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In what way are U.S. equity mutual fund flows and their relative performance affected by different risk factors and liquidity of mutual funds?

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Preface and Acknowledgments

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Abstract

This thesis provides an empirical analysis on 725 U.S. equity mutual funds in the time period January 2000 up to and including December 2015. Firstly, mutual funds excess returns are being analysed through fund-level cross-sectional regressions and quantile regressions. It turned out that the excess return on the market has the highest explanatory power out of the three risk factors from Fama and French. Thereafter, Treynor, J., & Mazuy, K. (1966) their methodology is used as a foundation to test for security selection skills and market timing ability. Results showcased that fund managers possess on average a security selection skill because the alpha was positive and significant at a 1% level. But there was definitely no sign of a market timing skill among all of the mutual funds since the variance of the excess return on the market turned out to be negative and significant at a 1% level as well. Lastly, the impact of the three liquidity measures from Pástor, Ľ., & Stambaugh, R. F. (2003) were utilized to find the impact of liquidity on mutual fund flows and subsequently the performance of mutual funds. The innovative and traded liquidity measure had a positive and significant impact on the mutual fund flows, whereas the aggregate liquidity measure had a negative and significant impact on the mutual fund flows.

Keywords: *mutual fund flows, market timing, performance, liquidity, mutual fund returns*

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1. Introduction

A mutual fund is an investment vehicle, which consists of bonds, stocks or other types of securities. Mutual funds are playing a more and more present role in the modern society nowadays than most people think. For retail investors, mutual funds are one of the most popular investing options out there in the stock market. Since the rise of globalization, mutual funds have become increasingly popular. In 2018, the U.S. mutual funds net assets value reached the immense amount of $17.71 trillion. This is expected to be $23.37 trillion by 2024 (US Mutual Funds Industry, 2018). There are several reasons why mutual funds are being chosen by investors: portfolio diversification, seeking liquidity and to get investment expertise at a low cost. When an event is happening in our lives, which affects our well-being, investors might react sometimes in an emotional way when it comes to their investments (Seo, M. G., & Barrett, L. F. 2007). This has an effect on the mutual funds' performance as well. In some cases, this leads to a run on mutual funds.

During the last financial crisis in 2008, asset classes which made use of an intermediary, like ETF's and short-duration bond funds, experienced a lot of running behaviour (Schmidt, L., Timmermann, A., & Wermers, R. 2016). The meaning of running behaviour is that retail investors take their money very quickly out of a mutual fund. Mutual funds who have fewer liquid assets in their possession are affected the most. Funds usually do not keep a significant amount of their assets in cash holdings; they invest it somewhere else. So, in case of run-like behaviour of retail investors, these funds are assumed to be the first ones in trouble.

It is for sure not the first time that mutual funds are being used as a thesis topic. However, it can still be a very challenging and relevant topic, if the right angle is being touched upon. As far as my knowledge reaches there is no existing literature about U.S. equity mutual funds returns decomposition in combination with the influence of liquidity factors and market timing ability.

Nowadays, liquidity is still a broad concept and there is not one clear definition available. Pástor, Ľ., & Stambaugh, R. F. (2003) aim to clarify this and define liquidity as the ability to trade quantities in a quick manner and at a low cost, without actually moving the price. In general, investors tend to require higher expected returns on assets whose returns are more sensitive to liquidity. For example, when an investor needs to liquidate their assets it will be more costly if the liquidity is lower. Therefore, the investor wants to be compensated with higher returns to cover those costs to a certain extent. Pástor, Ľ., & Stambaugh, R. F. (2003)

introduced multiple liquidity measures which will be applied in the empirical analysis part of this thesis.

There can arise a situation where investors take their money out of mutual funds in a very short time period. This naturally has a price impact on the concerned shares. We are also experiencing this right now. A news article came out on March 20, 2020 which stated that Dutch households lost approximately 15 billion Euros of stocks since 20 February of this year because of the ‘fear’ about the impact of the Covid-19 virus. The question here is: are investors acting on an emotional basis or on a rational basis? Sure, it is unavoidable that companies will lose money and some people are going to lose their jobs, but is this a temporary effect or a long-term effect? Of course, it still remains guessing, yet I don’t think that this virus will stay for a long time in our very modern society.

Within this thesis, the focus will be on US equity mutual funds and their behaviour regarding liquidity, market timing and the decomposition of their fund returns. All in all, this thesis attempts to answer the following research question:

In what way are U.S. equity mutual fund flows and their relative performance affected by different risk factors and liquidity of mutual funds?

This thesis is going to give a thorough and complete answer to the above research question. The U.S. is chosen because the database that will be used is most compatible with the U.S., there will be an elaboration about this in the Methodology & Data part. Besides that, it is convenient to focus on a market where one currency is used and the U.S. will definitely cover enough data when it comes to equity mutual funds. The chosen timeframe will be 1 January 2000 up to and including 31 December 2015. To strengthen the research question, three other hypotheses will be formulated in the Methodology & Data section.

Empirical analysis will form the foundation of this thesis. Abnormal returns of mutual funds will be calculated by using the excess monthly fund returns and the impact of the Fama and French risk factors. This is relevant for predicting whether fund managers have a market timing ability and or a security selection skill. Treynor’s model for market timing ability forms the basis of this part. Lastly, liquidity factors from Pástor, Ľ., & Stambaugh, R. F. (2003) and their influence on performance of mutual funds will be analyzed.

The starting mutual fund sample consists of 725 equity mutual funds, all based in the United States. The remainder of this thesis is organized as follows. Section 2 describes the literature review, to build a stronger foundation around the research question and the corresponding hypotheses. In Section 3, the methodology and data will be set out. The obtained results will be described and evaluated in Section 4. Section 5 concludes and offers room for further research and touches upon the limitations of this research. The references and appendix can be found in respectively Section 6 and 7.

2. Theoretical Framework

Chapter 2 provides an overview of the existing literature regarding mutual funds. Firstly, there will be an elaboration on the main driving factors and definitions of this thesis. After that the most important papers will be described. These papers are being used as an inspiration and support for my thesis and will form the foundation of the literature review. All taken together, these papers are helpful and will definitely contribute to my research question and hypotheses.

Paragraph 2.1 gives a broad explanation about mutual funds and different share classes. Portfolio selection and market timing ability will be touched upon in paragraph 2.2. Asset fire sales and purchases will be described in paragraph 2.3. Paragraph 2.4 is about literature of runs on money market mutual funds. Literature about fund manager skills will be clarified in paragraph 2.5. Lastly, the effect of capital commitment will be reviewed in paragraph 2.6.

Stock prices are so volatile these days, which gives opportunities for retail investors to achieve great abnormal returns. How do mutual fund flows react when there is a change in the liquidity of a mutual fund? In some cases, mutual funds might have to sell their shares at a lower price than the market value price. Which means that investors with enough liquidity can profit from that situation and can buy them at a nice discount. Are mutual fund managers able to time the market in some way? Most of the existing literature is about mutual fund performance on itself, or in combination with asset fire sales for example. However, the combination with market timing, liquidity and the fund performance has not been covered in existing literature as far as my knowledge reaches. So, to dive into the matter whether mutual funds can prepare themselves and how they react in case of change of liquidity, is for sure very relevant and interesting.

2.1 Mutual Funds

Mutual funds are the main subject of this thesis. Therefore, it is needed to give some more background information about mutual funds. A mutual fund is an investment vehicle, which consists of bonds, stocks or other types of securities. Mutual funds are managed by fund managers, who allocate the securities of a specific fund and their goal is to get a high return for the investors. An advantage for small investors is that they have access to large, professionally managed portfolios of stocks through a mutual fund. On the other hand, this implies that every investor is responsible and will be proportionally accounted for any gains or losses that are being made by the fund. Furthermore, the investor has to decide whether they invest an actively or passively managed mutual fund. If an investor decides to invest in an actively managed fund, higher management fees have to be paid. Jensen M.C. (1968) argues that is only beneficial to invest in active funds if fund managers are being able to increase the returns of the fund through prediction of future stock price movements and if they are minimizing the insurable risk through efficient diversification. The Net Asset Value of a fund is determined by the total value of all the securities, divided by the number of the fund's outstanding shares. Some of the funds charge transactions fees. Examples are the front and back-end load, which means that you have to pay a fee when you respectively buy or sell a stock or bond.

2.1.1 Sharpe Ratio

Sharpe, W. F. (1966) published one of the first prominent papers about mutual funds and their performance. This paper aims to extend the work of Treynor, J., & Mazuy, K. (1966). Sharpe, W. F. (1966) introduced a new predictor of mutual fund performance in his paper. He looked into the performance of 34 different domestic mutual funds in the time period 1954 through 1963. The performance is described as the annual rate of return, implying the sum of capital gains distributions, dividend payments and changes in the net asset value (Sharpe, W. F. 1966). The theory of portfolio analysis is in essence normative; selecting portfolios of securities by means of predictions on the performance of individual securities. Expected return and potential risk are the main drivers of this paper.

As stated above, a new performance measure is introduced in this paper, namely the reward-to-variability measure, which is more commonly known as the Sharpe Ratio. This ratio looks into the performance of a fund, adjusted for riskiness. The author found that there was a small correlation between the reward-to-variability measure in the first period and the subsequent period. This indicates that the measure can predict the future performance of the fund to a certain extent. However, there are still differences between funds, and those differences are not completely temporary. Up to some point, they can be explained by the expense ratio. Nonetheless, past performance is still responsible for some of the differences. All in all, this paper was a very good starting point in the literature regarding mutual funds and the famous Sharpe Ratio is still widely being used as a performance measure of mutual funds.

2.1.2 Jensen's Alpha and Security Market Line

Jensen, M. C. (1968) published a paper which investigated mutual fund performance from 1945 to 1964. What those two papers have in common is the following: both of them laid the foundation for the current literature of mutual fund performance and are still being used nowadays. Jensen, M.C. (1968) elaborates on two different assumptions of the concept portfolio performance: the fund manager aims to get a positive return on the securities by successfully predicting the security prices and the fund manager minimizes the amount of risk through efficient diversification. Thus far it has been hard to evaluate these two assumptions because the measurement of 'risk' is still questionable. To try to understand the riskiness of securities in a better way, the performance of 115 mutual funds in the period 1945-1964 are being evaluated. The author substantiated that up till then most of the mutual fund performance was measured through relative performance instead of absolute performance. This led to the introduction of another performance measure, namely Jensen's Alpha. This measures the risk adjusted performance of a mutual fund in comparison to a passive benchmark portfolio.

Evidence showcased that the 115 mutual funds were on average not able to forecast stock prices in such a way that they outperformed a buy-and-hold strategy. Besides that, there is little evidence that an individual fund performed significantly better than expected. Just like Sharpe, W. F. (1966), Jensen, M.C. (1968) concluded that mutual funds are quite useful for the diversification of the assets of investors. The key takeaway in both studies is the relationship between risk and return and investing in perilous assets. This relationship is accurately illustrated by the Security Market Line (SML) in the famous Capital Asset Pricing Model (CAPM) (Fama, E. F., & French, K. R. 2004):

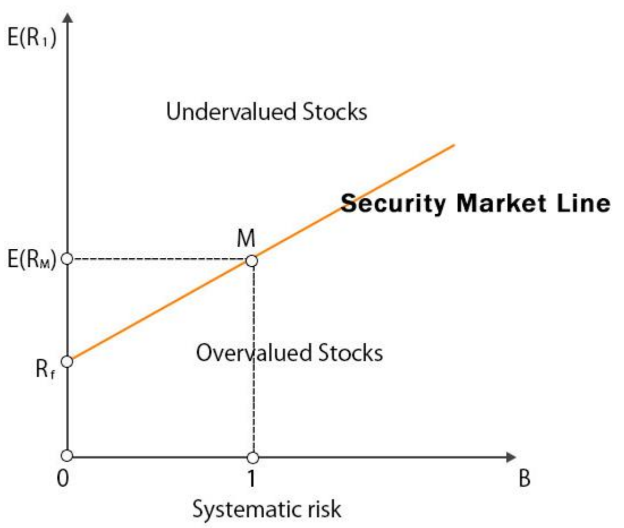

Figure 1: Security Market Line

the above figure denotes the graphical representation of the CAPM and provides the expected return an investor would achieve given different levels of systematic or market risk relative to the market. To get a better understanding, the following equation is constructed:

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

Equation 1: Security Market Line

where $E(R_i)$ is the expected return of the portfolio. This return is calculated by the risk-free rate (R_f) plus the systematic risk β_i times the expected market return $E(R_m)$ minus the risk free rate (R_f). $[E(R_m) - R_f)]$ is also known as the market risk premium. The CAPM functions as the theoretical foundation of performance evaluation of mutual funds. SML indicates whether the performance of not actively managed portfolios (read deviations) would indicate any over- or underperformance (Jensen, M.C. 1968). Those deviations have a relation with the performance measure introduced by Jensen, M.C. (1968), which is known as Jensen's alpha:

$$\alpha_j = R_i - [R_f + \beta_{iM}\left(R_m - R_f\right)]$$

Equation 2: Jensen's Alpha

where Jensen's alpha is calculated as follows: the realized return of the portfolio (R_i) minus the risk-free rate (R_f) plus the market beta of the portfolio (B_{iM}) times the market return (R_m) minus the risk-free rate (R_f). Alpha is the portion of the excess return that is not explained by the systematic risk (see Equation 1). Two constant values are very interesting to notice from the above equation. Namely the alpha 'α' and beta 'β', they represent respectively the absolute returns from the portfolio and the relative performance of the portfolio compared to the market. These outcomes might give some predictive power for changes in future stock prices.

2.1.3 Different Types of Share Classes

Within mutual fund investing, there exist several different share classes. The fees described in paragraph 2.1 are coherent with these share classes. To avoid overpaying on fees, one should consider carefully which class of mutual fund shares is the most suitable. There are three main types of classes: A, B and C. The big difference lies in the loads and fees. Class A shares charge upfront fees and have lower expense ratios. This is more suitable for the long-term investor. On the other hand, with class B shares one need to pay a fee after the shares are being sold. Class B shares have a higher expense ratio. This type of shares is suited for investors with little investment cash, while class A shares are more appropriate for investors with a lot of money to invest. Lastly, there are Class C shares, which are a type of level-load fund. Once again, these shares have a higher expense ratio then class A shares and a small exit fee. This is a popular choice for retail investors and investors with a short-term investment horizon.

2.2 Portfolio Selection and Market Timing Ability

Two aspects are very relevant when evaluating fund performance: selection of the portfolio and market timing. The general intention of a fund manager is to pick-out securities with a solid risk-reward ratio. Besides that, fund managers aim to predict future stock price movements by means of adjusting the risk and the selection of their stock portfolio. There has been written plenty of papers about this topic. Within this thesis, two papers are being outlined to elaborate on this subject.

Henriksson, R. D., & Merton, R. C. (1981) dived into the market timing aspect and the accompanying performance of the fund. They developed a model, where a forecaster tries to predict whether stocks will outperform bonds and the other way around. Parametric and nonparametric statistical procedures are being developed to test the forecasting skills. Interesting to notice is that the Efficient Market Hypothesis is being violated if significant evidence of forecasting skills is being found. The Efficient Market Hypothesis implies that all the available information about a stock is reflected in the share price (Timmermann, A., & Granger, C. W. 2004). So, when there is evidence of a superior forecasting skill, this hypothesis does not hold anymore. Within the forecasting skills there is a distinction between two components. Namely micro-forecasting and macro-forecasting. The first one forecasts price movements of individual stocks and the latter forecasts price movements of the stock market in general compared to fixed income securities (Fama, E. F. 1972). Eventually a method for testing market timing has been derived, which does not rely on any distributional assumptions regarding the returns on stocks. The forecaster's confidence levels can vary over time, and if this occurs, the test can be adjusted and executed again for every single variation. It is possible to distinguish separate returns from micro-and macro-forecasting without having any restrictions on the distribution of forecasts. The only aspects that are required are returns, the portfolio itself and riskless stocks (Henriksson, R. D., & Merton, R. C. 1981).

In addition, Treynor, J., & Mazuy, K. (1966) investigated whether mutual funds are able to outguess the market. It is a long-standing question whether fund managers are successful in anticipating and adjusting their portfolio for certain events in the stock market. The authors used the annual returns of 57 different mutual funds. There is a general consensus that common stocks tend to be more volatile than others. So, when investigating whether fund managers can outguess the market, the focus will be on fluctuations of the general stock market. The main question that was stated is the following question: “Is there evidence that the volatility of the fund was higher in years when the market did well than in years when the market did badly?” (Treynor, J., & Mazuy, K. 1966)

The authors plotted the returns of the funds against a so-called characteristic line, which represents for example the market average of the S&P 500. If this line turns out to be straight, then there is almost no scatter around the characteristic line. This shows that the fund is very well diversified. Results showed that all the funds tried to outguess the market, but none of them gave statistical evidence that fund managers were able to outguess the market. It can be assumed that all of the characteristic lines in this sample will be straight. To conclude, every investor is, in principle dependent on fluctuations on the general stock market.

2.3 Asset Fire Sales and Purchases

Coval, J., & Stafford, E. (2007) looked into asset fire sales and purchases. A simplified definition of asset fire sales is the following: assets that are being sold at an undervalued price because of financial distress. The focus of the paper is to create a setting in which asset fire sales are unlikely to happen and where there is a high form of transparency. A requirement is that retail investors need to follow a specialized investment strategy. This means that they need to have an overlap with other retail investors who follow the same strategy and that they have concentrated positions in securities with limited extent of ownership.

The next step is to identify deviations between fundamental values and transaction prices following a forced transaction. In order to do that, systematic patterns in abnormal returns over time need to be studied. Transactions are seen as forced, based on their capital flows as a percentage of their beginning monthly total net assets. Mutual fund flows are estimated by the monthly total net assets and the mutual fund returns. Next to that, the regression model from Fama, E. F., & MacBeth, J. D. (1973) is used to forecast fund flows based on past performance. Another important thing to notice is that in order to have a stock fire sale, there need to be many sellers relative to the potential buyers; only when many funds are forced to sell the same stock at the same time, significant price pressure can be observed.

Results show that asset fire sales by financially distressed mutual funds give transaction prices below their fundamental value. This result is not so striking, but the fact that mutual funds with large capital inflows are buying more securities which they already own is strange. Because this is a trait of constrained mutual fund which has large capital outflows. Important to notice is that Coval, J., & Stafford, E. (2007) concluded that abnormal returns ignore two important costs. Firstly, the cost of gaining information about an investment strategy and secondly, information acquisition costs associated with individual securities. To summarize, this paper is very useful to get a thorough understanding about asset fire sales and how to measure this with the use of abnormal returns and the monthly total net assets.

2.4 Runs on Money Market Mutual Funds

Schmidt, L., Timmermann, A., & Wermers, R. (2016) dived into runs on financial institutions during the week of the Lehman failure in September 2008. The paper is mainly focused on money market mutual funds (MMMF's) and ultra-short bond funds. Both of them had huge flows of money in September and October 2008. There is a distinction between sophisticated and unsophisticated investors, this is measured by two aspects: expense ratio and basis points per year. If the expense ratio is below the median and the bps per year is below 35, then we can appoint an investor as a sophisticated investor.

iMoneyNet is used for the data gathering, it covers more than 2000 U.S. MMMF's and their expense ratios. The expense ratio, which is given to every share, is an estimation for the level of sophistication. The consensus is that, the lower the expense ratio, the higher the amount of money invested. Results showed that sophisticated investors redeemed a lot more of their shares during the crisis week. And that those investors had a stronger incentive to invest in information about potential gaps between market and book values.

In principle, ultra-short bond funds and MMMF shares are hard to compare, because ultra-short bond funds have a client base which consists mostly of retail investors. The results showcased that both of the asset classes have the same direction of flows, although the ultra-short bond funds had half of the magnitude compared to MMMF share classes during the crisis week. Schmidt, L., Timmermann, A., & Wermers, R. (2016) argued that strategic complementarities are very important when it comes to the actions of investors during the financial crisis of 2008. Furthermore, is was hard to find out which funds are the most sensitive to runs. Large investors have an advantage because they possess more information about the fund and about the characteristics of other investors in a particular fund.

2.5 Assessing Fund Managers Skills with Factors and Industry Aspects of Mutual Funds

The next paper has been written by Barber, B. M., Huang, X., & Odean, T. (2016). They investigated whether investors use widely used factors and industry aspects of mutual funds when they asses fund managers skills. Investors will not ignore risk factors, unless the costs outweigh the benefits. Barber, B. M., Huang, X., & Odean, T. (2016) estimated mutual fund alphas by using six different empirical models of skill. They wanted to predict which measure predicts the flows most accurately, by competing the measures against each other and divide mutual fund returns in factor-related returns and the alpha. To give more insight about these returns; the returns are divided into eight components: alpha, market beta, size, momentum, value and three industry components.

Sophisticated investors are less likely to reward fund managers for positive returns in comparison to unsophisticated investors. To determine if an investor is sophisticated or not, three proxies are being used: the sample is divided into direct sold stock and stock sold through a broker, periods of extreme inflows in combination with high investor sentiment and wealth is used as a measure for investor sophistication. Mutual fund flows for a specific fund are calculated in the same way as is in most of the existing literature:

$$F_{pt} = \frac{TNA_{pt}}{TNA_{p,t-1}} - (1 + R_{pt})$$

Equation 3: Calculation of a fund flow for a specific fund

where TNA_{pt} is the total net assets under management of a certain fund p at the end of month *t*. R_{pt} is the total return of fund p in month *t*. The authors want to make a model where they rank the different empirical models to see which model explains the choice of capital allocation of investors in the best possible way. It turned out that the partial effect of CAPM is almost twice as large as the other empirical models. Actually, CAPM is in every scenario the best predictor of fund flows. Furthermore, market risk is the most prominent factor that investors keep in mind when evaluating fund performance. They tend to give less attention to value, size and industry factors. In the most extreme scenario, sophisticated investors will pay attention to every single factor and unsophisticated investors will only consider market-adjusted returns to assess a fund’s performance. However, in the real world, investors are merely interested about market risk and are quite ignorant about other relevant factors. In brief, investors who comply with the three proxies for investors sophistication, give less attention to returns associated with factors and are more aware of returns which do not correlate with the skills of a fund manager.

2.6 Effect of Capital Commitment on Investment Horizon and Fund Performance

Gómez, J. P., Prado, M. P., & Zambrana, R. (2020) wrote a paper about capital commitment and the subsequent investment decisions fund managers make. The main objective of the paper was to find out whether information about load fees affects the investment horizon of managers, their portfolio composition and subsequently the fund performance. The authors expected on beforehand that higher capital commitment goes along with more stable fund flows and that these flows are less sensitive to fund performance and are better to predict. Besides that, Chordia, T. (1996) showcased that if a fund has higher capital commitment, that they hold more cash a buffer in comparison to similar funds with a lower percentage of load shares. Load shares are shares with a front or back-end load, which means that you need to pay a commission or sales charge when you buy or sell the investment (O'Neal, E. S. 1999). Locked-up capital, also called capital commitment, is the percentage of the total net assets that is invested through funds with front or back-end loads (Gómez, J. P., Prado, M. P., & Zambrana, R. 2020).

The authors gathered information about the funds and their management from the CRSP database and the fund level redemption fees were derived from the Morningstar database. Funds with front and back-end loads are used to calculate the fraction of assets under management with capital commitments. Nanda, V. K., Wang, Z. J., & Zheng, L. (2009) advocated that investors with a longer horizon are more likely to opt share class A or B, which has lower annual fees and charges and have a front and or back-end load. Whereas investors with shorter investment horizons rather prefer share class C. In order to find out how long an investment is being held upon, the authors implemented the Simple Horizon Measure, which implies the length of time from the initiation of a position to the time that the stock is fully liquidated by the fund.

The authors discovered that the higher the locked-up capital flows were, the more investments in illiquid assets were made and that their cash holdings were lower. Next to that, Gómez, J. P., Prado, M. P., & Zambrana, R. (2020) concluded that if there is a shock to locked-up capital flows, it is mainly affecting the funds liquidity management. This ensures that fund managers prefer to invest in arbitrage capital that is slow-moving (Duffie, D. 2010). The results showed that a lack of explicit capital commitment leads to an effect on the trading horizon of investors, the fund performance and the portfolio selection as well. The expectations of the authors turned out be correct, since the mutual fund managers who have more capital commitment are experiencing a longer investment horizon, they have less cash holdings and have more illiquid assets in their portfolio.

3. Methodology & Data

Chapter 3 describes the methodology and elaborates on how the needed data is obtained. Paragraph 3.1 starts off with describing the hypotheses, which are useful and relevant for giving a thorough answer to the research question. Paragraph 3.2 discusses the methodology and the economic intuition behind it. Lastly, paragraph 3.3 is dedicated to the step-by-step approach on how the data is narrowed down and which databases are used.

3.1 Hypotheses

To build a better foundation around the research question, three hypotheses are being established. For a further elaboration about economic intuition and the corresponding methodology, see paragraph 3.3. The first one is about equity mutual fund returns. Fund returns tend to be the least sensitive to market risk. Is this due to the lack of knowledge of investors or is this just how the market operates? To find out how equity mutual funds flows behave, one first has to know how fund returns respond in general. So, it is rational to start with the following hypothesis:

Hypothesis 1: How do fund excess monthly returns respond to different risk factors?

Secondly, it might be interesting to look into the prediction of returns. Equity mutual funds should not be able to outperform the market according to the Efficient Market Hypothesis (Timmermann, A., & Granger, C. W. 2004). In reality, this is an unrealistic assumption. Therefore, it is interesting to dive into the matter to what extent mutual funds have a security selection skill and a market timing ability:

Hypothesis 2: To what extent are U.S. equity mutual funds able to time the market and possess a security selection skill?

Monthly mutual fund flows are a great indicator of mutual fund performance since it captures the change in total net assets and the total return of the fund in a certain month (Barber, B. M., Huang, X., & Odean, T. 2016). Liquidity is inextricably linked to the performance of a mutual fund, because liquidity is estimated by using the returns and the daily volume of a fund. The tendency is that less liquid stocks have higher returns on an average basis and therefore perform better. To investigate whether this is the case within this thesis, the following hypothesis has been established:

Hypothesis 3: What is the influence of liquidity on the mutual fund flows and therewith the mutual fund performance?

3.2 Methodology

The methodology part is divided into three parts. In that way it is very clear how each hypothesis is going to be answered and which regression belongs to which hypothesis. As the research question reveals, the focus of this thesis will be on the fund performance of U.S. equity mutual funds. Empirical analyses will form the foundation of this thesis. Besides that, a theoretical framework will be constructed to explain the research question and the accompanying hypotheses. The econometric software which will be used are Excel and STATA. It starts with making a dataset in Excel and exporting it afterwards to STATA. Excel works perfectly fine in the beginning stages. However, for making regressions, cross-correlations and many other statistical analyses, STATA is much more adequate.

3.2.1 Mutual Funds Returns

An important first step is to start with calculating the excess monthly fund returns. These are calculated by using the Center for Research in Security Prices series of monthly fund returns and subtracting the one-month Treasury bill rate. Return and risk form the basis of performance evaluation from an investors' perspective. Therefore, returns on itself are not sufficient enough to measure fund performance, because they are not risk-adjusted. This leads to the addition of the three risk factors from Fama and French which will serve as performance benchmarks.

The factors that will be used are the excess return on the market, small minus big and high minus low. Which are more commonly known as respectively the RMFR, SMB and HML factor. They will be added one by one to see the contribution of each factor on the excess monthly fund returns (for a further elaboration on the three-factor model from Fama and French, see paragraph 3.3.1). Abnormal returns of equity mutual funds are calculated per month. To give equal weight to each observation, time-series of the mean abnormal returns for statistical inference are used to control for cross-sectional dependence for the abnormal returns. The time period for these factors will be the same as for the returns, which means January 2000 up to and including 2015. Carhart, M. M. (1997) employed two different models of performance measure in his paper, the CAPM model and the Carhart 4-factor model which embroiders on the Fama and French 3-factor model. This thesis focusses on whether performance can be explained by common factors of stock returns, therefore the above three factors are being utilized. All taken together, this leads to the following regression:

$$R_{it} = \alpha_i + r_i RMRF_t + s_i SMB_t + h_i HML_t + \varepsilon_{pt}$$

Equation 4: Breakdown of the fund flow return into different components

where α_i are the excess monthly fund returns and thus the intercept and R_{it} is the abnormal monthly return of mutual funds in excess of the one-month T-bill return (i.e. the risk-free rate), RMRF if the excess return on the market, SMB means Small Minus Big and HML is the average return of two value portfolios and two growth portfolios and ε_{pt} is the error term of the regression.

3.2.2 Market Timing and Prediction Skills

As discussed in paragraph 2.2 mutual funds should be unable to outperform the market according to the Efficient Market Hypothesis (Timmermann, A., & Granger, C. W. 2004). However, it is unrealistic to think that at any point in time all the available information is reflected in the stock prices. Therefore, it is interesting to dive into the matter whether equity mutual funds have the skills to predict their own flows and 'time' the market.

Treynor, J., & Mazuy, K. (1966) are called the founders of the market timing ability among mutual funds. Their regression model using ex post returns of mutual funds and their benchmarks is still widely being used nowadays. Important to notice is that Treynor, J., & Mazuy, K. (1966) made use of annual mutual fund data, whereas monthly data is being used in this thesis. Their approach is that in a bull market, fund managers would keep less cash and in a bear market they would increase their cash holdings. This is in a state where fund managers are able to time the market somehow. A big advantage of Treynor and Mazuy's model is the fact that it is convenient to use and the significance of the outcome. The aforementioned CAPM forms the basis of the model and the foundation of measuring performance of mutual funds in general. To test the market timing ability and prediction skills, the model from Treynor and Mazuy and the Fama and French three factor model have been merged to create the following regression:

$$R_i - R_f = \alpha + r_i RMRF + s_i SMB_t + h_i HML_t + r_i RMRF^2 + \varepsilon_{pt}$$

Equation 5: Extension of Treynor's model for market timing ability where (R_i) is the realized return of the portfolio and (R_f) is the risk-free rate. The alpha represents the selection ability of fund managers and is the dependent variable in this regression. When alpha is positive, fund managers have a superior stock picking ability, and the other way around when the coefficient is negative. The variance of the market risk premium can be seen as an indicator for market timing. If $RMRF_2$ is positive, the fund managers can be seen as successful in predicting changes in the market environment. When this coefficient is negative, the fund managers do not possess a market timing ability.

Next to this regression, a quantile regression will be executed as a robustness check. A quantile regression is an extension a normal linear regression and estimates the conditional median instead of a conditional mean. There will be four quantiles, meaning that for example for the 25_{th} quantile, there is a chance of 25% that the outcome is below the prediction and 75% that the outcome is above the prediction.

3.2.3 Liquidity and Mutual Fund Performance

Mutual funds have to deal with a constant trade-off between keeping cash or investing it in assets. Liquid assets generate on average lower returns, but it is less costly to liquidate. On the other hand, illiquid assets provide a premium but are more costly to liquidate (Amihud, Y. 2002). Funds with a higher percentage of locked-up capital tend to increase their cash holdings and therewith also their liquidity of the assets. Liquidity has many dimensions as it can be measured in many ways. The first measure that will be used is the monthly aggregate liquidity measure, which captures the cross-sectional average of individual stock liquidity measures (Pástor, Ľ., & Stambaugh, R. F. 2003). The aggregate liquidity coefficient is constructed by the daily returns and volume data within a certain month. Besides this, two other liquidity measures are used as a robustness check, see paragraph 4.4 for an elaboration on this. On balance, this leads to the next regression:

$$R_i - R_f = \alpha + \beta_1 ExcessReturn + r_i RMRF + s_i SMB_t + h_i HML_t + A_i AggLIQ + \varepsilon_{pt}$$

Equation 6: Mutual Fund Flows and the effect of liquidity

where α represents the dependent variable, which measures the fund performance; namely the mutual fund flows, β_1 stands for the excess monthly fund returns, after that the three Fama and French factors are included and AggLIQ stands for the aggregate liquidity factor from Pástor, Ľ., & Stambaugh, R. F. (2003). Lastly, ε_{pt} is the error term of the regression.

3.3 Data Sources

The main database will be the Center for Research in Security Prices (CRSP), which is accessible through WRDS and not unimportantly, accessible from home, which is needed during these strange times where we can't go to the university and do not have access to all the databases. CRSP is needed to gather data about the monthly total net assets and returns of the mutual funds. Data about total net assets and returns is available from 1962 onwards. Since the timeframe is from the first of January 2000 up to and including 31 December 2015, this should be perfectly fine. Because the focus in this thesis lies on the U.S. mutual funds, CRSP is very useful as well, since CRSP is specialized in U.S. companies and businesses. Important to notice is that the database is updated quarterly and is distributed with a monthly lag. The Kenneth French Data Library is being utilized for the latest information about industry portfolios and the Fama and French Research Factors. Lastly, the liquidity factors proposed by Pástor, Ľ., & Stambaugh, R. F. (2003) are obtained from the website of the University of Chicago Booth School of Business.

3.3.1 Data Selection and Specification

Malkiel, B. G. (1995) showed that estimations of performance of mutual funds are upward biased when there is a survivorship bias. A survivorship bias occurs when one has a dataset which consists only of winners and not of losers. Meaning that only 'surviving' funds are included, while funds that have been dropped, merged or discarded are not included (Rohleder, M., Scholz, H., & Wilkens, M. 2011). However, CRSP provides a survivorship bias free database, which is therefore suitable for this thesis. Nevertheless, a selection bias can still occur when favoring historical data files of the best past performing private funds that became public. This leads to the situation where only successful private fund histories are included. In order to counteract this, the SEC started to permit funds with prior returns histories from private funds to add these to the start of their public return histories.

Furthermore, equity mutual funds that are based in the U.S. but trade exclusively in foreign stock markets are excluded from the dataset. Equity mutual funds are funds who have at least 50% of their portfolio invested in equity during the sample period (Chen, Q., Goldstein, I., & Jiang, W. 2010). Within a share class, there are multiple combinations of transaction fees, front-end loads and requirements. This leads to different incentives and actions of investors. To account for that, the analysis of fund flows will be conducted at a fund-share level.

As stated before, the timeframe of the dataset will be from January 2000 up to and including December 2015. Furthermore, there are two important factors that define this dataset. These are the Lipper assets codes and the monthly total net assets. Mutual funds will be selected on the basis of the Lipper assets codes. The Lipper asset codes are determined by the language that a fund uses in their prospectus to describe how it intends to invest. In this thesis funds with the Lipper asset code 'EQ' will be used, EQ stands for equity fund. Regarding the total monthly net assets, only mutual funds with total net assets at the end of the month over 5 billion dollars were included in the dataset. Before performing any statistical analyses, all the variables were winsorized at the 1st and 99th percentile to deal with any potential outliers. Lastly, all the missing variables were removed to prevent biased results. All in all, this leads to the following sample of mutual funds:

Variable	**Output**	**Notes**
Country	U.S.	United States
Timeframe	2000-2015	January 2000 - December 2015
Lipper Asset Code	EQ	Equity Funds
Number of Funds	725	
Average TNA	14223,27	Reported in U.S. millions
Average NAV	40,26	Reported in U.S. millions
Average Turnover Ratio	0,37	37%
Average Expense Ratio	0,006	0,6%
Average Return per Share	0,006	0,6%

Table 1: Descriptive Statistics of the Mutual Fund Sample

The 725 equity mutual funds have on average total net assets of $14,23 billion. This average is so high because only funds with at least 5 billion dollars of total net assets are included in the dataset. Furthermore, the average Net Asset Value lies around 40 million dollars and the and the turnover ratio at 37%. The expense ratio can be seen as quite low with 0,6% Lastly, the return per share is also 0,6% on average. Before the results will be described, some summary statistics on the factor portfolios of Fama, E. F., & French, K. R. (1993) will be provided.

					Cross - Correlations			
Factors	*Mean*	*Std.Dev*	*Min*	*Max*	*RMRF*	*SMB*	*HML*	*RMRF2*
RMRF	0,004247	0,044627	-0,1723	0,1135	1,0000			
SMB	0,002548	0,312753	-0,1687	0,2170	0,2669	1,0000		
HML	0,002188	0,030397	-0,1118	0,1287	0,0142	-0,2178	1,0000	
RMRF2	0,002009	0,003292	0,0000	0,0296	-0,2319	-0,0547	-0,0039	1,0000

Table 2: Descriptive Statistics of Fama and French 3-Factor Model in the time period 2000-2015,

The output shown in Table 2 needs some extra background information. The Fama and French risk factors are briefly discussed in paragraph 3.2.1, but this paragraph will provide some more clarification. The factors are based on 6 value-weighted portfolios formed on size and book-to-market. RMRF stands for the excess return on the market. It is the value-weighted return of all the U.S. based mutual funds minus the one-month Treasury bill rate, commonly known as the risk-free rate. SMB stands for Small Minus Big and is the average of three small portfolios minus the average return of three big portfolios. HML is the average return on two value portfolios minus the average return on two growth portfolios. Lastly, the RMRF2 is the variance of the excess market return and is an indication whether fund managers are successful in predicting market changes. A lot of the existing literature also used the one-year momentum as a risk factor. Carhart, M. M. (1997) showed with his analysis that the one-year momentum returns are not that high because fund managers tend to follow successful momentum strategies, but rather due to the fact that funds hold on by chance larger positions in stocks which rose a lot the year before. Therefore, this thesis uses the three factors from Fama and French and omits the one-year momentum factor. The results of Table 2 reveal that there is a high variance and a quite low correlation between most of the factors. This implies that multicollinearity does not substantially affect the estimations of the three factors and that these factors can explain sizeable time-series variation.

Before calculating the abnormal returns, two datasets were merged. Namely the dataset with the Fama and French factors and the dataset with the monthly returns from every single mutual fund. Every month has a specific Fama and French factor and a specific return and those were manually combined for fifteen years of returns of 725 funds.

4. Results

Chapter 4 describes the obtained results. The results are divided by means of the three hypotheses. Paragraph 4.1 discusses the results on mutual fund returns and their relationship with the three factors from Fama and French. Secondly, paragraph 4.2 describes if and how mutual funds are being able to time the market. Paragraph 4.3 rounds off with the results of the liquidity measures and their impact on the mutual fund flows and subsequently the mutual fund performance.

4.1 Results on Mutual Fund Returns

As documented in paragraph 3.2.1, excess monthly fund returns will be regressed on the three factors of Fama and French to obtain the abnormal returns. The excess monthly returns are calculated by subtracting the one-month T-bill returns from the monthly fund returns which are obtained from the CRSP database. Firstly, a cross-correlation between the excess monthly fund returns and the three factors from Fama and French will be executed to determine whether there is a relationship between two or more time series. The results are being displayed in the below Table 3:

Cross-Correlation	*Excess Monthly Returns*	*RMRF*	*SMB*	*HML*
Excess Monthly Returns	1,0000			
RMRF	0,6815***	1,0000		
	(0,0000)			
SMB	0,1990***	0,2669***	1,000	
	(0,0000)	(0,0000)		
HML	0,0353***	0,0142***	-0,2178***	1,0000
	(0,0000)	(0,0000)	(0,0000)	

*Table 3: Cross correlation between excess monthly fund returns and three factors from Fama and French, where the Pearson P-values are reported in parentheses and *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively*

Looking at the results in Table 3, six out of the six correlations are statistically significant at a significance level of 1%. The first thing that can be observed is that the excess return on the market (RMRF) has a strong positive and significant effect on the Excess Returns, it has a coefficient of 0,6815 with a Pearson P-value of lower than 0,0001. Both of the coefficients of SMB are positive; the correlation between SMB and RMRF is positive with 0,2669 and a Pearson P-value of below 0,0001. This means that the higher the SMB, the higher the excess return on the market, which implies that the average return on small portfolios is higher than the average return on big portfolios. Moreover, two of three coefficients of the High Minus Low (HML) factor are slightly positive and one of them is negative and significant at 1% with a coefficient of -0,2187. All in all, when considering all the coefficients, it can be concluded that the results won't be biased when it comes to the correlation between excess monthly returns of the mutual funds and the three factors from Fama and French. Furthermore, there appears to be no multicollinearity since the coefficients are not extremely high (read close to 1 or -1) and the VIF factor test does not exceed 10 (Chatterjee, S., & Price, B. 1991). The outcome of the VIF factor test can be found in Appendix II.

To examine the relationship between the excess monthly fund returns and abnormal returns, a regression will be executed where the three factors will be added one at a time to the dependent variable, namely the excess monthly fund returns. In Model I, the excess monthly fund returns are regressed on the RMRF factor, in Model II the SMB factor is added and Model III includes all the three risk factors. Important to notice is that the time-series average of cross-correlations and the accompanying time-series T-test statistics are reported in parentheses. The outcome of these regressions is being displayed in the below Table 4:

Variable	*Model I*	*Model II*	*Model III*
Alpha (Dependent	0,0009675***	0,0009054***	0,0007536***
Variable)	(7,44)	(6,95)	(5,77)
RMRF	0,9026961***	0,8960444***	0,8928158***
	(310,73)	(297,39)	(295,68)
SMB		0,0355789***	0,0495921***
		(8,29)	(11,25)
HML			0,0604705***
			(13,81)
Adjusted R_2	0,4644	0,4648	0,4657
Observations	111.343	111.343	111.343
Number of Funds	725	725	725

*Table 4: Fund-level cross-sectional regressions between excess monthly fund returns and three factors from Fama and French in the time period 2000-2015, where the T-values are reported in parentheses and *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively*

Table 4 presents the results of regressing the excess monthly fund returns (alpha) on the three factors of Fama and French. In Model I, the excess monthly fund returns are regressed on the RMRF factor. The estimated coefficient of RMRF is positive with a coefficient of 0,903 and statistically extremely significant as well with a T-value of 310,73. This result indicates that the excess return on the market moves in het same direction as the excess monthly fund returns. Implying the following: when the RMRF rises with 1%, the dependent variable (excess monthly fund returns) increases with 0,90%. Furthermore, Model I explains 46,44% of the variation in excess monthly fund returns. Regarding the size of the dataset, this can be seen as quite high. Results show that the alpha is consistently slightly positive and significant at 1% in all the three models. When considering how the excess monthly fund returns are being calculated, namely the monthly fund returns minus the the one-month T-bill return (risk-free rate), this result is explicable. Because when evaluating the risk-free rate factor from the Kenneth French Data Library, there can be observed that the average over the whole data sample is relatively low with 0,0012409. Concluding, the primary outcome of this table is the positive and significant relationship between the three factors and the excess monthly fund returns and the positive influence of the RMRF factor on the returns.

4.2 Results on Market Timing and Prediction Skills

The approach for this hypothesis has some of the same characteristics as hypothesis 1. This time the variation of the excess return on the market is included to find out whether fund managers are successful in predicting changes in the market. The alpha in this regression is the dependent variable and represents the monthly fund returns and the SMB and HML factors from Fama and French are included as well. Furthermore, the interpretation of the coefficients is different from hypothesis 1, there will be an elaboration on this in the interpretation part below. This approach aims to determine the ability of market timing for mutual funds and their security selection skills as well. Model I regresses the monthly fund returns on the excess return on the market and the variation of the excess return on the market. Model II adds the SMB factor and in Model III are all the factors from Fama and French included. The output of this regression is displayed in Table 5:

Variable	*Model I*	*Model II*	*Model III*
Alpha (Dependent Variable and Indicator for Selection Ability)	0,0028769*** (18,54)	0,0028187*** (18,15)	0,0026409*** (16,98)
$RMRF_2$ (Market Timing Ability)	-0,3118996*** (-7,96)	-0,3144832*** (-7,75)	-0,3142394*** (-7,76)
RMRF	0,8924102*** (298,34)	0,8855568*** (285,86)	0,8817888*** (284,16)
SMB		0,0364236*** (8,47)	0,0527958*** (11,96)
HML			0,0706511*** (16,11)
Adjusted R_2	0,4608	0,4611	0,4624
Observations	111.343	111.343	111.343
Number of Funds	725	725	725

*Table 5: Fund-level cross-sectional regressions to test for market timing and selection ability for the time period 2000-2015, where the T-values are reported in parentheses and *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively*

Table 5 provides the results of regressing the monthly fund returns on the Fama and French factors plus the variance of the RMRF factor to test for market timing ability and security selection. In line with previous work from Kacperczyk, M., Nieuwerburgh, S. V., & Veldkamp, L. (2014). and Daniel, K., Grinblatt, M., Titman, S., & Wermers, R. (1997) there can be observed that mutual funds have a security selection ability since the alpha is positive in all the models. Admittedly the coefficient is lightly positive, but it is still positive and significant at 1% as well.

Another important coefficient to describe is the $RMRF_2$ coefficient, which shows whether mutual fund managers are successful in predicting market changes. The coefficient is negative in all the models, implying that managers cannot be seen as successful when it comes to their market timing skills. This concurs with the conclusion of Treynor, J., & Mazuy, K. (1966) where they concluded that there is statistical evidence for the fact that mutual fund managers cannot outguess the market. The adjusted R_2 can be seen as high since it explains 46% on average of the variation in returns. Unfortunately, the SMB and HML do not have a great influence on the outcome of the model since their coefficients are very small and the coefficient of the dependent variable barely changes when they were added to the model.

However, what is interesting to see is that the explanatory power of the SMB coefficient almost doubles when the HML factor is added to the model. To conclude, in this regression, mutual fund managers have a security selection ability but are definitely not able to time the market.

4.3 Results of Liquidity on Mutual Fund Performance

As described in paragraph 3.2.3, the mutual fund flows will be regressed on the excess monthly returns, the three risk factors from Fama and French and the aggregate liquidity factor from Pástor, Ľ., & Stambaugh, R. F. (2003). Before looking at the results of this regression, a cross-correlation between the dependent and the independent variables will be performed. The focus will mainly lie on the relationship between the aggregate liquidity factor and the returns and flows from the mutual funds. The outcome of this correlation is represented in Table 6:

Cross-Correlation	*Mutual Fund Flows*	*Excess Monthly Returns.*	*RMRF*	*SMB*	*HML*	*Agg. Liquidity*
Mutual Fund Flows	1,0000					
Excess Monthly Ret.	0,0022 (0,4734)	1,0000				
RMRF	0,0263*** (0,0000)	0,6815*** (0,0000)	1,0000			
SMB	0,0025*** (0,4098)	0,1990*** (0,0000)	0,2669*** (0,000)	1,0000		
HML	0,0186*** (0,0000)	0,0353*** (0,000)	0,0142*** (0,0000)	-0,2178*** (0,0000)	1,0000	
Agg. Liquidity	0,0042 (0,1630)	0,1567*** (0,000)	0,2308*** (0,0000)	0,0168*** (0,0000)	0,0205*** (0,0000)	1,0000

*Table 6: Cross correlation between mutual funds flows, excess monthly fund returns, the three factors from Fama and French and the aggregate liquidity factor from Pástor and Stambaugh , where the Pearson P-values are reported in parentheses and *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively*

Interpreting the results in Table 6, the first thing that comes to mind is the small and not significant relationship between the mutual fund flows and excess monthly returns. Implying that the relationship between those two variables is almost neglectable and weak with a coefficient of 0,0022 and a Pearson P-value of 0,4734. Observing the other correlations with the mutual fund flows, two out of the five correlations are insignificant and weak. Most of the Fama and French factors have a positive and significant relationship with each other, which is consistent with the results of Carhart, M. M. (1997) and the cross-correlation in Table 3. Lastly, the aggregate liquidity measure has a positive and significant correlation with all the variables except for the mutual fund flows variable. Considering that mutual fund flows have a weak correlation with two out of the five the variables, this is more related to the weak explanatory power of the mutual fund flows than to the explanatory power of the aggregate liquidity variable. To conclude, there appears to be no multicollinearity within these variables, since the VIF factor does not exceed 10. See Appendix VI for the outcome of this test.

To examine the impact of liquidity on the mutual fund flows and hence the mutual fund performance, an Ordinary Least Squares regression will be executed with the mutual fund flows as the dependent variable. Model I regresses the fund flows and on the aggregate liquidity variable from Pástor, Ľ., & Stambaugh, R. F. (2003). Model II adds the excess monthly fund returns. Model III up to and including Model V, adds respectively the RMRF, SMB and HML factor. The outcome of these regressions is shown in Table 7:

Variable	*Model I*	*Model II*	*Model III*	*Model IV*	*Model V*
Fund Flows	0,0077***	0,0077***	0,00722***	0,0072***	0,0071***
(Dependent)	(21,89)	(21,62)	(20,14)	(20,18)	(19,67)
Aggregate	0,0068	0,0064	-0,0031	-0,0035	-0,0037
Liquidity	(1,40)	(1,30)	(-0,63)	(-0,69)	(-0,73)
Excess Monthly		0,0028	-0,0539***	-0,0536***	-0,0555***
Ret.		(0,51)	(-7,13)	(-7,10)	(-7,34)
RMRF			0,1140***	0,1169***	0,1147***
			(11,20)	(11,27)	(11,06)
SMB				-0,1576	-0,0005
				(-1,43)	(-0,05)
HML					0,0678***
					(6,07)

*Table 7: Fund-level cross-sectional regressions to test the influence of liquidity and the three factors from Fama and French on the mutual fund flows timing for the time period 2000-2015, where the T-values are reported in parentheses and *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively*

The outcome of Table 7 is interesting. Firstly, the fact that all the five coefficients of aggregate liquidity are not significant is quite strange, since almost all the other variables are significant at a 1% level. Furthermore, the explanatory power of the aggregate liquidity measure can be called weak, the coefficient is very small and insignificant as well in every model. Therefore, it is hard to draw to any conclusions regarding the influence of the aggregate liquidity measure on the performance of mutual funds.

The dependent variable changes barely after the addition of other variables, indicating that these variables do not have a serious impact on the mutual fund flows. As one can see in Table 8, most of the coefficients are very small, except the RMRF coefficient.

Looking at the whole table, there can be observed that only the mutual fund flows, RMRF and HML coefficients are significant at 10% or higher. This indicates that the addition of the aggregate liquidity variable leads to a decrease of the explanatory power of the other variables when comparing this to Table 4 and 5. To conclude, the aggregate liquidity variable has not a serious and significant impact on the mutual fund flows and consequently the mutual fund performance since the coefficients are small and not significant.

4.4 Robustness Checks

It is very hard to come up with the 'perfect model' in the econometric field. Feldstein, M. (1982) made a striking quote in one of his papers: *"In practice all econometric specifications are necessarily false models".* One tries as hard as they can to make the most flawless models, but in practice it is really difficult to execute a 'perfect model'. Rather than trying to specify models correctly, we should test if the result obtained by our baseline model hold when the specifications of the baseline model are being adjusted. Paragraph 4.4.1 does this for market timing and security selection skills and paragraph 4.4.2 focusses on liquidity and performance of mutual funds.

4.4.1 Robustness Check on Market Timing and Security Selection Skills

As a first robustness check, multiple quantile regressions for Model III from paragraph 4.2 will be performed to investigate whether there is a distinction in market timing ability and selection ability between the lower and higher deciles of the monthly fund returns. There are three quantile regressions executed, where the sorting variable is the dependent variable (read monthly fund returns) and this variable is divided into different quantiles, namely the 25th, 50th and 75th percentile. Meaning that the 25th percentile contains the lowest monthly fund returns and the 75th percentile has the highest monthly fund returns. Besides that, is the influence of the three factors from Fama and French bigger when the monthly fund returns are higher or when they are lower? The outcome of these quantile regressions is presented in Table 6:

Percentile	*Alpha (Dependent Variable and Indicator for Selection Ability)*	*RMRF*	*SMB*	*HML*	*RMRF2 (Market Timing Ability)*
OLS	0,0026409***	0,8817888***	0,052795***	0,0706511***	-0,031423***
Model III	(16,98)	(284,18)	(11,96)	(16,11)	(-7,76)
25th	-0,0074***	0,9093***	-0,0113***	0,0266***	-1,4416***
	(-83,41)	(347,15)	(-3,00)	(7,32)	(-32,30)
Median	0,0015***	0,9181***	-0,0141***	0,0484***	-0,1956***
	(25,16)	(377,32)	(-4,92)	(20,25)	(-5,82)
75th	0,0109***	0,8509***	0,0513***	0,0984***	1,243***
	(105,01)	(283,05)	(12,19)	(-20,27)	(24,37)

*Table 8: Fund-level cross-sectional quantile regressions at the 25th, 50th and 75th percentile to test for market timing and selection ability for the time period 2000-2015, where the T-values are reported in parentheses and *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively*

Observing the results in Table 8 and comparing them with the results of the OLS regression, there are a few interesting outcomes. Firstly, the alpha, which indicates the selection ability skill of mutual fund managers, is positive in every model in the OLS regression. Whereas it is negative in the lower percentile of the quantile regression in Table 8. This indicates that mutual fund managers have a certain security selection skill from the median percentile and above. Just as in Table 5, all the coefficients of the alpha are significant at a 1% level.

Noteworthy is the decrease of the RMRF coefficient. This coefficient lies around 0,87 in the OLS regression and is 0,85 in the highest percentile. Indicating that the influence of the RMRF factor decreases in the highest percentile. Comparing the RMRF2 coefficients between the percentiles, there is a notable difference within the coefficients. This time, the coefficient is very negative and significant for the lowest percentile. Whereas it is positive and significant in the lowest percentile. This indicates that fund managers do possess a market timing ability skill when the mutual fund returns are higher. The influence of the Fama and French factors is almost the same as in the OLS regression. The coefficients increase gradually as the percentile increases.

4.4.2 Robustness Check on Liquidity and Performance

As can be seen in three out of the five models in Table 7, the aggregate liquidity has a slight negative, albeit no significant influence on the mutual fund flows and subsequently the mutual fund performance. As a robustness check, two other liquidity measures from Pástor, Ľ., & Stambaugh, R. F. (2003) are being added to see in what manner the baseline model in Table 7 changes. The first one is the innovative liquidity measure, which captures the innovations in the aggregate liquidity measure. For example, changes in growth and size of the stock market. Where the innovative liquidity measure focusses on the non-traded liquidity part, the traded liquidity measure is completely opposite and focusses on changes in portfolio returns which are divided into ten deciles. All in all, this leads to the following regression:

$$R_i - R_f = \alpha + \beta_1 ExcessReturn + r_i RMRF + \ s_i SMB_t + \ h_i HML_t + A_i AggLIQ \\ + I_i InnLIQ + T_i TrdLIQ + \varepsilon_{pt}$$

Equation 7: Robustness check of Mutual Fund Flows and the effect of multiple liquidity measures

where are the variables are the same as in Equation 6, the only difference is the addition of the variables InnLIQ and TrdLIQ; which have been introduced by Pástor, Ľ., & Stambaugh, R. F. (2003). These variables stand respectively for the innovative liquidity and the traded liquidity measure. The first column is the same regression as Model V in Table 7. Model II adds the innovative liquidity measure and Model III the traded liquidity measure. The results of these regressions are displayed in Table 9:

Variable	OLS Model V	Model II	Model III
Fund Flows (Dependent	0,0071***	0,0061***	0,0058***
Variable)	(19,67)	(15,87)	(15,00)
Aggregate Liquidity	-0,0037	-0,0401***	-0,0419***
	(-0,73)	(-5,77)	(-6,02)
Excess Monthly Ret.	-0,0555***	-0,0561***	-0,0586***
	(-7,34)	(-7,41)	(-7,73)
RMRF	0,1147***	0,1041***	0,1046***
	(11,06)	(9,94)	(9,99)
SMB	-0,0005	0,0026	-0,0048
	(-0,05)	(0,23)	(-0,42)
HML	0,0678***	0,0745***	0,0797***
	(6,07)	(6,66)	(7,10)
Innovative Liquidity		0,0061***	0,0568***
		(7,55)	(6,99)
Traded Liquidity			0,0518***
			(5,68)

*Table 9: Fund-level cross-sectional robustness check to test the influence of extra liquidity factors on the mutual fund flows timing for the time period 2000-2015, where the T-values are reported in parentheses and *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively*

Examining the results of Table 9, a first thing to notice is the change in significance for the aggregate liquidity measure variable. Whereas this variable was insignificant in the OLS regression, it has become significant at a 1% level after the addition of the innovative liquidity variable. This makes sense, since the innovative liquidity measure captures the innovations in the aggregate liquidity measure, which means that they have a strong relationship with each other. As can be seen in Appendix VII, the correlation between those two variables is 0,7118 and significant at a 1% level.

Both the innovative liquidity and the traded liquidity have a positive and significant contribution to the mutual fund flows and the aggregate liquidity. To conclude, the addition of the two extra liquidity measures has been helpful for the explanatory power of the aggregate liquidity measure. This measure has a slight negative and significant impact on the mutual fund flows and therefore the mutual fund performance. Where the innovative and traded liquidity measure have a slight positive and significant influence on the performance of mutual funds.

5. Conclusion & Limitations

Chapter 5 aims to give a thorough answer to the research question and the corresponding three hypotheses. Paragraph 5.1 is dedicated to briefly describing the used methodology and discusses the obtained results and finally provides a conclusion. Paragraph 5.2 leaves room for limitations and further research.

5.1 Conclusion

This thesis looks into the matter how mutual funds flows and returns respond to different risk factors from Fama and French, if fund managers have a market timing ability and dives into the impact of liquidity of mutual funds. It is by no means the first time that this has been investigated. However, the combination between liquidity, market timing and the Fama and French risk factors has been very fruitful and interesting to study. Besides that, as one can see in the references section, the existing literature about mutual funds is severely dated. Using data from January 2000 up to and including December 2015, this thesis captures the run-up and the aftermath of the financial crisis of 2008. This thesis studied mutual funds' performance of 725 U.S. mutual funds by using the Fama and French risk factors and the excess fund returns to obtain the abnormal returns. Furthermore, security selection and market timing ability of mutual funds is being analysed based on the methodology of Treynor, J., & Mazuy, K. (1966). The last hypothesis dives into mutual fund flows and the influence of liquidity measures on the flows and subsequently the fund performance.

Results showcased that the excess return on the market has a great and positive influence on the excess monthly fund returns. When the excess return on the market increases with 1%, the excess monthly fund returns increase on average with 0,88%. The other Fama and French factors are significant, but looking at their coefficients, their influence can be seen as negligible. The dependent variable, excess monthly fund returns, is positive and significant at a 1% level in every model. On average, equity mutual funds managers have a security selection skill, since the alpha is positive and significant in all the regressions in paragraph 4.2. Furthermore, there is definitely no sign of market timing ability, because the variance of the RMRF factor has a coefficient of -0,31 on average and is significant at a 1% level.

Three liquidity measures were being utilized to find out what their influence is on the mutual fund flows and subsequently the mutual fund performance. The aggregate liquidity measure is on itself weak and insignificant. However, after adding the innovative and traded liquidity measure as a robustness check, the aggregate liquidity measure became slightly negative and significant with a coefficient of 0,041 at a significance level of 1%. The innovative and traded liquidity measure have both a positive and significant influence on the mutual fund flows. All in all, there can be deduced that liquidity has a positive influence on the mutual fund flows and therewith the mutual fund performance of U.S. equity mutual funds.

5.2 Limitations and Further Research

The CRSP database provides a survivorship-free dataset of mutual fund returns and fund information. Nevertheless, quite some variables were dropped because of missing variables. This is inevitable since the collection of the data for CRSP is done manually. This thesis focusses solely on U.S. equity mutual funds, since CRSP is specialized in the U.S. and it is the only respectable and accessible mutual fund database which is accessible from home. However, to study whether there are cross-sectional variations in returns and liquidity impact between different equity funds, an extension to foreign equity funds would be a nice addition to this research. In this thesis, the only currency used is the U.S. dollar. Moreover, appreciation or deprecation of the currency is not accounted for. To use this as another control variable in further research would for sure be very intriguing. I used quite a large dataset with 725 mutual funds, this is useful to get credible and significant results. On the other hand, there is no opportunity to dive into each mutual fund specifically. Next to that, I looked into the influence of liquidity on mutual fund flows. It would be interesting to see what happens to mutual funds flows when that liquidity rises or shrinks due to something which is out of the hands of the mutual funds.

6. References

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US Mutual Funds Industry - (Segmented by Long Term & Money Market Mutual Funds and By Channel of Distribution) Growth, Trends, and Forecast (2019 – 2024)

7. Appendix

Variable	**Definition**
BPS	Basis Points
CAPM	Capital Asset Pricing Model
CRSP	Center for Research in Security Prices
EMH	Efficient Market Hypothesis
EQ	Equity Fund
HML	High Minus Low
MMMF	Money Market Mutual Fund
NAV	Net Asset Value
OLS	Ordinary Least Squares
RF	Risk-Free Rate
RMRF	Excess Return on the Market
SMB	Small Minus Big
SML	Security Market Line
TNA	Total Net Assets

Appendix I: List of variables and definitions used in this thesis

Variable	*VIF*	*1/VIF*
RMRF	1,08	0,9235
HML	1,06	0,9468
SMB	1,14	0,8798
Mean VIF	1,09	

Appendix II: VIF-factor test of the pairwise correlation between Excess Monthly Returns and the three factors from Fama and French

Quantile	*N*	*Mean*	*Std. Dev*	*Min*	*Max*	*Median*
1	25790	0,0011422	0,0504195	-0,134681	0,121046	0,004382
2	25790	0,0031509	0,0451733	-0,134681	0,121046	0,006197
3	25790	0,0081972	0,0426963	-0,134681	0,121046	0,010459
4	25790	0,0114978	0,0433936	-0,134681	0,121046	0,012541

Appendix III: Summary statistics of the Monthly Fund Returns divided into four quantiles

Quantile	*N*	*Mean*	*Std. Dev*	*Min*	*Max*	*Median*
1	25790	-0,0542937	0,0318579	-0,136369	-0,018894	-0,044390
2	25790	-0,0050854	0,0073870	-0,018892	0,007302	-0,004200
3	25790	0,0191013	0,0070737	0,007303	0,032084	0,018846
4	25790	0,0591610	0,0232959	0,032085	0,120091	0,052908

Appendix IV: Summary statistics of the Excess Monthly Fund Returns divided into four quantiles

Quantile	*N*	*Mean*	*Std. Dev*	*Min*	*Max*	*Median*
1	25790	-0,0648936	0,1554849	-0,7841654	-0,0100071	-0,0218693
2	25790	-0,041299	0,0032193	-0,010006	0,0013327	-0,0040477
3	25790	0,0092725	0,0052921	0,0013327	0,0200883	0,0086060
4	25790	0,899179	0,1045436	0,0200886	0,4664438	0,0488371

Appendix V: Summary statistics of the Mutual Fund Flows divided into four quantiles

Variable	*VIF*	*1/VIF*
Excess Monthly Fund Return	1,87	0,5359
RMRF	1,99	0,5021
HML	1,05	0,9488
SMB	1,14	0,8798
Aggregate Liquidity	1,06	0,9453
Mean VIF	1,42	

Appendix VI: VIF-factor test of the pairwise correlation between Mutual Fund Flows and the Excess Monthly Returns, the three factors from Fama and French and the Aggregate Liquidity factor

Cross-Correlation	*Aggregate Liq.*	*Innovative Liq.*	*Traded Liq.*
Aggregate Liq.	1,0000		
Innovative Liq.	0,7118	1,0000	
	(0,0000)		
Traded Liq.	0,1664	0,1970	1,0000
	(0,0000)	(0,0000)	

*Appendix VII: Cross correlation between the three liquidity measures Pástor and Stambaugh, where the Pearson P-values are reported in parentheses and *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively*