-1.31	-1.06	-0.86	-0.54	-0.26	-0.01	0.25	0.52	0.84	1.04	1.29	1.66	1.76	1.90	2.08	2.36
ACT	-3.46	-3.12	-2.95	-2.76	-2.63	-2.09	-1.71	-1.44	-0.93	-0.49	0.01	0.42	0.82	1.31	1.57	1.99	2.46	2.60	2.75	2.97	3.30
%<ACT	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	53.10	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00

8.1.2 Fund Return Observations Requirement

In our baseline measurement of mutual fund performance, a sample of funds which have at least 36 monthly return observations is used. Barras et al. (2010) show that there is no material impact on their main result, no matter which monthly return observation requirement is applied, 60 or 36 months. To check the robustness of our result, we repeat our analysis after adjusting the minimum fund return requirement from 36 to 60 months. We believe that any biases introduced from the 60-month requirement are minimal. This change provides us with a somewhat smaller sample of 2013 funds, as opposed to 2417 funds for the original fund population. Thus, our new fund sample is the 2013 actively managed U.S. equity funds existing for at least 60 months between 1984 and 2008 (hereafter, subsample 2).

First, we examine the existence of fund liquidity premium in this subsample by sorting funds into ten portfolios based on their LM12 and RtoV12 respectively. Panel A1 and Panel B1 of Table 8.5 report the holding period returns (for 1 month and 12 months) of each decile, and reveal that there are no significant liquidity premium over the 1-month or 12-month holding periods, no matter whether fund portfolios are sorted by LM12 or RtoV12. As we can see in Panel A1 (sorted by LM12), although the portfolio L-H discloses liquidity premium 0.218% per month for HPR1M and 3.669% per year for HPR12M, both of these are not significant (their t-statistics are only 1.11 and 1.29, respectively). The same outcome is shown in Panel B1 (sorted by RtoV12). In addition, we also test fund liquidity premium by controlling for risk using various models. Among all results in Panels A2 to A6 (sorted by LM12) and Panels B2 to B6 (sorted by RtoV12), almost all reveal that fund liquidity premium is little to none after controlling for risks, except for CAPM sorted by LM12 (in Panel A2). Although the CAPM alpha sorted by LM12 is significant positive (0.363% with t-statistic of 2.00), the alphas in other models are around zero (from -0.114% to 0.172%) with very low t-statistics, which indicates the liquidity premium is not significant. Consistent with our previous baseline results, in the subsample 2 there is absence of fund liquidity premium.

Second, we test the portfolio of funds performance in the subsample 2. Table 8.6 presents the annualized intercepts, t-statistics, and p-values for the intercepts for various models estimated on value-weighted net returns on the portfolios of actively managed equity funds in this subsample. According to the annualized intercepts of the CAPM, FF3F, FF+Mom, and FF+PS, the fund performance is poor. In Table 8.6, they are negative, ranging from -0.771% to -1.051% per year, with significant t-statistics from -2.36 to -3.22, which tells us that, on average, actively managed equity funds lack the ability to generate sufficient returns to cover the costs and expenses. However the result from the LCAPM tells us a different story. Although the model's annualized intercepts are negative at -0.120% per year, its t-statistic is only -0.35. That means the fund performance is insignificantly different with zero. In other words, the aggregate portfolio of funds mimics the performance of benchmarks. These results from subsample 2 are almost the same to our previous findings, so we can say our results concerning performance of portfolio of funds are robust to the change of mutual fund's monthly return observation requirement.

Third, we analyze the significance of actively managed equity fund performance (especially the t-statistics of alpha) by applying the residual-only resampling bootstrap method. Table 8.7 shows the results for actively managed equity funds in this subsample for FF3F, FF+Mom, and LCAPM respectively. Since the top funds' bootstrapped p-values are so small that reject the null hypothesis, we can conclude these fund managers achieve outperformance through true stock-picking skill rather than luck alone. The results in Panels A and B show that funds with t-statistic of alpha ranked in the top 5^{th} percentile and above generally exhibit significant bootstrapped p-values using the FF3F and FF+Mom. Using the LCAPM (in Panel C), the funds with significant outperformance are extended to top 20^{th} percentile and above. There are around 15% of funds shifted from lucky to skilled if we use LCAPM instead of FF3F or FF+Mom. Apparently, after considering a liquidity factor, the performances of equity funds are markedly better. These results also are identical to our baseline results.

Lastly, using the joint resampling bootstrap method for subsample 2, we compare the percentiles of the cross-section of t(alpha) estimates from actual fund returns and the average values of the percentiles from the simulations. Table 8.8 reports the CDF of t(alpha) at selected percentiles of the distribution of t(alpha) estimates for actual (ACT) net fund returns and the average of the 1000 simulation CDF (SIM); also, it offers likelihoods (%<ACT). In the tests that use the FF3F (in Panel A), the t(alpha) estimates from the actual net returns are above the average values from the simulations for only above 98^{th} percentile; and the %<ACT of the 98^{th} percentile of the cross-section of t(alpha) estimates is more than 50%. Using the FF+Mom (in Panel B), the percentile of the t(alpha) estimates for actual net fund returns are always below the average values from the simulations. Thus, the evidence of skill sufficient to cover costs is extremely weak with an adjustment for momentum exposure. However, the results from the LCAPM suggest widespread skill sufficient to cover costs after considering the adjustment for liquidity exposure. In the Panel C, the 50^{th} percentile for actual net return is above the average simulation 50^{th} percentile. In addition, the likelihood is 99.9% for the 50^{th} percentile of the cross-section of t(alpha) estimates. It means almost all of the 1000 simulation runs for the 50^{th} percentile t(alpha) estimates

fall below the ACT. This indicates that half of fund managers have skill if the liquidity factor is considered. Using this joint resampling bootstrap in this subsample, the result is still the same as our previous baseline findings.

After examining for the existence of a fund liquidity premium and testing the performance of fund portfolios for this subsample, we are able to declare that there is no material impact on our main results no matter which monthly return observation requirement is applied, 36 or 60 months. In other words, our results are robust to the change of the fund return observation requirement.

Table 8.5

Liquidity Premium of Fund Portfolios Sorted by LM12 (RtoV12) in the Subsample 2

The table reports the results for our 2013 actively managed U.S. equity funds existing for at least 60 months during the period 1984 to 2008. Panel A shows the holding period returns and risk-adjusted performance of the LM12-sorted fund portfolios; Panel B represents the holding period returns and risk-adjusted performance of the RtoV12-sorted fund portfolios.

	1 (H)	2	3	4	5	6	7	8	9	10 (L)	L-H
Panel A: Sorted by LM12				Panel A1: Holding Period Returns							
HPR1M	0.712%	0.797%	0.786%	0.791%	0.792%	0.814%	0.858%	0.917%	0.940%	0.930%	0.218%
t-statistics	1.93	2.85	3.07	3.03	3.02	3.03	3.21	3.26	3.27	3.39	1.11
HPR12M	8.872%	10.449%	10.948%	10.411%	10.757%	11.125%	11.294%	11.519%	11.808%	12.540%	3.669%
t-statistics	1.85	2.68	2.98	2.80	2.96	3.02	3.03	2.99	3.07	3.28	1.29
					Panel A2: CAPM-adjusted performance						
α	-0.287%	-0.087%	-0.067%	-0.073%	-0.070%	-0.052%	-0.002%	0.032%	0.052%	0.076%	0.363%
t-statistics	-1.73	-1.13	-1.35	-1.68	-1.30	-0.71	-0.02	0.38	0.53	0.69	2.00
					Panel A3: FF3F-adjusted performance						
α	-0.077%	-0.054%	-0.085%	-0.102%	-0.095%	-0.076%	-0.033%	0.095%	0.063%	-0.043%	0.033%
t-statistics	-0.65	-0.78	-1.74	-2.36	-1.75	-1.04	-0.42	1.51	1.03	-0.71	0.23
					Panel A4: FF+Mom-adjusted performance						
α	-0.136%	-0.119%	-0.094%	-0.101%	-0.071%	-0.053%	0.003%	0.038%	0.028%	-0.002%	0.134%
t-statistics	-1.14	-1.71	-1.85	-2.26	-1.29	-0.71	0.03	0.60	0.44	-0.03	0.90
					Panel A5: FF+PS-adjusted performance						
α	-0.110%	-0.080%	-0.105%	-0.094%	-0.078%	-0.043%	-0.001%	0.124%	0.098%	-0.026%	0.084%
t-statistics	-0.95	-1.16	-2.18	-2.17	-1.45	-0.59	-0.01	2.02	1.66	-0.43	0.58
					Panel A6: LCAPM-adjusted performance						
α	0.225%	0.056%	-0.015%	-0.053%	-0.059%	-0.048%	-0.005%	0.224%	0.255%	0.112%	-0.114%
t-statistics	1.46	0.71	-0.28	-1.15	-1.02	-0.61	-0.06	2.65	2.58	0.95	-0.64
Panel B: Sorted by RtoV12				Panel B1: Holding Period Returns							
HPR1M	0.733%	0.732%	0.741%	0.752%	0.834%	0.873%	0.910%	0.910%	0.932%	0.916%	0.183%
t-statistics	2.88	2.85	2.95	2.98	3.08	3.11	3.12	2.93	3.05	3.12	1.16
HPR12M	9.472%	9.380%	9.717%	10.580%	10.898%	11.245%	11.930%	12.086%	11.975%	12.404%	2.932%
t-statistics	2.40	2.48	2.61	2.92	2.81	2.96	2.96	2.94	3.06	3.08	1.05
					Panel B2: CAPM-adjusted performance						
α	-0.116%	-0.127%	-0.107%	-0.099%	-0.047%	-0.021%	0.001%	-0.017%	0.016%	0.035%	0.151%
t-statistics	-2.40	-3.86	-3.73	-3.09	-1.00	-0.33	0.02	-0.16	0.14	0.28	0.95
					Panel B3: FF3F-adjusted performance						
α	-0.037%	-0.089%	-0.107%	-0.107%	-0.039%	-0.013%	0.013%	0.029%	0.001%	-0.063%	-0.026%
t-statistics	-1.03	-3.18	-4.18	-3.36	-0.87	-0.23	0.21	0.46	0.02	-0.98	-0.31
					Panel B4: FF+Mom-adjusted performance						
α	-0.037%	-0.090%	-0.094%	-0.103%	-0.051%	-0.040%	-0.018%	-0.041%	-0.021%	-0.016%	0.021%
t-statistics	-1.00	-3.13	-3.59	-3.15	-1.10	-0.72	-0.29	-0.67	-0.34	-0.25	0.24
					Panel B5: FF+PS-adjusted performance						
α	-0.033%	-0.087%	-0.103%	-0.104%	-0.037%	-0.006%	0.026%	0.042%	0.023%	-0.041%	-0.008%
t-statistics	-0.91	-3.10	-4.01	-3.24	-0.82	-0.11	0.42	0.69	0.39	-0.64	-0.09
					Panel B6: LCAPM-adjusted performance						
α	-0.044%	-0.090%	-0.096%	-0.077%	0.055%	0.127%	0.181%	0.266%	0.238%	0.128%	0.172%
t-statistics	-0.87	-2.61	-3.14	-2.25	1.16	1.98	2.36	2.53	2.18	0.98	1.02

Table 8.6

Performance of Portfolio of Funds in the Subsample 2

The table reports the annualized intercepts (monthly alpha×12), t-statistics and p-values for the intercepts for a series of models estimated on value-weighted (VW) net returns on the portfolios in the subsample (actively managed U.S. equity funds existing for at least 60 months during the period 1984 to 2008).

Model		α (yearly)	β_mkt	β_smb	β_hml	β_pr1yr	β_liq_v	β_liq	R^2
CAPM	coef	-1.051%	0.9972						0.988
	t -statistic	-2.98	152.72						
	p-value	0.0031	<0.0001						
Fama-French three-factor model (FF3F)	coef	-0.771%	0.9747	0.0611	-0.0457				0.991
	t -statistic	-2.53	158.12	7.41	-4.73				
	p-value	0.0118	<0.0001	<0.0001	<0.0001				
Carhart four-factor model (FF+Mom)	coef	-0.992%	0.9784	0.0597	-0.0417	0.0178			0.991
	t -statistic	-3.22	158.03	7.34	-4.35	3.1			
	p-value	0.0014	<0.0001	<0.0001	<0.0001	0.0021			
Pastor-Stambaugh four-factor model (FF+PS)	coef	-0.722%	0.9759	0.0608	-0.0440		-0.0109		0.991
	t -statistic	-2.36	157.37	7.4	-4.54		-1.52		
	p-value	0.0187	<0.0001	<0.0001	<0.0001		0.1306		
Liu liquidity-augmented two-factor model (LCAPM)	coef	-0.120%	0.9457					-0.0779	0.990
	t -statistic	-0.35	106.84					-7.86	
	p-value	0.7256	<0.0001					<0.0001	

Table 8.7

Residual-Only Resampling Bootstrap Results of the Subsample 2

The table reports the statistics for actively managed equity mutual funds existing for at least 60 months during 1984 to 2008 for three typical asset pricing models. Panels A, B, and C show statistics from the Fama-French three-factor model (FF3F), Carhart four-factor model (FF+Mom), and Liu liquidity-augmented two-factor model (LCAPM), respectively. The first row in each panel reports the ex-post t-statistics of alpha for various points and percentiles of performance distribution, ranking from worst fund (bottom) to best fund (top). The second row presents the associated alpha for these t-statistics. The third and fourth rows report the parametric (standard) p-values and bootstrapped p-values of the t-statistics based on 1000 bootstrap residual-only resamples.

	bottom	3	5	1%	3%	5%	10%	20%	30%	40%	mdian	40%	30%	20%	10%	5%	3%	1%	5	3	top
Panel A: FF3F																					
t -stat	-4.719	-4.438	-4.194	-3.585	-2.992	-2.750	-2.183	-1.612	-1.192	-0.859	-0.532	-0.206	0.137	0.567	1.067	1.592	1.901	2.426	2.972	3.707	7.035
alpha	-0.31%	-0.43%	-1.79%	-0.38%	-0.27%	-0.20%	-0.41%	-0.15%	-0.10%	-0.09%	-0.09%	-0.04%	0.03%	0.15%	0.23%	0.36%	0.34%	1.04%	0.52%	0.58%	4.04%
p-value	0.000	0.000	0.000	0.000	0.003	0.006	0.032	0.109	0.234	0.392	0.596	0.837	0.891	0.572	0.288	0.114	0.058	0.017	0.004	0.000	0.000
p -boot	0.000	0.000	0.000	0.000	0.003	0.006	0.011	0.069	0.121	0.211	0.292	0.433	0.424	0.311	0.137	0.054	0.022	0.005	0.000	0.001	0.000
Panel B: FF+Mom																					
t -stat	-4.596	-4.246	-4.210	-3.431	-2.918	-2.689	-2.147	-1.621	-1.220	-0.904	-0.587	-0.267	0.090	0.464	1.000	1.489	1.795	2.401	3.125	3.369	6.746
alpha	-0.89%	-1.88%	-0.68%	-0.37%	-0.24%	-0.62%	-1.02%	-0.42%	-0.19%	-0.09%	-0.22%	-0.02%	0.02%	0.09%	0.15%	0.42%	0.24%	0.46%	0.83%	0.71%	3.91%
p-value	0.000	0.000	0.000	0.001	0.004	0.008	0.034	0.108	0.224	0.368	0.559	0.790	0.928	0.643	0.318	0.139	0.074	0.018	0.002	0.001	0.000
p -boot	0.000	0.000	0.000	0.001	0.000	0.002	0.016	0.039	0.121	0.186	0.270	0.398	0.447	0.297	0.187	0.057	0.044	0.011	0.001	0.000	0.000
Panel C: LCAPM																					
t -stat	-4.765	-4.320	-4.215	-3.463	-2.928	-2.588	-2.086	-1.417	-0.888	-0.388	0.111	0.539	0.989	1.477	2.104	2.599	2.881	3.460	4.317	4.425	6.190
alpha	-0.38%	-0.79%	-2.42%	-0.35%	-0.55%	-0.77%	-0.58%	-0.26%	-0.19%	-0.04%	0.02%	0.10%	0.29%	1.03%	0.54%	0.99%	0.47%	1.03%	1.17%	1.13%	4.50%
p-value	0.000	0.000	0.000	0.001	0.004	0.011	0.039	0.159	0.378	0.699	0.912	0.590	0.326	0.143	0.037	0.010	0.004	0.001	0.000	0.000	0.000
p -boot	0.000	0.000	0.000	0.000	0.001	0.006	0.023	0.080	0.194	0.352	0.440	0.302	0.159	0.073	0.017	0.003	0.002	0.000	0.000	0.000	0.000

Table 8.8

Joint Resampling Bootstrap Results of the Subsample 2

The table reports the values of t(alpha) at selected percentiles (PCT) of the distribution of t(alpha) estimates for actual (ACT) net fund returns. The table also shows the percent of the 1000 simulation runs that produce lower values of t(alpha) at the selected percentiles than those observed for actual fund returns (%<ACT). SIM is the average value of t(alpha) at the selected percentiles from the simulation after ranking the funds by their simulated t(alpha) in each run. Panels A, B, and C show results for the Fama-French three-factor model (FF3F), Carhart four-factor model (FF+Mom), and Liu liquidity-augmented two-factor model (LCAPM), respectively. The subsample 2 is these 2013 actively managed equity mutual funds existing for at least 60 months between 1984 and 2008.

	bottom 1%					bottom 10%					median					top 10%					top 1%
PCT	1%	2%	3%	4%	5%	10%	15%	20%	30%	40%	50%	60%	70%	80%	85%	90%	95%	96%	97%	98%	99%
Panel A: FF3F																					
SIM	-2.42	-2.12	-1.94	-1.79	-1.68	-1.31	-1.06	-0.86	-0.53	-0.26	0.00	0.25	0.52	0.84	1.04	1.29	1.66	1.76	1.90	2.08	2.36
ACT	-3.62	-3.21	-3.00	-2.88	-2.76	-2.19	-1.87	-1.61	-1.19	-0.86	-0.53	-0.21	0.14	0.56	0.78	1.06	1.58	1.69	1.89	2.09	2.42
%<ACT	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	4.90	6.30	39.40	57.20	76.00
Panel B: FF+Mom																					
SIM	-2.45	-2.15	-1.96	-1.81	-1.70	-1.32	-1.06	-0.86	-0.53	-0.26	0.00	0.26	0.54	0.87	1.07	1.32	1.70	1.81	1.95	2.14	2.42
ACT	-3.46	-3.19	-2.92	-2.81	-2.69	-2.15	-1.87	-1.62	-1.22	-0.90	-0.59	-0.27	0.09	0.46	0.69	1.00	1.48	1.61	1.79	2.02	2.39
%<ACT	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.30	3.20	35.50
Panel C: LCAPM																					
SIM	-2.61	-2.28	-2.08	-1.93	-1.80	-1.40	-1.12	-0.91	-0.56	-0.27	0.01	0.28	0.58	0.92	1.13	1.40	1.80	1.92	2.07	2.26	2.57
ACT	-3.49	-3.09	-2.93	-2.71	-2.60	-2.09	-1.69	-1.42	-0.89	-0.39	0.11	0.54	0.99	1.47	1.75	2.10	2.59	2.69	2.88	3.08	3.45
%<ACT	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	99.90	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00

8.2. Subperiod Analysis

Most people will be troubled by a question: with mutual fund industry growing so fast in recent decades, is mutual fund performance better than before? Barras et al. (2010) provide at least partial answer: many mutual fund managers with good track records left to manage hedge funds, whereas a large number of new managers simply have inadequate skills. For instance, they observe that the proportion of skilled funds sharply decreases from 1990 to 2006 (14.4% to 0.6%), while the proportion of unskilled funds increases considerably (9.2% to 24.0%) during the time period. Thus, it becomes necessary to check for changes in mutual fund performance and the effect of liquidity over our sample period. To ensure that our previous results are not time-dependent, we examine two subperiods of roughly equal lengths (1984 to 1995, subperiod 1, and 1996 to 2008, subperiod 2).

First of all, by sorting funds into ten portfolios based on their LM12 (or RtoV12), we examine the existence of fund liquidity premium for both subperiods. Tables 8.9 and 8.10 report the holding period returns (for 1 month and 12 months) and risk-adjusted performance of each decile for subperiod 1 and subperiod 2, respectively. Both tables reveal that there are not significant liquidity premium over the 1-month or 12-month holding periods, no matter whether fund portfolios are sorted by LM12 or RtoV12. Also, we test fund liquidity premium by controlling for risk using various models. Among the results from Panels A2 to A6 (sorted by LM12) and Panels B2 to B6 (sorted by RtoV12) in both tables, almost all reveal that the liquidity premium at fund level is little to none after controlling for risks, except for the FF+Mom sorted by LM12 (in Panel A44 of Table 8.9, subperiod 1). Consistent with our previous baseline results, in both subperiods, there is no liquidity premium at fund level. Thus, our results about fund liquidity premium are robust, and evidence on the no liquidity premium at fund level is not due to any particular subperiod.

Then, we test the performance of portfolio of funds for both subperiods. Table 8.11 presents the annualized intercepts, t-statistics, and p-values for the intercepts for various models estimated on value-weighted net returns on the portfolios of actively managed equity funds for each subperiod. In Panel A of Table 8.11, all t-statistics of alpha of each model are insignificant no matter they are positive or negative, which means the fund performance just mimics the benchmarks in the first subperiod. In the second subperiod (Panel B of Table 8.11), the CAPM, FF3F, FF+Mom, and FF+PS offering significant negative alphas tell us that, on average, actively managed equity funds have no ability to generate sufficient returns to cover the expenses. However, the result from the LCAPM is insignificantly different with zero. In other words, the aggregate portfolio of funds is close to the benchmarks if we consider the liquidity factor. Thus, if we use the first four models, we would find that the performance in the first subperiod is better than the second subperiod; whereas, using the LCAPM, the fund performance is same in both subperiods (i.e. the aggregate portfolio of funds mimics the benchmarks). We can likely provide another answer to the question at the beginning of this section. If we consider the liquidity factor when examining the fund performance, the results of performance does not change due to any particular subperiod.

Next, we analyze the significance of actively managed equity fund performance (the t-statistics of alpha) by applying the residual-only resampling bootstrap method. Table 8.12 shows the results for equity funds for both subperiods in Panel A and Panel B, respectively. The results in both panels show that funds with t-statistic of alpha ranked in the top 10^{th} percentile and above generally exhibit significant bootstrapped p-values using the FF3F and FF+Mom in the first subperiod. Using the LCAPM (in

Panel A3), the funds with significant outperformance are extended to top 20^{th} percentile and above. In the second subperiod, we also find that the same results as that in the first subperiod. Apparently, in both subperiods, there are roughly 10% to 15% of sample funds that move to skilled from lucky, if we use the LCAPM instead of FF3F or FF+Mom. Apparently, after considering the liquidity factor, the performances of equity funds are clearly improved.

Finally, using the joint resampling bootstrap method for both subperiods, we compare the percentiles of the cross-section of t(alpha) estimates from actual fund returns and the average values of the percentiles from the simulations, and then turn to likelihood statements about whether the cross-section of t(alpha) estimates for actual fund returns points to the existence of skill. Table 8.13 reports the CDF of t(alpha) at selected percentiles of the distribution of t(alpha) estimates for actual (ACT) net fund returns and the average of the 1000 simulation CDF (SIM). At the same time, we also offer likelihoods (%<ACT) in Table 8.13. In the first subperiod (Panels A1, A2, and A3) using the FF3F, FF+Mom, and LCAPM, the t(alpha) estimates from the actual net returns are above the average values from the simulations for above 60^{th} percentile, 70^{th} percentile, and 30^{th} percentile; and the %<ACT of the 60^{th}, 70^{th}, and 30^{th} percentile of the cross-section of t(alpha) estimates is more than 50%. As to the results from the second subperiod (Panels B1, B2, and B3), they are similar to the results of our baseline tests. We might say that the performance of the first subperiod is better than that of the second subperiod, because of more skilled funds. However, after considering the liquidity factor, there is only little difference between the performance of the first subperiod and the second subperiod.

In general, we are able to declare that the change of research period has no effect on the result about the absence of fund liquidity premium. Although the fund performance in the first subperiod is a little better than the second subperiod when using the other asset pricing models, there is little difference with our baseline results if LCAPM is used. This confirms again the importance of considering the liquidity factor in examining the mutual fund performance.

Table 8.9

Liquidity Premium of Fund Portfolios Sorted by LM12 (RtoV12) in the Subperiod 1

The table reports the results for actively managed U.S. equity funds during the period 1984 to 1995 (Subperiod 1). Panel A shows the holding period returns and risk-adjusted performance of the LM12-sorted fund portfolios; Panel B represents the holding period returns and risk-adjusted performance of the RtoV12-sorted fund portfolios.

	1 (H)	2	3	4	5	6	7	8	9	10 (L)	L-H
Panel A: Sorted by LM12				Panel A1: Holding Period Returns							
HPR1M	1.107%	1.181%	1.130%	1.172%	1.214%	1.270%	1.285%	1.287%	1.253%	1.129%	0.023%
t-statistics	3.00	3.60	3.63	3.30	3.29	3.22	3.26	3.21	3.12	2.97	0.18
HPR12M	15.046%	15.191%	14.879%	14.966%	15.978%	16.374%	16.229%	16.566%	16.388%	16.031%	0.985%
t-statistics	3.68	4.18	4.23	3.89	4.01	4.01	3.91	3.66	3.72	3.36	0.49
				Panel A2: CAPM-adjusted performance							
α	-0.177%	-0.031%	-0.045%	-0.091%	-0.071%	-0.058%	-0.041%	-0.046%	-0.077%	-0.137%	0.040%
t-statistics	-2.28	-0.88	-0.96	-1.74	-1.01	-0.63	-0.45	-0.43	-0.69	-1.03	0.31
				Panel A3: FF3F-adjusted performance							
α	-0.065%	-0.037%	-0.061%	-0.020%	0.048%	0.115%	0.128%	0.157%	0.114%	0.036%	0.101%
t-statistics	-0.98	-1.21	-1.60	-0.42	0.90	1.89	2.41	2.76	2.09	0.70	1.20
				Panel A4: FF+Mom-adjusted performance							
α	-0.133%	-0.071%	-0.064%	-0.051%	0.028%	0.075%	0.089%	0.100%	0.115%	0.049%	0.182%
t-statistics	-2.03	-2.38	-1.62	-1.08	0.51	1.21	1.66	1.79	2.04	0.93	2.20
				Panel A5: FF+PS-adjusted performance							
α	-0.055%	-0.038%	-0.058%	-0.003%	0.059%	0.136%	0.136%	0.169%	0.126%	0.045%	0.101%
t-statistics	-0.84	-1.22	-1.53	-0.08	1.14	2.36	2.57	3.02	2.37	0.89	1.19
				Panel A6: LCAPM-adjusted performance							
α	-0.025%	-0.009%	-0.007%	0.032%	0.099%	0.169%	0.144%	0.157%	0.094%	-0.103%	-0.079%
t-statistics	-0.31	-0.24	-0.14	0.62	1.43	1.90	1.58	1.42	0.80	-0.71	-0.56
Panel B: Sorted by RtoV12				Panel B1: Holding Period Returns							
HPR1M	1.182%	1.170%	1.156%	1.151%	1.228%	1.214%	1.263%	1.282%	1.235%	1.137%	-0.045%
t-statistics	3.72	3.52	3.44	3.36	3.39	3.16	3.13	3.17	2.99	2.79	-0.24
HPR12M	15.112%	15.165%	15.133%	15.360%	15.850%	16.041%	16.055%	16.675%	16.548%	15.748%	0.637%
t-statistics	4.01	4.14	3.88	4.21	3.93	3.99	3.72	3.87	3.60	3.21	0.22
				Panel B2: CAPM-adjusted performance							
α	-0.007%	-0.051%	-0.075%	-0.089%	-0.047%	-0.098%	-0.077%	-0.051%	-0.113%	-0.178%	-0.171%
t-statistics	-0.17	-1.37	-2.21	-2.01	-0.74	-1.15	-0.76	-0.45	-0.92	-1.17	-0.95
				Panel B3: FF3F-adjusted performance							
α	-0.017%	-0.033%	-0.042%	-0.035%	0.045%	0.052%	0.121%	0.168%	0.097%	0.047%	0.064%
t-statistics	-0.53	-0.97	-1.32	-0.87	0.84	0.89	2.12	2.66	1.77	0.77	0.89
				Panel B4: FF+Mom-adjusted performance							
α	-0.037%	-0.078%	-0.066%	-0.076%	-0.003%	0.040%	0.063%	0.128%	0.075%	0.083%	0.120%
t-statistics	-1.13	-2.46	-2.10	-1.93	-0.06	0.66	1.13	2.01	1.33	1.35	1.67
				Panel B5: FF+PS-adjusted performance							
α	-0.011%	-0.030%	-0.038%	-0.028%	0.054%	0.069%	0.132%	0.179%	0.111%	0.065%	0.076%
t-statistics	-0.36	-0.87	-1.20	-0.69	1.01	1.23	2.36	2.88	2.09	1.12	1.07
				Panel B6: LCAPM-adjusted performance							
α	0.048%	-0.002%	0.009%	0.019%	0.085%	0.114%	0.134%	0.183%	0.056%	-0.109%	-0.158%
t-statistics	1.05	-0.04	0.28	0.45	1.34	1.40	1.32	1.58	0.43	-0.66	-0.80

Table 8.10

Liquidity Premium of Fund Portfolios Sorted by LM12 (RtoV12) in the Subperiod 2

The table reports the results for actively managed U.S. equity funds during the period 1996 to 2008 (Subperiod 2). Panel A shows the holding period returns and risk-adjusted performance of the LM12-sorted fund portfolios; Panel B represents the holding period returns and risk-adjusted performance of the RtoV12-sorted fund portfolios.

	1 (H)	2	3	4	5	6	7	8	9	10 (L)	L-H
Panel A: Sorted by LM12				Panel A1: Holding Period Returns							
HPR1M	0.343%	0.415%	0.460%	0.438%	0.408%	0.388%	0.441%	0.582%	0.622%	0.727%	0.383%
t-statistics	0.54	0.93	1.16	1.15	1.09	1.06	1.21	1.45	1.51	1.83	1.04
HPR12M	2.961%	5.173%	7.037%	5.660%	5.453%	5.610%	6.350%	6.004%	6.770%	8.850%	5.889%
t-statistics	0.34	0.76	1.08	0.91	0.92	0.95	1.06	0.99	1.10	1.48	1.08
				Panel A2: CAPM-adjusted performance							
α	-0.254%	-0.113%	-0.048%	-0.062%	-0.087%	-0.099%	-0.042%	0.079%	0.119%	0.235%	0.489%
t-statistics	-0.84	-0.79	-0.65	-0.95	-1.12	-1.00	-0.35	0.60	0.75	1.36	1.55
				Panel A3: FF3F-adjusted performance							
α	-0.136%	-0.147%	-0.127%	-0.121%	-0.123%	-0.136%	-0.085%	0.070%	0.008%	-0.055%	0.080%
t-statistics	-0.72	-1.28	-1.92	-2.06	-1.85	-1.60	-0.80	0.69	0.09	-0.67	0.37
				Panel A4: FF+Mom-adjusted performance							
α	-0.200%	-0.221%	-0.148%	-0.122%	-0.101%	-0.101%	-0.034%	0.015%	-0.027%	-0.015%	0.185%
t-statistics	-1.05	-1.96	-2.20	-2.03	-1.50	-1.17	-0.32	0.14	-0.28	-0.19	0.86
				Panel A5: FF+PS-adjusted performance							
α	-0.156%	-0.157%	-0.128%	-0.117%	-0.113%	-0.119%	-0.059%	0.101%	0.065%	-0.028%	0.128%
t-statistics	-0.82	-1.35	-1.91	-1.96	-1.68	-1.38	-0.55	0.99	0.70	-0.34	0.59
				Panel A6: LCAPM-adjusted performance							
α	0.356%	0.062%	-0.019%	-0.082%	-0.133%	-0.165%	-0.104%	0.266%	0.352%	0.274%	-0.081%
t-statistics	1.33	0.44	-0.24	-1.19	-1.65	-1.61	-0.83	2.09	2.31	1.52	-0.28
Panel B: Sorted by RtoV12				Panel B1: Holding Period Returns							
HPR1M	0.323%	0.317%	0.347%	0.375%	0.466%	0.534%	0.595%	0.555%	0.613%	0.698%	0.375%
t-statistics	0.83	0.83	0.94	1.01	1.16	1.30	1.41	1.18	1.35	1.65	1.51
HPR12M	3.813%	3.294%	4.436%	5.388%	6.186%	6.373%	7.364%	7.168%	6.953%	8.878%	5.066%
t-statistics	0.57	0.53	0.72	0.89	0.94	1.00	1.10	1.02	1.11	1.37	1.03
				Panel B2: CAPM-adjusted performance							
α	-0.180%	-0.187%	-0.148%	-0.121%	-0.045%	0.020%	0.078%	0.024%	0.090%	0.196%	0.376%
t-statistics	-2.30	-3.71	-3.33	-2.64	-0.64	0.21	0.66	0.13	0.50	1.02	1.50
				Panel B3: FF3F-adjusted performance							
α	-0.048%	-0.123%	-0.139%	-0.130%	-0.078%	-0.044%	-0.013%	-0.086%	-0.091%	-0.099%	-0.051%
t-statistics	-0.92	-3.08	-4.15	-3.15	-1.19	-0.53	-0.14	-0.88	-1.03	-1.17	-0.47
				Panel B4: FF+Mom-adjusted performance							
α	-0.052%	-0.119%	-0.123%	-0.116%	-0.082%	-0.080%	-0.043%	-0.169%	-0.115%	-0.055%	-0.002%
t-statistics	-0.98	-2.92	-3.65	-2.77	-1.22	-0.95	-0.47	-1.80	-1.29	-0.65	-0.02
				Panel B5: FF+PS-adjusted performance							
α	-0.025%	-0.113%	-0.127%	-0.130%	-0.084%	-0.049%	-0.003%	-0.056%	-0.055%	-0.071%	-0.046%
t-statistics	-0.49	-2.80	-3.80	-3.09	-1.26	-0.58	-0.03	-0.57	-0.62	-0.84	-0.41
				Panel B6: LCAPM-adjusted performance							
α	-0.122%	-0.167%	-0.172%	-0.129%	0.048%	0.139%	0.249%	0.324%	0.332%	0.307%	0.428%
t-statistics	-1.51	-3.18	-3.73	-2.68	0.69	1.45	2.19	1.87	1.90	1.54	1.63

Table 8.11

Performance of Portfolios of Funds for Subperiods

The table reports the annualized intercepts (monthly alpha×12), t-statistics and p-values for the intercepts for a series of models estimated on value-weighted (VW) net returns on the portfolios for two subperiods. Panel A stands for the period 1984 to 1995 (Subperiod 1); Panel B is for the period 1996 to 2008 (Subperiod 2).

Model		α (yearly)	β_mkt	β_smb	β_hml	β_pr1yr	β_liq_v	β_liq	R^2
Panel A: Subperiod 1 (1984-1995)									
CAPM	coef	-0.497%	0.9834						0.986
	t -statistic	-0.99	100.72						
	p-value	0.3237	<0.0001						
Fama-French three-factor model (FF3F)	coef	0.175%	0.9565	0.0875	-0.0767				0.991
	t -statistic	0.41	104.73	5.58	-4.54				
	p-value	0.6836	<0.0001	<0.0001	<0.0001				
Carhart four-factor model (FF+Mom)	coef	0.000%	0.9550	0.0919	-0.0755	0.0193			0.991
	t -statistic	0	104.52	5.79	-4.49	1.56			
	p-value	0.9993	<0.0001	<0.0001	<0.0001	0.1212			
Pastor-Stambaugh four-factor model (FF+PS)	coef	0.263%	0.9503	0.0769	-0.0797		-0.0291		0.991
	t -statistic	0.62	102.27	4.81	-4.8		-2.53		
	p-value	0.5345	<0.0001	<0.0001	<0.0001		0.0125		
Liu liquidity-augmented two-factro model (LCAPM)	coef	0.646%	0.9294					-0.0956	0.989
	t -statistic	1.31	72.01					-5.72	
	p-value	0.1937	<0.0001					<0.0001	
Panel B: Subperiod 2 (1996-2008)									
CAPM	coef	-1.416%	1.0071						0.988
	t -statistic	-2.85	114.17						
	p-value	0.005	<0.0001						
Fama-French three-factor model (FF3F)	coef	-1.368%	0.9843	0.0573	-0.0349				0.992
	t -statistic	-3.25	120.07	5.88	-2.99				
	p-value	0.0014	<0.0001	<0.0001	0.0033				
Carhart four-factor model (FF+Mom)	coef	-1.668%	0.9941	0.0531	-0.0280	0.0241			0.993
	t -statistic	-4.04	119.47	5.62	-2.46	3.67			
	p-value	<0.0001	<0.0001	<0.0001	0.015	0.0003			
Pastor-Stambaugh four-factor model (FF+PS)	coef	-1.356%	0.9856	0.0576	-0.0338		-0.0035		0.992
	t -statistic	-3.15	108.66	5.87	-2.77		-0.34		
	p-value	0.002	<0.0001	<0.0001	0.0064		0.7342		
Liu liquidity-augmented two-factro model (LCAPM)	coef	-0.671%	0.9568					-0.0682	0.990
	t -statistic	-1.4	76.94					-5.34	
	p-value	0.1639	<0.0001					<0.0001	

Table 8.12

Residual-Only Resampling Bootstrap Results of the Subperiods

The table reports the residual-only resampling bootstrap results of actively managed equity mutual funds during 1984 to 2008 for two subperiods. Panels A and B present the results for the subperiod 1 (1984-1995) and subperiod 2 (1996-2008), respectively.

	bottom	3	5	1%	3%	5%	10%	20%	30%	40%	mdian	40%	30%	20%	10%	5%	3%	1%	5	3	top
Panel A: Subperiod 1 (1984-1995)										Panel A1: FF3F											
t-stat	-6.061	-3.423	-3.341	-3.059	-2.567	-2.284	-1.717	-1.175	-0.728	-0.352	-0.057	0.319	0.733	1.264	1.916	2.556	2.888	3.750	4.439	7.313	18.784
alpha	-1.38%	-0.60%	-0.75%	-0.21%	-0.71%	-0.38%	-0.33%	-0.22%	-0.13%	-0.23%	-0.05%	0.05%	0.12%	0.81%	1.33%	0.34%	0.30%	1.15%	1.40%	0.51%	1.98%
p-value	0.009	0.001	0.003	0.003	0.018	0.027	0.092	0.253	0.469	0.731	0.958	0.750	0.465	0.222	0.088	0.012	0.005	0.000	0.004	0.005	0.000
p -boot	0.007	0.001	0.005	0.004	0.009	0.009	0.035	0.118	0.220	0.388	0.485	0.402	0.245	0.111	0.029	0.001	0.004	0.000	0.001	0.002	0.000
										Panel A2: FF+Mom											
t-stat	-4.867	-4.382	-3.749	-3.408	-2.667	-2.352	-1.772	-1.148	-0.778	-0.466	-0.137	0.197	0.575	1.013	1.804	2.291	2.529	3.054	3.539	3.783	6.559
alpha	-2.74%	-4.47%	-1.58%	-1.23%	-0.30%	-0.47%	-0.52%	-0.11%	-0.23%	-0.10%	-0.04%	0.03%	0.06%	0.42%	0.25%	0.51%	0.26%	0.90%	1.01%	1.05%	1.71%
p-value	0.129	0.048	0.064	0.001	0.009	0.022	0.082	0.253	0.444	0.643	0.892	0.846	0.567	0.315	0.074	0.029	0.013	0.003	0.001	0.000	0.022
p -boot	0.073	0.030	0.023	0.000	0.001	0.007	0.038	0.101	0.197	0.344	0.429	0.443	0.294	0.151	0.032	0.020	0.004	0.002	0.000	0.000	0.010
										Panel A3: LCAPM											
t-stat	-4.215	-3.202	-3.034	-2.740	-2.319	-1.915	-1.466	-0.882	-0.419	-0.079	0.242	0.627	0.982	1.410	1.985	2.542	2.930	3.452	3.761	3.958	4.157
alpha	-2.42%	-0.59%	-0.25%	-0.34%	-2.60%	-0.28%	-0.35%	-0.43%	-0.17%	-0.01%	0.08%	0.80%	3.01%	0.57%	0.21%	0.82%	0.23%	1.91%	2.91%	1.32%	0.62%
p-value	0.000	0.004	0.003	0.007	0.259	0.061	0.146	0.388	0.679	0.937	0.810	0.545	0.382	0.162	0.050	0.013	0.004	0.002	0.001	0.000	0.000
p -boot	0.000	0.001	0.000	0.003	0.254	0.026	0.072	0.183	0.362	0.466	0.420	0.261	0.238	0.061	0.023	0.003	0.002	0.001	0.001	0.000	0.000
Panel B: Subperiod 2 (1996-2008)										Panel B1: FF3F											
t-stat	-6.269	-4.954	-4.547	-3.617	-3.068	-2.771	-2.204	-1.632	-1.216	-0.875	-0.566	-0.249	0.089	0.476	0.987	1.434	1.768	2.433	3.783	5.077	7.035
alpha	-0.04%	-0.99%	-0.19%	-0.43%	-0.57%	-1.01%	-0.46%	-0.17%	-0.54%	-0.05%	-0.23%	-0.04%	0.04%	0.05%	0.36%	0.21%	0.20%	0.57%	3.75%	2.37%	4.04%
p-value	0.000	0.000	0.000	0.000	0.003	0.007	0.030	0.105	0.228	0.383	0.572	0.804	0.929	0.635	0.379	0.154	0.081	0.016	0.001	0.000	0.000
p -boot	0.000	0.000	0.000	0.000	0.003	0.000	0.010	0.053	0.124	0.199	0.267	0.413	0.462	0.342	0.179	0.085	0.045	0.005	0.000	0.000	0.000
										Panel B2: FF+Mom											
t-stat	-15.965	-5.056	-4.658	-3.594	-2.951	-2.690	-2.232	-1.631	-1.244	-0.943	-0.620	-0.296	0.033	0.441	0.983	1.452	1.749	2.421	3.496	4.216	6.746
alpha	-0.27%	-0.47%	-0.96%	-0.44%	-0.60%	-0.47%	-0.21%	-0.56%	-0.15%	-0.18%	-0.07%	-0.07%	0.00%	0.06%	0.52%	0.56%	0.34%	0.82%	0.74%	1.11%	3.91%
p-value	0.040	0.000	0.000	0.001	0.004	0.008	0.027	0.109	0.215	0.348	0.537	0.768	0.973	0.661	0.329	0.154	0.089	0.021	0.001	0.148	0.000
p -boot	0.022	0.000	0.000	0.000	0.002	0.008	0.012	0.052	0.095	0.170	0.274	0.382	0.506	0.335	0.163	0.063	0.042	0.006	0.000	0.106	0.000
										Panel B3: LCAPM											
t-stat	-6.649	-4.988	-4.535	-3.595	-2.947	-2.569	-2.034	-1.384	-0.909	-0.441	0.029	0.439	0.849	1.286	1.846	2.357	2.646	3.344	4.184	4.996	7.173
alpha	-0.04%	-0.56%	-0.49%	-1.01%	-0.33%	-0.44%	-0.60%	-0.20%	-0.14%	-0.11%	0.01%	0.16%	0.29%	0.30%	0.53%	0.61%	0.68%	0.42%	0.83%	1.13%	0.98%
p-value	0.000	0.000	0.000	0.001	0.004	0.011	0.046	0.169	0.365	0.661	0.977	0.662	0.399	0.200	0.068	0.020	0.009	0.001	0.000	0.015	0.002
p -boot	0.000	0.000	0.000	0.000	0.001	0.006	0.028	0.091	0.171	0.340	0.487	0.349	0.202	0.097	0.026	0.007	0.006	0.000	0.000	0.030	0.001

Table 8.13

Joint Resampling Bootstrap Results of the Subperiods

The table reports the entire cases (joint) resampling bootstrap results of actively managed equity mutual funds during 1984 to 2008 for two subperiods. Panels A and B present the results for the subperiod 1 (1984-1995) and subperiod 2 (1996-2008), respectively.

	bottom 1%					bottom 10%					median					top 10%					top 1%
PCT	1%	2%	3%	4%	5%	10%	15%	20%	30%	40%	50%	60%	70%	80%	85%	90%	95%	96%	97%	98%	99%
Panel A: Subperiod 1 (1984-1995)											Panel A1: FF3F										
SIM	-2.37	-2.06	-1.87	-1.74	-1.63	-1.25	-1.00	-0.81	-0.51	-0.25	-0.01	0.23	0.49	0.80	0.99	1.24	1.60	1.71	1.83	2.01	2.28
ACT	-3.07	-2.79	-2.58	-2.38	-2.29	-1.72	-1.43	-1.18	-0.73	-0.35	-0.06	0.31	0.73	1.25	1.50	1.91	2.53	2.65	2.85	3.15	3.59
%<ACT	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.30	7.70	98.90	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
											Panel A2: FF+Mom										
SIM	-2.52	-2.16	-1.94	-1.81	-1.68	-1.28	-1.02	-0.83	-0.52	-0.25	-0.01	0.23	0.49	0.80	0.99	1.24	1.62	1.73	1.86	2.04	2.32
ACT	-3.46	-2.93	-2.69	-2.49	-2.38	-1.78	-1.43	-1.15	-0.78	-0.47	-0.14	0.20	0.57	1.00	1.38	1.80	2.28	2.40	2.50	2.76	3.05
%<ACT	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	18.60	98.70	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
											Panel A3: LCAPM										
SIM	-2.37	-2.06	-1.86	-1.72	-1.61	-1.22	-0.98	-0.79	-0.48	-0.22	0.02	0.25	0.51	0.82	1.02	1.26	1.65	1.76	1.91	2.10	2.41
ACT	-2.78	-2.45	-2.33	-2.08	-1.92	-1.47	-1.12	-0.89	-0.42	-0.08	0.24	0.63	0.98	1.41	1.65	1.98	2.52	2.61	2.91	3.08	3.44
%<ACT	0.10	0.00	0.00	0.00	0.00	0.00	0.20	1.00	93.90	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Panel B: Subperiod 2 (1996-2008)											Panel B1: FF3F										
SIM	-2.46	-2.14	-1.95	-1.81	-1.69	-1.31	-1.06	-0.86	-0.54	-0.27	-0.01	0.24	0.52	0.83	1.03	1.28	1.65	1.76	1.89	2.07	2.36
ACT	-3.68	-3.25	-3.08	-2.90	-2.78	-2.21	-1.89	-1.63	-1.22	-0.88	-0.57	-0.25	0.09	0.47	0.70	0.98	1.43	1.58	1.77	2.03	2.43
%<ACT	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.10	0.70	28.20	81.20
											Panel B2: FF+Mom										
SIM	-2.49	-2.16	-1.97	-1.83	-1.71	-1.32	-1.07	-0.86	-0.54	-0.26	0.00	0.26	0.54	0.86	1.06	1.31	1.69	1.81	1.94	2.12	2.42
ACT	-3.72	-3.22	-2.96	-2.82	-2.70	-2.23	-1.91	-1.63	-1.25	-0.95	-0.62	-0.30	0.03	0.44	0.68	0.98	1.45	1.55	1.75	2.01	2.42
%<ACT	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	3.70	49.30
											Panel B3: LCAPM										
SIM	-2.63	-2.28	-2.08	-1.92	-1.80	-1.39	-1.12	-0.90	-0.56	-0.27	0.01	0.28	0.57	0.91	1.12	1.38	1.78	1.90	2.04	2.23	2.54
ACT	-3.65	-3.16	-2.95	-2.80	-2.57	-2.04	-1.68	-1.39	-0.91	-0.45	0.03	0.44	0.85	1.29	1.56	1.85	2.35	2.51	2.64	2.82	3.31
%<ACT	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	79.70	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00

CHAPTER 9: CONCLUSIONS

9.1. Summary

Based on two incentives: (i) to examine whether the mutual fund industry as a whole has stock-picking skill; (ii) to verify the efficient-market hypothesis, in this thesis, we study mutual fund performance from a new insight: liquidity effect on the performance of fund. Although a great deal of research has been published about mutual fund performance, little has been documented as to the relation between fund liquidity and performance. Our research, to fill this gap, not only constructs new fund liquidity measures and analyzes the liquidity characteristics of actively managed equity funds, but also verifies the liquidity premium at fund level, as well as the effect of fund liquidity on performance.

This study takes a new look at returns of 2417 diverse U.S. equity mutual funds during the period of 1984 to 2008 and utilizes a new data sample that includes the liquidity measures of stocks held by funds in each month over the 25-year period. Besides using the classification of Thomson Reuters CDA/Spectrum, we apply the proportion of the stock-holdings in a fund to identify the equity funds. At the same time, we also construct fund liquidity measures (FLMs) based on value-weighted average of the liquidity measure of individual stocks held by a fund. Among all FLMs, Liu’s trading discontinuity measure (LM12) and Amihud’s price impact ratio (RtoV12) are the most representative proxies for fund liquidity. Moreover, from the changing trend of FLMs, we discover that the equity funds have recently greatly favoured highly liquid stocks. Specifically, the stocks held by a typical equity fund have the following trends on liquidity properties: fewer no-trading days, higher trading turnover ratio, lower price-impact ratio, and slightly lower effective cost of trading. Additionally, we notice a steep increase in market capitalization and obvious fall of B/M ratio, which indicates equity funds prefer to hold big companies and growth companies. Further, we use the CAPM, Fama-French three-factor model (FF3F), Carhart four-factor model (FF+Mom), Pastor-Stambaugh four-factor model (FF+PS), and Liu liquidity-augmented two-factor model (LCAPM) to evaluate risk-adjusted fund performance and check the effect of liquidity factor on fund performance.

In conclusion, we test whether there is any liquidity premium at fund level; test whether the actively managed equity funds as a whole can outperform the benchmarks; and test whether the “star” equity funds are due solely to luck or to genuine selection skills. After sorting funds into ten portfolios based on their LM12 or RtoV12, we find no significant fund liquidity premium over the 1-month or 12-month holding periods. Additionally, we reveal that fund liquidity premium is little to none after controlling for risks. Apparently, fund liquidity premium is a different story from stock liquidity premium. To test the aggregate fund performance, we construct the portfolio of funds in each month and run time-series regression for the cross-section of these portfolios’ net returns. Under the CAPM, FF3F, FF+Mom, and FF+PS, the significant negative alphas tell us on average actively managed equity funds do not have the ability to generate sufficient returns to cover the costs. However, the result from the LCAPM is totally different: we find the actively managed equity funds in aggregate mimics the performance of benchmarks. Thus, we attribute the underperformance of funds mooted in earlier work to failure to consider liquidity. Moreover, we also distinguish skilled from lucky for individual funds via two different bootstrap simulation methods (residual-only resampling and entire cases resampling). We find that the performance of a few best funds cannot be explained solely by sampling variability, which means these fund managers’ performances are not due to luck alone. Moreover, we find that more funds can be called skilled funds when using LCAPM model than using the earlier models. Apparently, after considering a liquidity factor, the measured performances of equity funds are improved markedly. Fund managers' holding of large amounts of highly liquid stocks results in adverse impact on the fund performance.

9.2. Suggestions

Overall, our research provides empirical evidence for considering liquidity as a risk factor in mutual fund returns. Liquidity is a non-negligible determinant in the evaluation of mutual fund performance. The results of our study have a number of important implications for future research in the mutual fund area.

First of all, liquidity as a vital factor has effectively been paid a great deal of attention by mutual fund managers in making investment decisions. From the liquidity characteristics of stock-holdings of funds, we reveal that a typical equity fund favours highly liquid stocks, such as those stocks, on average, have few no-trading days, high trading turnover ratio, and low price-impact ratio. Moreover, our result, absence of fund liquidity premium, confirms again the significance of liquidity in mutual fund industry. That is, most actively managed equity funds hold a great deal of liquid stocks and, as a result, it is impossible to find significant liquidity premium within these highly liquid portfolios.

Next, since the liquidity is a vital factor for mutual funds, our research, from a liquidity-considered standpoint, applies the Liu LCAPM to evaluating the fund performance. By testing the performance of portfolio of funds, we find that U.S. actively managed equity funds as a group mimics the performance of the benchmarks. It is safe to conclude that the previous research results of underperformance of mutual fund are mainly due to lack of consideration of the liquidity factor in the earlier models.

Thus, the difference in performance is supposed to be attributed to whether a liquidity factor is considered. Here, we strongly propose employing a liquidity-considered asset pricing model (such as Liu LCAPM) to examine mutual fund performance.

Our research shows that the hypothesis of normal distribution of residual is not tenable. This strong finding of non-normal residuals (i.e. roughly half of funds have alphas are drawn from a distinctly non-normal distribution) challenges the validity of earlier research that relies on the normality assumptions. Accordingly, this phenomenon indicates the need to bootstrap, especially in the tails, to determine whether significant performance is due to fund manager’s stock-picking ability or to luck alone. Based on residual-only resampling and entire cases resampling, the results of earlier models exhibit few funds having genuine skills. However, using Liu LCAPM, many more funds show significant outperformance. Hence, after considering the liquidity factor, more equity funds are classified to skilled funds from lucky funds. That echoes our previous suggestions. For whatever reason, fund managers holding of a great amount of liquid stocks adversely impacts fund performance.

Last but not least, we also recommend using the t-statistic of the estimated alpha as a measure of fund performance, rather than the estimated alpha itself. The t-statistic can scale alpha by its standard error, which tends to be larger for shorter-lived funds and for funds that take higher levels of risk. Hence, the distribution of bootstrapped t-statistics of alpha in the tails is likely to reveal better properties than the distribution of bootstrapped alpha. Moreover, for each ranked fund we compare bootstrapped p-values with parametric standard p-values that correspond to the t-statistics of these individual ranked funds.

Overall, our research provides empirical evidence for the importance of liquidity as a risk factor in mutual fund returns, i.e. liquidity is a vital determinant in the evaluation of a mutual fund's performance. Thus, we strongly propose employing a liquidity-based asset pricing model when examining the performance of mutual funds in the future. At the very least, our research provides this sensible advice: the performance of equity fund may be not only because of alpha (risk-adjusted returns, management skills), but also due to some beta (systematic liquidity risk factor).

9.3. Future Work

As mentioned earlier, all models we used in this paper, no matter conventional models or liquidity-based models, are unconditional models. However, an active fund manager may employ dynamic strategies to change portfolio holdings and weights depending on publicly available information. So these unconditional models may generate unreliable results. Although Ferson and Schadt (1996), Christopherson et al. (1998), and Christopherson et al. (1999) advocate using time-varying conditional models (introduce time-variation in alpha and use conditional betas) to examine whether managerial performance is indeed constant or if it varies over time as a function of information, capturing time variation in the regression slopes and intercept poses thorny problems, and so we leave this potentially important issue for future research.[53] In future work, we might look at conditional fund performance measurement. First, we could use time-varying conditional expected returns and conditional betas instead of the usual, unconditional betas:

$$\beta_{i,t} = \beta_{i,0} + B_i^{'} Z_{t-1} .$$

Thus, the unconditional LCAPM will have a conditional version:

$$r_{i,t} = \alpha_i + \beta_{m,0} r_{m,t} + B^{'}_{m,i} Z_{t-1} r_{m,t} + \beta_{l,0} LIQ_t + B^{'}_{l,i} Z_{t-1} LIQ_t + \varepsilon_{i,t} .$$

[53] Recently, Barras et al. (2010) documents that using unconditional or conditional models has no material impact on their results about fund performance.

Next, we could assume that alpha depends linearly on Z_{t-1}, so that:

$$\alpha_{i,t} = \alpha_{i,0} + A_i^{'} Z_{t-1} .$$

Then the LCAPM can be transformed further to the following equation:

$$r_{i,t} = \alpha_0 + A_i^{'} Z_{t-1} + \beta_{m,0} r_{m,t} + B_{m,i}^{'} Z_{t-1} r_{m,t} + \beta_{l,0} LIQ_t + B_{l,i}^{'} Z_{t-1} LIQ_t + \varepsilon_{i,t} .$$

Applying these two conditional versions of LCAPM, we might verify whether liquidity factor still has material effect on mutual fund performance.

In the whole research, we always assess the performance of fund manages on fund net returns (i.e. whether they have enough picking-stock ability to cover costs and expenses). Although fund performance on net returns is the most crucial issue to mass investors, it is possible that the fruits of skill do not show up more generally on net returns because they are absorbed by expenses. As Fama and French (2010) note, the issue in the tests on net returns is whether fund managers have sufficient skill to produce expected returns that cover their costs, while the issue in the tests on gross returns is whether they have skill that causes expected returns to differ from those of comparable passive benchmarks. Thus, we could evaluate fund performance on gross returns in future research. For this purpose, we would like to use fund returns measured before all costs and expenses, which means the regressions could focus on fund manager skill. Because the fund return values from CRSP-MF database are based on net returns, fund gross returns pose much more difficult measurement issues. Our fund gross returns, following the method in Fama and French (2010), are before the cost in expense ratios (including management fees), but they are net of other costs, primarily trading costs[54]. This is a simple and approximate approach to define the gross returns (only net returns plus the costs in expense ratios):

[54] Funds do not report trading costs, however, and estimates are subject to large error. In addition, the trading costs vary through time.

$$\text{Gross RET} = \text{Net RET} + \text{Expenses}(\text{inc. Management Fees}) + \left[\text{Other Costs (Trading Costs)}\right].$$

Equivalently, the tests based on gross returns say that a fund management has skill only if it is sufficient to cover the missing costs (primarily trading costs). It seems like a reasonable definition of skill since an efficiently managed passive fund can apparently avoid these costs.

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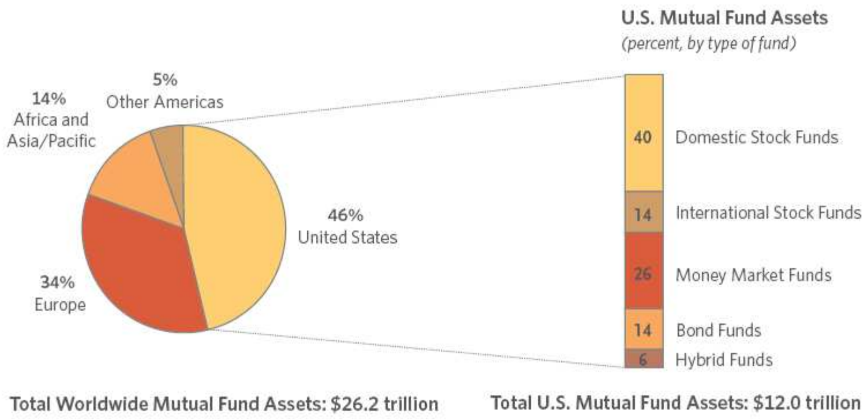
APPENDICES

Appendix 1: Total Net Assets in the U.S. Mutual Fund Industry and, Total Net Assets of Mutual Funds for Each Investment Objective (Billions of U.S. Dollars, 1984-2009)

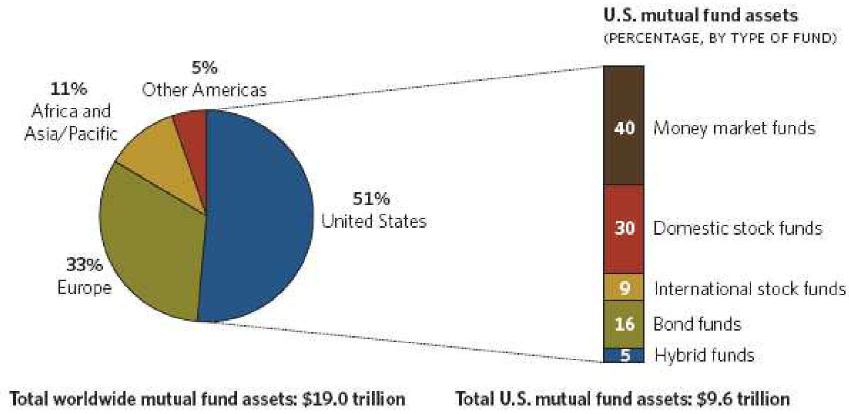
		Long-term funds			
Year	Total	Equity funds	Hybrid funds	Bond funds	Money market funds
1984	$370.68	$79.73	$11.15	$46.24	$233.55
1985	495.39	111.33	17.61	122.65	243.80
1986	715.67	154.45	25.76	243.31	292.15
1987	769.17	175.45	29.25	248.37	316.10
1988	809.37	189.38	26.35	255.69	337.95
1989	980.67	245.04	35.64	271.90	428.09
1990	1,065.19	239.48	36.12	291.25	498.34
1991	1,393.19	404.73	52.23	393.78	542.44
1992	1,642.54	514.09	78.04	504.21	546.19
1993	2,069.96	740.67	144.50	619.48	565.32
1994	2,155.32	852.76	164.40	527.15	611.00
1995	2,811.29	1,249.08	210.33	598.87	753.02
1996	3,525.80	1,726.01	252.58	645.41	901.81
1997	4,468.20	2,368.02	317.11	724.18	1,058.89
1998	5,525.21	2,977.94	365.00	830.59	1,351.68
1999	6,846.34	4,041.89	378.81	812.49	1,613.15
2000	6,964.63	3,961.92	346.28	811.19	1,845.25
2001	6,974.91	3,418.16	346.32	925.12	2,285.31
2002	6,383.48	2,662.46	325.49	1,130.45	2,265.08
2003	7,402.42	3,684.16	430.47	1,247.77	2,040.02
2004	8,095.08	4,383.98	519.29	1,290.48	1,901.34
2005	8,891.11	4,939.70	567.30	1,357.28	2,026.82
2006	10,396.51	5,910.50	653.15	1,494.41	2,338.45
2007	12,000.64	6,515.87	718.98	1,680.03	3,085.76
2008	9,602.60	3,704.27	499.50	1,566.60	3,832.24
2009	11,120.73	4,957.58	640.75	2,206.20	3,316.20

Sources: 2010 Investment Company Fact Book, Investment Company Institute

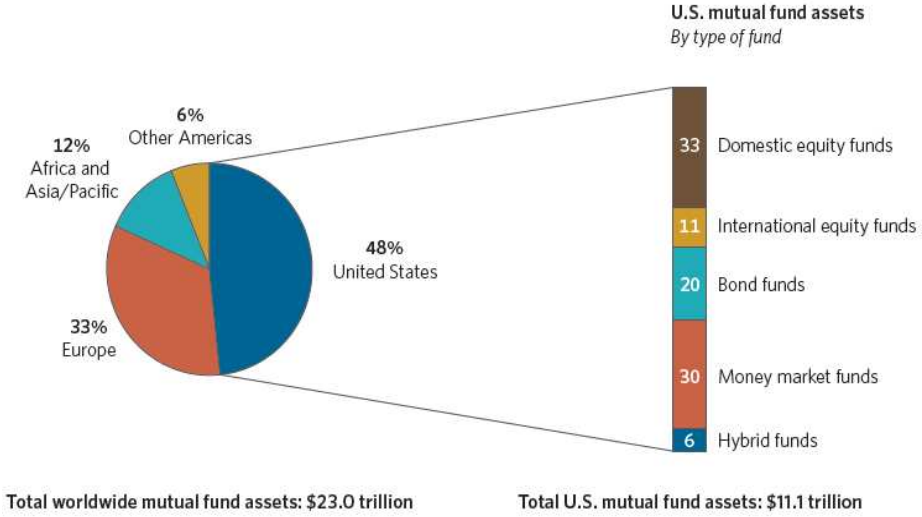
Appendix 2: Asset Proportion by Type of Fund in the U.S. Mutual Fund Market, the World's Largest Fund Market (at the end of 2007, 2008, and 2009)



Year-End 2007



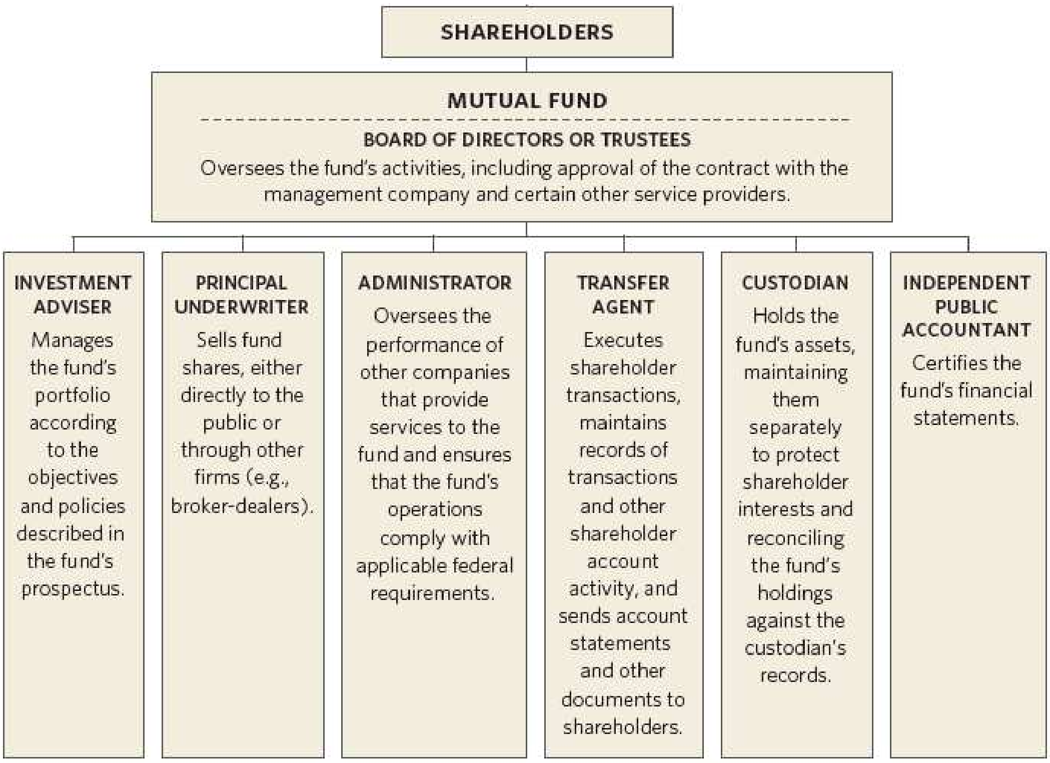
Year-End 2008



Year-End 2009

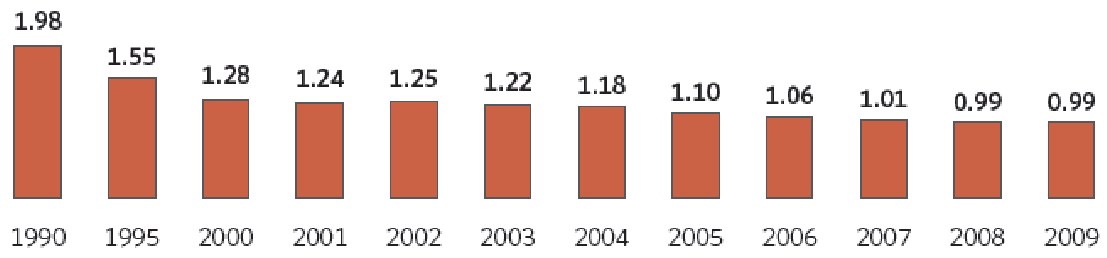
Sources: Investment Company Institute, European Fund and Asset Management Association, and other national mutual fund associations

Appendix 3: The Structure of a Typical Mutual Fund



Sources: 2010 Investment Company Fact Book, Investment Company Institute

Appendix 4: Trend of Fees and Expenses Incurred by Equity Fund Investors (%, 1990, 1995, 2000-2009)



Sources: Investment Company Institute and Lipper

Appendix 5: Net Cash Flow to Mutual Funds by Load Structures (Billions of U.S. Dollars, 2003-2009)

	2003	2004	2005	2006	2007	2008	2009
All long-term funds	**$216**	**$210**	**$192**	**$227**	**$223**	**-$226**	**$388**
Load	**48**	**44**	**30**	**33**	**14**	**-146**	**39**
Front-end load[1]	33	49	47	48	20	−99	19
Back-end load[2]	−19	−38	−48	−48	−44	−39	−24
Level load[3]	27	21	19	21	25	−12	37
Other load[4]	8	13	11	12	13	5	8
No-load[5]	**126**	**130**	**145**	**170**	**185**	**-54**	**323**
Retail	83	94	79	77	59	−104	138
Institutional	43	35	66	93	126	50	185
Variable annuities	**42**	**36**	**18**	**24**	**25**	**-27**	**26**

Sources: Investment Company Institute and Lipper

Appendix 6: Expenses Ratios for Selected Investment Objectives (%, 2009)

Investment objective	10th percentile	Median	90th percentile	Average *Asset-weighted*	Average *Simple*
Equity funds	**0.82**	**1.44**	**2.28**	**0.87**	**1.52**
Aggressive growth	0.91	1.49	2.33	1.03	1.58
Growth	0.78	1.33	2.16	0.91	1.43
Sector funds	0.92	1.62	2.50	0.98	1.70
Growth and income	0.52	1.21	2.00	0.56	1.25
Income equity	0.75	1.24	1.98	0.85	1.32
International equity	0.99	1.60	2.45	1.02	1.67
Hybrid funds	**0.63**	**1.20**	**2.00**	**0.84**	**1.28**
Bond funds	**0.52**	**0.96**	**1.73**	**0.65**	**1.08**
Taxable bond	0.50	0.99	1.80	0.65	1.09
Municipal bond	0.55	0.92	1.62	0.64	1.07
Money market funds	**0.22**	**0.50**	**0.91**	**0.34**	**0.54**

Sources: Investment Company Institute and Lipper