# Liquidity level in mutual fund industry. Liquidity style and performance in the UK market.

**Auteur :** Sajnetdinov, Valeria

**Promoteur(s) :** Bazgour, Tarik

**Faculté :** HEC-Ecole de gestion de l'ULg

**Diplôme :** Master en sciences économiques,orientation générale, à finalité spécialisée en Economics and Finance

**Année académique :** 2015-2016

**URI/URL :** http://hdl.handle.net/2268.2/1843


# Liquidity level in mutual fund industry

## Liquidity style and performance in the UK market

Jury

Supervisor :

Dr. Tarik Bazgour

Reader :

Prof. Dr. Burghof

Leif van Neuss

Master thesis submitted by

**Valeria Sajnetdinov**

in partial fulfilment of the requirements for the degree of Master of Science in Economics and Finance

Academic year : 2015-2016

# Executive Summary

Liquidity has been proved in many studies as a missing investment style which contributes to the asset's return. The paper "The Liquidity style of mutual funds" investigates the influence of fund's liquidity on its performance analyzing U.S. mutual funds universe covering the period from February 1995 to December 2009. The results of this study show that less liquid funds exhibit a risk premium and, therefore, outperform the more liquid funds. Doing robustness check of the model, authors didn't attain the same relation for non-U.S. stocks. For this reason, the same analysis has been carried out for UK mutual funds universe over the period from January 2007 to May 2016 within the framework of this work. The goal was to find out, whether the same relation is valid for market outside the U.S., but focusing on one particular market. UK, as one of the largest mutual funds market worldwide, has been picked. Interesting findings have been obtained: Less liquid UK mutual funds do not have a higher average return. Furthermore, there is no monotonic relation between the fund's liquidity and its performance. However, it must be taken into account that the sample might be too small to be representative. Moreover, the period covered is mainly financial crisis which can lead to biased results. In both cases further and more comprehensive researches spread to other aspects, such as regulation, is needed.

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# II. List of abbreviations

| | |
|---|---|
| ADV | Average Daily Volume |
| AILLIQ | Amihud illiquidity measure of market |
| Bps | Basis points |
| DJIA | Dow Jones Industrial Average |
| ETF | Exchange Traded Funds |
| FTSE 100 | Financial Times Stock Exchange 100 Index |
| GLS | Generalized Least Squares |
| HML | (High Minus Low) Book-to-Market ratio |
| iid | Independent and identically distributed |
| ILLIQ | Amihud illiquidity measure of stocks |
| ILLIQMA | Mean-adjusted Amihud illiquidity measure of stock |
| ISSM | Institute for the Study of Security Markets |
| KIID | Key Investor Information Document |
| NASDAQ | National Association of Securities Dealers Automated Quotations |
| NAV | Net Asset Value |
| NYSE | New York Stock Exchange |
| OEICs | Open-End Investment Companies |
| OLS | Ordinary Least Squares |
| S&P 500 | Standard & Poor's 500 Index |
| SEC | Securities and Exchange Commission |
| SML | (Small minus Large) Firm size |
| TO | Turnover |
| UCITS | Undertaking for collective investment in transferable securities |

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[1] Source: Ibbotson, R. G., Chen, Z., Kim, D. Y.-J., Hu, W.J,(2012):*Liquidity as an Investment Style*, p. 8

# *1.* Introduction

Over the last 15 years the importance of fund investments has been grown significantly. In particular, investing in mutual funds exhibits considerable growth over the decades and has gained the large attention of investors. Investigating factors which influence the fund's performance leads to improved and more profitable investments, which is the main goal of fund investors.

In addition to broadly recognized and established investments styles, size, market return excess, valuation and momentum, the asset's liquidity has been proposed as the fifth investment style which determines its return. Several studies have been carried out to prove the significant impact of liquidity on the performance. Idzorek, Xiong and Ibbotson investigated the same relation on the fund-level and could establish a negative relation: a group of less liquid funds outperformed the more liquid ones and indicated a positive and significant intercept value regressing returns against group's average value and Fama-French factors. This indicates another, not captured by the model explanatory variable, which is liquidity. However, by carrying out the same analysis on non-U.S. funds, the same relation could not be observed. Does this relation apply not for all market? Or the composition of heterogeneous markets provided a biased result due to different market specifics? In order to check the validity of the assumption the UK, as the biggest European funds market, has been chosen for closer investigation. The focus of this work is set on UK open-ended mutual funds due to big size of data set. These funds serve as a good representation of markets, covering a large amount of various stocks.

This work is organized as follows. Section 2 describes the fund industry as whole and addresses different types of funds regarding their management style, compositions and investors. Further, two general types of funds, mutual fund and hedge fund, are compared and their advantages and drawback are discussed respectively. Chapter 3 address the liquidity concept describing its types, purposes and several measurement methods. In the following chapter the study of Idzorek et al. will be examined thoroughly, the methodology and the results will be introduced. The $5^{th}$ chapter covers the practical part of this work and provides the data description, methodology and results. The problems and criticism of the practical work and methodology in general will finish the practical part and is followed by conclusion with summary.

# 2. Fund industry

The core business of investment companies is aimed at investing the client's money in bonds, equity, money or special property market. The investors obtain their share of fund assets which ensures a return from diversified portfolio. Since we are speaking of delegated investments, where agents act as fund manager and the investor are principals, adequate governance compositions, its control and contracts are to be designed appropriately, so that agent-principal conflicts are prevented.[2] Most common instruments which ensure fund managers acting in interest of asset owner are outcome-based contracts where the fund manager is either rewarded when the portfolio performance reaches a certain level or outperforms its peer group. Another instrument is entering behavior-based contracts which restrict the fund manager in trading volume or assets, risk level or leverage. In inference-based contracts the manager's remuneration depends on her diligence. Creating a good monitoring system, such as introducing boards of asset owner representors, could also prevent opportunistic behavior of agents. Besides governance[3] and contracts structure which motivate the agent to act risk avoiding and profit maximizing, the good reputation is another factor which pursues the same goal in long run. A good reputation gives rise to a higher demand and therefore higher rewards for fund manager.[4] The Securities and Exchange Commission (SEC) in U.S. introduced the Investment Company Act of 1940 which aimed to protect investors by issuing rules for four[5] kinds of funds which should facilitate the selection of investing companies and funds and minimizing conflicts of interest. This act contains disclosure rules of financial conditions and investments policies.[6] Similarly, the Financial Conduct Authority in UK introduces the UCITS (undertaking for collective investment in transferable securities) Key Investor Information Document (KIID)[7] framework making fund conditions transparent and comparable among each other.[8]

In general, there are two main types of how the fund's investments are chosen: actively and passively. Actively managed funds are composed of assets being picked by fund managers and based on their investment strategies. Depending on the fund manager's skills and economic situation these type of fund could outperform their peers and could pose a fund investment opportunities with highest returns. However, inflexible strategies and some economical-

[2] Cf. Ang, A. (2012), *Asset Management. A systematic approach to factor investing*., p.491
[3] The mutual funds complex is illustrated in Appendix a)
[4] Cf. Ang, A. (2012), *Asset Management. A systematic approach to factor investing*, p. 495
[5] Mutual funds, closed-end funds, unit investment trusts and exchange-traded funds
[6] Cf. Ang, A. (2012), *Asset Management. A systematic approach to factor investing*, pp. 522-523
[7] Which has been introduced in all European Union members
[8] Cf. IMA (2012), *Enhanced disclosure of fund charges and costs*, September

ly unfavourable conditions could decrease the return of even outperforming funds. Passive or index-funds manager tracks certain index and invests proportionally into components of this index based on their market capitalisation, e.g. S&P 500, DJIA, NASDAQ, FTSE 100, The fund, therefore, reflect index's performance. The idea behind it is that constant outperformance the market is usually linked with a higher risk. Therefore, it can be desirable for some investors not to take a higher risk than prevailing one on the current market. As it can be already derived, the performance of these funds will not be greater than the performance of the benchmark/peer and this is one of the drawbacks of index funds. However, the main benefit of tracking funds are lower fees, since no active management is required and also reduced costs due to low turnover. Furthermore, the risk of adverse selection caused by human error can be reduced. In general, the allocation and diversification strategy is straightforward and does not need any further development by fund managers. The risk faced by portfolio will be exactly the same the market will face.[9] Although the average return after fees of actively managed funds does not exceed the index fund's return, the demand for tracking funds does not disappear or diminish. Investigating German mutual funds market, Mueller and Weber could not observe any dependencies between lack of financial expertise and tendency to invest in actively managed funds. Neither could they find any relationship between financial literacy and investment fees. They explained this effect with smart investors able to identify good investments and choose funds with outperforming returns. Surprisingly, there was no significant evidence of selected funds by literate investors and a higher performance. Mueller and Weber address the notion of "better-than-average thinking" of sophisticated principals which hinder them to invest in index funds. They also consider the existence of a part of less literate investors who do not know about index funds and rely on fund manager's expertise.[10] Regarding the US market, Baks, Metrick and Wachter examined 1437 fund managers and used Bayesian method to adjust prior beliefs on managerial skills (alpha) with posterior beliefs, alpha derived using the Fama-French three factor model. The result of this analysis provides that extremely skeptical expectation about manager's skill lead to no investment, however, numerous investors even with weak belief do invest in active funds.[11]

One can also distinguish funds with respect to the investment objectives. There are three main investment asset classes in which funds managers invest:

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[9] Cf. Investopedia(2016a): *Fund Management Issues*, Author: Richard Loth, retrieved from http://www.investopedia.com/university/quality-mutual-fund/chp6-fund-mgmt/

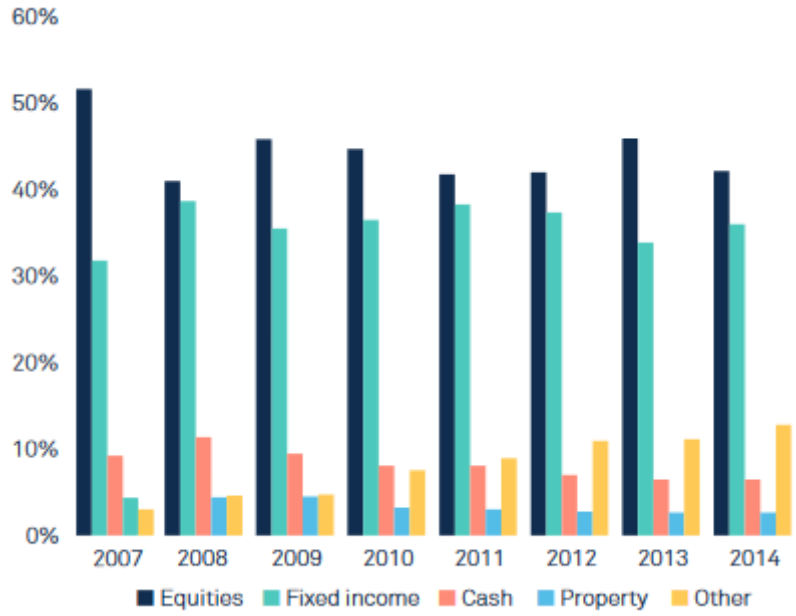
[10] Cf. Müller, S., Weber, M. (2010): *Financial Literacy and Mutual Fund Investments: Who Buys actively managed funds*?

[11] Cf. Baks, K. P., Metrick, A., Wachter, J. (2001): *Should Investors Avoid All Actively Managed Mutual Funds? A Study in Bayesian Performance Evaluation*

- Fixed income securities (bond funds)
- Common and preferred stocks (equity funds)
- Money market investing funds
- Several types of security (hybrid funds)[12]

Although equity is considered to be the most popular asset class in the fund industry, its percentage has decreased on the UK market in the last few years. Figure 1 illustrates the development of asset allocations of UK-managed assets for the period of 2007-2014. Investment in equity does still dominate other assets, but the growing importance of alternative asset classes, such as commodities, private equity and infrastructure, is evident.[13]

Figure 1 Overall Asset Allocation of UK-managed assets




Source: The Investment Association Annual Survey

In general, one can distinguish between mutual funds and hedge funds. A target group of mutual funds are small investors who contribute with modest amount of money, but also institutions can participate. Mutual funds pose an opportunity for small investors to benefit from diversified portfolio without investing large amount of money. In contrast, hedge funds entice large institutional clientele, such as pension funds, foundations, endowments or wealthy private investors. This thesis will primarily focus on the mutual funds, but a short description of hedge funds will be provided in the later chapters.

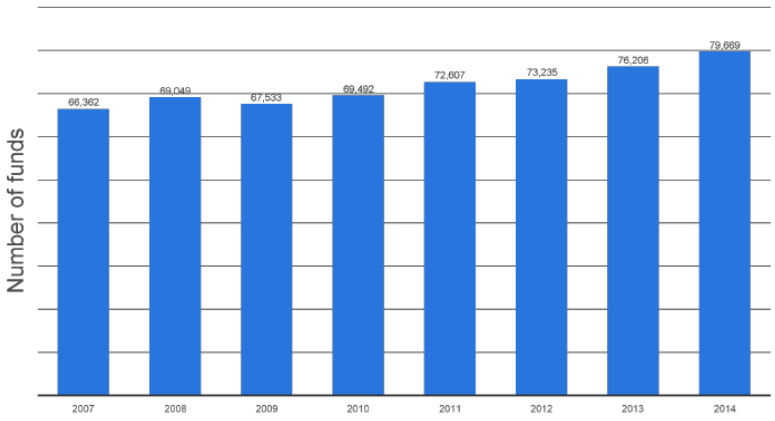
[12] Cf. Hull, C. F., (2015): *Risk Management and Financial Institutions*, p.72
[13] Cf. The Investment Association (2015): *Asset Management in the UK 2014-2015*. The Investment Association Annual Survey, p. 16

## 2.1.Fund types

### 2.1.1. Mutual funds

As already mentioned the main function of mutual funds is to pool money from small investments and invest them in well diversified portfolio. Each investor holds a share of this portfolio and receives returns. There were 79,669 mutual funds on the world market in 2014[14] and the slight but monotonous growth of its number in the last years can be seen on Figure 2:

Figure 2 Number of mutual funds worldwide from 2007 to 2014[15]




The highest percentage of mutual funds represents open-end funds. The amount of shares is not limited, increases with every additional purchase and shrinks when the shares are redeemed. The Net Asset Value of fund's share (NAV) is calculated by dividing the total value of funds16 by the outstanding number of shares.17 Contrary to open-end fund, the closed-end funds have a determined number of shares which does not allow redemption of fund shares. The shares can be traded on the secondary market and their price can differ from their NAVs (closed-end fund discount puzzle).18 There are four main funds types on the UK market which are illustrated by means of

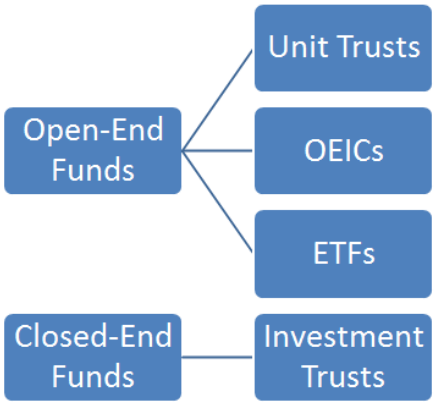
Figure 3.

Unit Trust is one of the most common funds on the UK market. It is usually used as synonym for "mutual funds", but differs from mutual funds in the US. The profit is paid directly to unit

[14] Cf. statista.com(2016a): *Statistics and facts on mutual funds*, retrieved from http://www.statista.com/topics/1441/mutual-funds/
[15] Source: Mutual funds - Statista Dossier
[16] The total value off und ist he sum of values of component assets
[17] Cf. Hull, (2015): *Risk Management and Financial Institutions*, p.72
[18] Cf. Ang, A. (2012), *Asset Management. A systematic approach to factor investing*, p. 546

holders and will not be reinvested in the funds. The fund is set up under trust deed and is monitored and controlled by independent party, trustee. Although the unit trust is assigned to mutual funds, the price does not necessarily correspond with NAV, but both bid and offer prices are quoted. The bid price is received by unit seller and the offer price is paid by the unit buyer. The difference between bid and offer prices, the bid- offer spread, is usually collected by financial adviser or fund manager.[19]

Figure 3 Main Types of Funds on UK Market[20]




The Open-End Investment Companies are new and fast growing type of mutual funds which are similar to Unit Trusts in their concept. Unlike the Unit Trust, The OEICs quote only one price which is NAV. This simplifies the trade and is more attractive to the investors. Another benefit is the UCITS fund regulation framework which enables trading across European counties. [21]

The exchange traded funds (ETFs) are, as the name suggests, fund shares which are traded on an exchange. The quoted price is thus not the NAV, but is close to it due to no-arbitrage pricing. The composition of underlying securities, "creation basket", usually equates to tracking portfolio or index. Since ETFs are open-end funds, the number of shares is not fixed and varies with transactions; the shares are redeemed to the fund but sold on the secondary market. However, like the closed-end funds they can be sold promptly and provide liquidity. Combin-

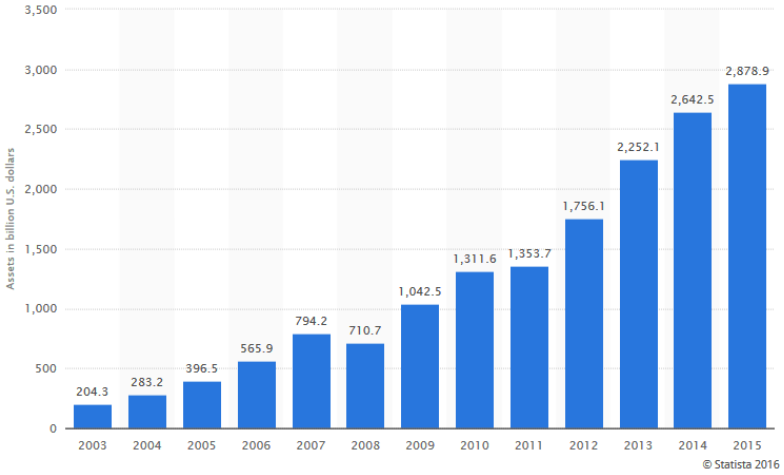
[19] Cf. Investopedia: *Unit Trust – UT*, retrieved from http://www.investopedia.com/terms/u/unittrust.asp, Morningstar: *Fund ABCs: Types of Funds*, retrieved from http://www.morningstar.co.uk/uk/news/62085/fund-abcs-types-of-funds.aspx

[20] Source: own construction

[21] Cf. Morningstar: *Fund ABCs: Types of Funds* , retrieved from http://www.morningstar.co.uk/uk/news/62085/fund-abcs-types-of-funds.aspx

ing advantages from open-end and closed-end funds, the ETFs gain in importance and amounted about 2,879 billion US dollar worldwide in 2015, which can be seen on Figure 4.[22]

Figure 4 Development of assets of global ETFs 2003-2015 in $ bn[23]




Besides the various benefits, such as immediate liquidity, transparency and ability to sell the share throughout the trading day, there are also some disadvantages related to ETFs traits. As it has been already proved by Odean (1999), Barber and Odean(2000), a frequent trading leads to losses caused by pro-cyclical trading activities. Second disadvantage is related to large variety of ETFs which increases the risk of choosing not well diversified portfolios and draw a higher losses in bad times.[24]

Closed-end fund Investment Trust issues fund shares once and does not buy them back or issue another shares under regular conditions. As every share traded on the secondary market, its price deviates from the NAV. Furthermore, additional brokerage commissions must be paid for each transaction. A good point, especially from asset manager's perspective, is that the underlying remains stable throughout the entire fund's lifetime. This means a stable management fee which is directly related to the fund volume. Investment trust offers to the investors the ability to borrow the money, "gear" their portfolio, e. g. by using derivatives[25]. On the one hand, this could increase the investors return significantly. On the other hand, this could also increase the potential loss. Another controversial point is the right of investment trust to retain up to 15% of the income in any year. This would clearly increase income in further

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[22] Cf. Morningstar: *Fund ABCs: Types of Funds* , retrieved from http://www.morningstar.co.uk/uk/news/62085/fund-abcs-types-of-funds.aspx

[23] Statista.com(2016b): *Development of assets of global Exchange Traded Funds (ETFs) from 2003 to 2015,* retrieved from http://www.statista.com/statistics/224579/worldwide-etf-assets-under-management-since-1997/

[24] Cf. Ang, A.(2014): *Asset Management. A systematic approach to factor investing*, p. 549,
Cf. Odean, T. (1999): *Do investors trade too much*?, pp.1279–1298.
Cf. Barber, B. M., Odean, T. (2000): *Trading is hazardous to your wealth. The common stock investment performance of individual investors*

[25] Gearing unit trust and OEIC portfolios is limited to 10%

years with smaller returns, but this decision is not made by investor herself. However, likely to shareholders of regular companies, investment trust shareholders have vote rights for important fund's decisions and changes. Regarding pricing, the investment trust charges lower fees than OEICs since the operating costs are smaller.[26]

### 2.1.2. Hedge funds

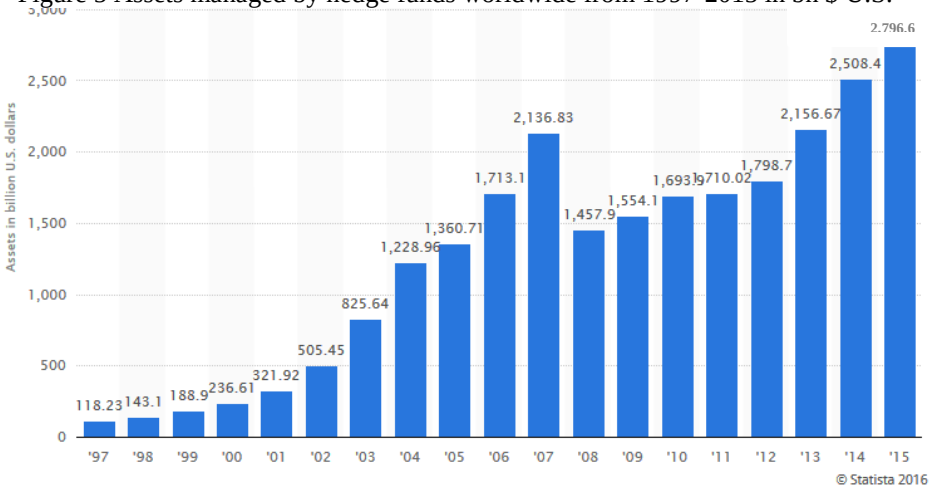
Fabozzi defines hedge funds as:

"*A privately organized investment vehicle that manages a concentrated portfolio of public securities and derivative instruments on public securities, that can invest both long and short, and can apply leverage*"

Hedge funds are less regulated and are set up for more sophisticated investors. In the US, for instance, according to SEC the mutual funds cannot have more than 100 investors, whereas hedge funds can have more and the net worth of which usually exceeds $ 5 million. As hedge funds don't have a large number of securities benchmarks, decision taking is based on manager's skills and opinion. As the "benchmark" risk does not exist and the managers are inclined to narrow investment strategy, the asset allocation within the fund is likely to be concentrated on certain branches or securities. Hedge fund managers use derivatives in their strategies more often than mutual fund managers do which imply non-linear cash-flow related risks. Therefore, hedge fund managers have to face additional risk correspondingly. Unlike the mutual fund manager, the hedge fund manager can take both short and long positions in her investment strategy for return increase or risk management purposes. And the last trait of hedge fund is unlimited amount of leverage the managers can exercise. This instrument can undoubtedly multiply the investor's return, but poses also a certain risk. In general, hedge fund managers enjoy the freedom of instrument choice and can thus increase the returns significantly, but the risk is correspondingly high and must be managed simultaneously.[27] In order to represent it visually , the development of hedge funds worldwide is shown below in Figure 5. Despite the difficult accessibility, the hedge fund demand and therefore volume increase notably.

[26] Cf. J.P.Morgan (2016): What is an Investment Trust?, retrieved from http://am.jpmorgan.co.uk/investment-trusts/explained/what-is-an-investment-trust.aspx
Cf. Morningstar: Fund ABCs: Types of Funds , retrieved from http://www.morningstar.co.uk/uk/news/62085/fund-abcs-types-of-funds.aspx
[27] Cf. Fabozzi, F.J (2002): *The Handbook of financial instruments*, pp. 605-607

Figure 5 Assets managed by hedge funds worldwide from 1997-2015 in bn $ U.S.[28]




After the basic fund types have been introduced, the main differences are to be described and commented in the next chapter.

## 2.2. Fund comparison

In this chapter two main types of funds, mutual funds and hedge funds, will be compared and their advantages and drawbacks will be illustrated correspondingly.

Although hedge funds and mutual funds represent the same principle: pooled money invested in diversified portfolio which is managed by fund manager and investors hold shares and receive returns on the regular basis, they have different target groups and cannot be interchangeably made use of. As described above, the hedge funds are less regulated than mutual funds. The reason is that the hedge funds are not meant for the broad public, but for small number of well-informed, wealthy investors. It is also not required to disclose the policies and investment strategies, since the hedge funds do not track any benchmarks and their returns are strongly influenced by manager's skills. A looser regulation constrains result in more freedom in strategies and ability to obtain higher profits. This is, however, closely linked with higher risks. The investors must rely on the manager's choice of assets and risk management. The mutual fund managers have to disclose their investment strategy and are required to explain their investment policy, according to the Investment Company Act of 1940 in US and UCITS in EU for the purposes of protecting the investors.[29]

The hedge funds are not only subject to little regulation, but have less rules regarding investment and are unrestricted in use broad spectrum of trading strategies. Whereas mutual funds are long-only portfolios and are restricted in leveraging, hedge fund manager can take both,

[28]Cf. Statista.com (2016c): *Assets managed by hedge funds worldwide from 1997 to 2015*, retrieved from http://www.statista.com/statistics/271771/assets-of-the-hedge-funds-worldwide/

[29] Cf. Connor, G., Woo, M.: *An Introduction to Hedge Funds. Introductory Guide*, pp.8-10

short and long positions. This enables reducing the correlation with the market, using extra leveraging and benefiting from over- and undervalued securities. Moreover, hedge managers often use derivatives and convertible securities which are usually not used in mutual funds.[30]
Hedge funds are privately offered investments to investors with particular net wealth and require consequently higher fees[31] than publicly offered mutual funds. Such a high level of fee is meant to attract talented fund manager.[32] A high fee means to investors not only high expenses, but also higher risk: Incentive fee for investment managers as percentage of profit encourage them to invest in high-return and simultaneously risky assets. Then again, this means also a higher profit in average.[33] The mutual fund investors have the possibility to invest in well diversified portfolio paying a low fee. They are also protected by law and face a relative small risk.
As hedge funds are privately offered investment vehicles, they cannot raise money publicly and advertise broadly, whereas mutual funds enjoy this advantages.

## *3.* Liquidity concept

In order to examine the relationship between liquidity of mutual fund and its performance, both concepts will be introduced. The performance means simply the fund's return, whereas liquidity is more complex concept. In the following chapter we discuss the notion of liquidity and why does it have such a great importance. It is important to draw a distinction between liquidity level and liquidity risk. Liquidity risk describes the sensitivity of liquidity change in the market.[34] These two notions pose different attributes: liquidity level is considered as mean of liquidity and liquidity risk as its volatility which are, according to Lou and Sadka (2011), slightly correlated with each other.

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_i^{Ret}\left(R_{m,t} - R_{f,t}\right) + \beta_i^{Liq} L_{m,t} + \varepsilon_{i,t} \quad (1)$$

where the excess return between $R_{i,t}$ stock's return at t and $R_{f,t}$ risk-free rate is determined by impact $\beta_i^{Ret}$ of market excess return $\left(R_{m,t} - R_{f,t}\right)$ and liquidity risk factor $L_{m,t}$. The sensitiv-

[30] Connor, G., Woo, M.: *An Introduction to Hedge Funds. Introductory Guide*, pp.8-10
[31] The hedge funds fees depends on its performance
[32] The annual management fee lies between 1%-3% of assets value and incentive fee id about 15%-30% of the profit in the US (Hull)
[33] Cf. Hull, C. F., (2015): *Risk Management and Financial Institutions*, p.67
[34] Cf. Idzorek, M, Xiong, J. X., Ibbotson, R. G. (2012): *The liquidity style of mutual funds*, p. 38

ity of stock's return to market liquidity change is measured by $\beta_i^{Liq}$.[35] The calculation of liquidity level will be provided later in this work.

## 3.1. Definition of Liquidity

The concept of liquidity is used in different areas:

- *-Asset liquidity:* Liquidity describes how easily one share can be converted into legal tender. The "ease" mainly means the ability to sell the share within a short period and without bearing big losses. We mainly refer to transaction cost and immediacy when we speak of asset liquidity.
- *Asset's market liquidity:* In general, it exhibits how easily the asset can be sold on the market, if no price-altering information is available. Sarr and Lybek (2002) provide extended definition of market liquidity with 5 following traits:
    - *Tightness:* A low transaction cost which is expressed as the bid-ask spread and implicit costs.
    - *Immediacy:* The ability to carry out a sale sufficiently fast. This time encompasses trading, clearing and settlement.
    - *Depth:* Trade interest exists up to a sufficient low price.
    - *Breadth:* A high number or volume of order can be satisfied without impacting the price significantly
    - *Resiliency:* A fast inflow of new trades with corrective effect on imbalances.[36]

A liquid market is also desired macroeconomically because it enables a smooth transmission of central bank policies to the market, acceptance of asset-liability mismatches and attracts more investors.[37]

- *Financial market's liquidity* primarily focuses on the substitutability among several asset types and their liquidity.
- *Institutional liquidity* is present if in case of asset's mismatch the financial institution can easily intervene in order to correct it.[38]

Clearly, it is hard to find a measure that captures all these characteristic features. For this reason several approaches has been proposed and used, which represent proxies for some aspects of liquidity. In this work we are interested in asset's liquidity, as we want to establish a relationship between single equity's liquidity and return.

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[35] Cf. Lou, X, Sadka, R (2011): *Liquidity Level or Liquidity Risk? Evidence from the Financial Crisis*, p. 51
[36] Cf. Sarr, A., Lybek, T. (2002): *Measuring Liquidity in Financial Markets*, p. 5
[37] Cf. Sarr, A., Lybek, T. (2002): *Measuring Liquidity in Financial Markets*, p. 4
[38] Cf. Sarr, A., Lybek, T. (2002): *Measuring Liquidity in Financial Markets*, pp. 7-8

## 3.2. Liquidity Measurement

All liquidity measurement can be roughly divided into three categories: spread-related, price- and volume-based measures.[39] In the following chapters these approaches will be described briefly and an examples will be provided correspondingly.

### 3.2.1. Spread-related measures

Spread is the difference between the highest price the buyer is willing to pay and the lowest price the seller is willing to receive for certain equity. Under normal condition, this difference is always positive. If negative bid ask price occurs, the market is referred to as crossed market. This comes about in volatile and high volume trading when the order entries are made before the day's trading session started.[40] Usually, a higher bid-ask spread indicates a lower liquidity (a higher illiquidity), since the difference is considered to be the transaction costs among others[41].[42] It is evident that a stock with a higher demand has a smaller bid-ask-spread, since the buyers are willing to pay a higher price and the spread reduces. Therefore, this stock will exhibit a higher liquidity.

Using the bid-ask spread one can create further measures, e.g. express spread as percentage:

$$pS = \frac{A+B}{Mid} \tag{2}$$

Where $Mid = \frac{A-B}{2}$ is the midpoint on the bid (B) - ask (A) spread. This spread is also called the dealer spread. As alternative spread measure the market spread can be used which represents the highest bid and lowest ask.[43]

Petersen and Fialkowski (1993) pointed out the significant and robust difference between the posted and actual spreads in the market. The estimated effective spread is set up to high as well. Furthermore, not only the discrepancy could be shown by the authors, but also a weak correlation which makes the derivation of effective spread changes based on quoted spread development difficult. Hence, the estimation of transaction cost and therefore liquidity measure cannot be calculated accurately.[44]

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[39] Cf. Danyliv, O, Bland, B, Nicholass, D (2014*): Convenient liquidity measure for financial markets*, p. 2
[40] Cf. Investopedia.com (2016c): *Crossed market,* retrieved from : http://www.investopedia.com/terms/c/crossedmarket.asp
[41] e.g. fixed transaction costs, asymmetric information cost, etc.
[42] Cf. Hasbrouck, J.(1999): *The dynamics of discrete bid and ask quotes*, p. 2136
[43] Cf. Gabrielsen, A., Marzo, M., Zagag, P.(2011): *Measuring market liquidity: An introductory survey*, pp. 19-20
[44] Cf. Petersen, M., Fialkowski, D. (1993): *Posted versus effective spreads. Good prices or bad quotes?*, p. 290

### 3.2.2. Price-based measures

Some measures use price changes in order to derive a proxy for liquidity. Marsh and Rock calculate the liquidity ratio as price effect per transaction, assuming that the price is not affected by trade size:

$$LR_i = \frac{1}{F_i}\sum_{f=1}^{F_i}\left|\frac{P_f - P_{f-1}}{P_{f-1}}\right| \times 100 \quad (3)$$

where $F_i$ is the number of transaction of asset i within a certain time horizon and $P_f$ is the price of this asset received in f[th] transaction. Instead of trading volume, Marsh and Rock use number of transactions as scaling variable. As the result depends on the time horizon it is applied for, it is advisable to use it for short time periods.[45]

### 3.2.3. Volume-based measures

Some liquidity measures use average trading volume of a stock per day (ADV) as liquidity indicator. These measures are widely used in the praxis. The higher is the traded volume of certain stock, the more liquid is it. The most frequently applied measures are the Amihud measure, which is also used by regulators, and turnover method due to simplicity and data availability.[46]

Amihud illiquidity measure (ILLIQ) is the average ratio of absolute value of return to product of volume by adjusted price per day. It is interpreted as price impact, the price change per one monetary unit (dollar) of trade of stock I on day d. The annual illiquidity is calculated as follows:

$$ILLIQ_i = \frac{1}{D}\sum_{d=1}^{D}\frac{|R_{i,d}|}{P_{i,d}Vol_{i,d}} \quad (4)$$

where *D* is number of annually trading days, $P_{i,d}$ is the adjusted price for stock i on day d, $|R_{i,d}|$ is its absolute return and $Vol_{i,d}$ is its trading volume. Further, Amihud uses cross-sectional average illiquidity of stocks to calculate the market illiquidity (AILLIQ):

$$AILLIQ = \frac{1}{N}\sum_{i}^{N} ILLIQ_i \quad (5)$$

[45] Cf. Gabrielsen, A., Marzo, M., Zagag, P.(2011): *Measuring market liquidity: An introductory survey*, p. 13
[46] Cf. Danyliv, O, Bland, B, Nicholass, D (2014*): Convenient liquidity measure for financial markets*, p. 2

where N is the number of stocks on the market. Due to variable cross-sectional illiquidity over the year, the annual ILLIQ is adjusted by its mean:

$$ILLIQMA_i = \frac{ILLIQ_i}{AILLIQ} \tag{6}$$

Sometimes the logarithmic version of Amihud measure is used, but this does not change the ordinal order of the stocks' liquidity.[47]

Another frequently used measure is the trading turnover. This proxy poses the relation of number of traded share within certain period and the number of outstanding stocks:

$$TO_i = \frac{1}{D}\sum_{d=1}^{D}\frac{T_{i,d}}{M_{i,d}} \tag{7}$$

Here $T_{i,d}$ is the number of traded shares and $M_{i,d}$ is the number of outstanding shares on day d, $TO_i$ represents thus the daily average liquidity in a certain year. It has been proved that the stock liquidity correlates with its trading frequency, therefore, we can assume the trading ratio being the proxy variable for liquidity. Another reason for using it as liquidity metric is the data availability even for long periods and the ease to retrieve them.[48]

And the next liquidity measure of this category which will be introduced in this chapter is the Hui and Heubel liquidity ratio. This index provides the relation of greatest price change within the last 5 days and ratio of volume and market capitalization. Mathematically expressed:

$$L_{HH} = \frac{(P_{max}-P_{min})/P_{min}}{\frac{V}{M\times E(P)}} \tag{8}$$

where $P_{max}$ is the maximal price, $P_{min}$ is the minimal price of stock and $V$ is the traded dollar volume over the last 5 days, $M$ is the number of outstanding shares and $E(P)$ is the

[47] Cf. Amihud, Y (2002): *Illiquidity and stock returns: Cross-section and time-series effects*
[48] Cf. Datar, V. T., Naik, N.Y., Radcliffe, R.(1998): *Liquidity and stock returns: An alternative test*, p.205

average closing price over the same horizon. Comparable with ILLIQ, the higher is the measure, the lower is the liquidity.[49]

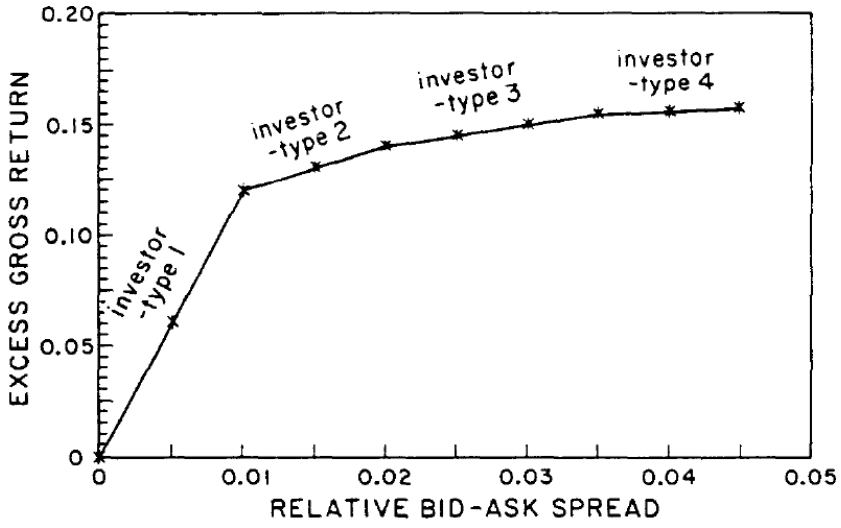
## 3.3. Liquidity's effect on asset's returns

Regardless of the liquidity measure, the economists have found a connection between the asset's liquidity and its rate of return. In the following chapters three main researches in this area will be presented.

### 3.3.1. Amihud and Mendelson

Amihud and Mendelson defined illiquidity as cost for prompt execution expressed as bid-ask spread. The bid-ask spread consist of buying premium required for instant purchase and selling concession for instant sell. Amihud and Mandelson predicted to have a concave return-spread relation: The asset's return increases with the spread, but the growth rate diminishes the higher is the spread as shown in Figure 6. They considered this relation as adequate reaction of the market on the existence of spread (illiquidity) and not as market inefficiency.[50]

Figure 6 Relation between excess gross return and relative spread[51]




It is assumed, that there are M types of investors with different expected holding time. Arbitrary investor type $i$ is endowed with wealth $W_i$ buys stocks at ask price and holds it within

[49] Cf. Danyliv, O, Bland, B, Nicholass, D (2014*): Convenient liquidity measure for financial markets,* p. 12
Cf. Gabrielsen, A., Marzo, M., Zagag, P.(2011): *Measuring market liquidity: An introductory survey*, p. 8
[50] Cf. Amihud, Y., Mendelson, H(1986): *Asset pricing and the bid-ask spread*, pp. 246-247
[51] Source: Amihud, Y., Mendelson, H(1986): *Asset pricing and the bid-ask spread*

time $T_i$, which has an expected value of $E(T_i) = \mu_i^{-1}$. Each investor is expected to sell this asset at the end of the type specific holding period at bid price and leave the market. The assumed distribution of investor arrival at the market is Poisson distribution and for holding period is exponential distribution. In order to verify this assumed relation, Amihud and Mendelson solve maximization problem for present value of holding portfolio for investor i:

$$max \sum_{j=0}^{N} x_{ij}\left[d_j + \mu_i V_j\left(1 - S_j\right)\right] \tag{9}$$

subject to wealth $\sum_{j=0}^{N} x_{ij} V_j \leq W_i$ and no short position constraint $x_{ij} \geq 0$ for all assets j=0,1,…, N. $x_{ij}$ is the holding of asset j, $d_j$ is its generated perpetual cash flow and $\mu_i V_j\left(1 - S_j\right)$[52] is expected liquidation expressed as discounted bid price. The detailed maximization problem is shown in Appendix b. The authors define expected asset's return as the difference between the gross market return and liquidation cost per unit time or spread adjustment:

$$r_{ij} = \frac{d_j}{V_j} - \mu_i S_j \tag{10}$$

For given bid and ask prices the investors would choose the assets which maximize their income (return) $r_i^* = \max_{j=0,1,2,\ldots,N} r_{ij}$ with $r_{ij} = \frac{d_j}{V_j} - \mu_i S_j$. Therefore, in equilibrium it holds:

$$V_j^* = \frac{d_j}{r_j^*} - \mu_i V_j^* S_j / r_i^* \tag{11}$$

Where the first term is with higher spread-adjusted return discounted perpetual cash flows and the last term represents the discounted expected transaction cost cash flow. This expression allowed Amihud and Mendelson to make following propositions about market microstructure and assets pricing:

1) The higher is spread of an asset, the longer is the expected holding period

2) In equilibrium, the observed market return is an increasing and concave piecewise-linear function of the relative spread.[53]

[52] Ask price vector is therefore **V**

[53] Cf. Amihud, Y., Mendelson, H(1986): *Asset pricing and the bid-ask spread*

The second statement is of prime importance for this topic and it has been proven empirically and with some examples, ordering and grouping investors by types based on expecting holding horizon. The results are graphically represented by Figure 6.[54]

This result was suspected by Eleswarapu and Reinganum (1993) who claimed that this relation occurred seasonally, mainly in January. Lee (1993) considers the bid-ask spread as noisy indicator, because a large number of big trades happen outside the spread and are, therefore, not captured by their model.[55]

### 3.3.2. Brennan and Subrahmanyam

Brennan and Subrahmanyam (1995) address the illiquidity as the adverse selection costs caused by asymmetric information and exploring the impact of fixed and variable[56] components of transaction cost on the asset returns. They discovered statistically significant return premium connected to both fixed and variable parts of transaction cost. [57]

Brennan and Subrahmanyam use data set for years 1984 and 1988 from Institute for the Study of Security Markets (ISSM) which contains all stock's ask and bid prices, time-stamped transaction prices and quantities.

In order to form portfolio and estimate cost of illiquidity two parameters, λ (variable cost) and ψ (fixed cost) from two different models, the Glosten-Harris model and the Hasbrouck-Foster-Viswanathan model, have been calculated respectively.

*The Glosten-Harris model* describes the expected value of security by means of the following formula:

$$m_t = m_{t-1} + \lambda q_t + y_t \qquad (12)$$

where $q_t$ is the observed order flow in the market, $y_t$ is a public information signal and $\lambda$ is the inverse market depth parameter. In order to allow the fixed cost component Brennan and Subrahmenyam added variable $D_t$, which denotes the sign of the incoming order, to the expected value of security and ψ as fixed cost component:

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[54] Cf. Amihud, Y., Mendelson, H(1986): *Asset pricing and the bid-ask spread*

[55] Cf. Brennan, M. J., Subrahmanyam, A. (1996):Market microstructure and asset pricing: On the compensation for illiquidity in stock return, p. 2,
Cf. Eleswarapu, V., Reinganum, M. (1993): The seasonal behavior of the liquidity premium in asset pricing
Cf. Lee, C. (1993): Market fragmentation and price-execution in NYSE-listed securities

[56] Part of cost which varies with the value of transaction

[57] Cf. Brennan, M. J., Subrahmanyam, A. (1996):Market microstructure and asset pricing: On the compensation for illiquidity in stock return, p. 2,

$$p_t = m_t + \psi D_t \tag{13}$$

Hence, combining both equations we receive:

$$p_t = m_{t-1} + \lambda q_t + \psi D_t + y_t \tag{14}$$

And in terms of change:

$$\Delta p_t = \lambda q_t + \psi[D_t - D_{t-1}] + y_t \tag{15}$$

The Glosten-Harris model is used to derive parameter $\lambda$ which will be used in further analysis.

*The Hasbrouck-Foster-Viswanathan model* captures price reaction on unexpected volume and is used to measure adverse selection part mentioned above. The idea behind is not to consider predictable part of price (e.g. which is caused by autocorrelation) in the information content calculation. Originally, the model applied to bid-ask quotes, but in our Brennan and Subahmenyam take transaction cost instead. The quantity $q_t$ which results from price change is assumed to be dependent on its n lags:

$$q_t = \alpha_p + \sum_{j=1}^{n} \beta_j \Delta p_{t-j} + \sum_{j=1}^{n} \gamma_j q_{t-j} + \tau_t \tag{16}$$

And the informativeness term $\tau_t$ is entered in equation (13):

$$\Delta p_t = \alpha_p + \psi[D_t - D_{t-1}] + \lambda \tau_t + \nu_t \tag{17}$$

which now contains both, the fixed cost coefficient $\psi$ and variable cost coefficient $\lambda$.

Authors calculated fixed cost and variable cost components from equations (15), (16) and (17) using OLS on each of assets and the measure for variable cost is therefore $C_n \equiv \lambda n/P$[58].

Grouping terms by liquidity and analysing, they came to the following conclusions:

The main finding of their work was the significant relation between the asset's return and both, fixed and variable components of transaction cost. Furthermore, Brennan and Subrahmanyam found out a concave relation between the return and variable costs in the less liquid

[58] n denotes the number of outstanding shares. Taking q , average size of transaction can be used instead.

stocks, which party complies with findings of Amihud and Mendelson, In contrast, the relation of returns and fixed cost components exhibited a convex relation. Also contrary to Eleswarapu and Reinganum, no evidence of seasonality of return-transaction costs relation could be found.[59]

### 3.3.3. Datar, Naik and Radcliffe

Another paper which handles with the impact of stock's liquidity on its return is the work of Datar, Naik and Radcliffe (henceforth DN&R). Instead of using bid-ask spread as illiquidity proxy, as Amihud and Mendelson did, DT&R use turnover rate (7) as illiquidity measure. The reason for choosing this liquidity measure was a restricted availability of monthly bid- ask spread over a long time and, as already mentioned above, this measure is considered to be not sufficiently accurate proxy for liquidity, according to Petersen and Fialkowski (1993). In turn, the strong correlation between trading frequency and turnover rate, its theoretical appeal and easy data obtainability make turnover rate an attractive liquidity measure.[60]

As the turnover rate measure is proportional to Amihud and Mendelson's expected holding period μ. Based on their proposition that the return increases with holding period, it should also have a reverse relation with turnover rate, lower return by high turnover rate. In order to investigate the cross-sectional return's variation caused by liquidity, DN&R use refined method of Fama-MacBeth elaborated by Litzenberger and Ramaswamy. Given $N_t$ securities in time *t* and T is the observation duration, the return on security i is assumed to be:

$$R_{it} = \gamma_{0t} + \sum_{k=1}^{K} \gamma_{kt} x_{it} + \varepsilon_{it} \tag{18}$$

The return determining factors, such as SMB, HML, firm risk and liquidity are represented by corresponding $x_{it}$. Instead of using OLS for relation assessment, DN&R use GLS estimator

$$\hat{\gamma}_k = \sum_{t=1}^{T} Z_{kt} \gamma_{kt} \text{ [61]} \tag{19}$$

If $\gamma_k$ for each k is serially uncorrelated, $\hat{\gamma}_k$ consists of weighted serial $\gamma_k$ for all t. The weights depend on their variances:

---

[59] Cf. Brennan, M. J., Subrahmanyam, A. (1996): *Market microstructure and asset pricing: On the compensation for illiquidity in stock returns*

[60] Cf. Datar, V. T., Naik, N. Y., Radcliffe, R. (1998): *Liquidity and stock returns: An alternative test*, pp. 204-205

[61] The variance of GLS estimator is therefore $Var(\hat{\gamma}_k) = \sum_{t=1}^{T} Z_{kt}^2 Var(\hat{\gamma}_{kt})$

$$Z_{kt} = \frac{[Var(\hat{\gamma}_{kt})]^{-1}}{\sum_{t=1}^{T}[Var(\hat{\gamma}_{kt})]^{-1}} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (20)$$

Using Fama-French methodology would imply equal weightings for all slope coefficients $\widehat{\gamma_{kt}}$, assuming stationary distribution.[62]

The authors used data from the period 1962 to 1991and examined the effect of turnover rate on cross-section asset's return. Next, they controlled the Fama-French factors and checked again the effect on its existence and significance. Regression of return on the liquidity and other variables contains monthly results which then are generalized using formulas (19) and (20). By means of univariate and multivariate regression each single factor and all factors jointly have been proved. The findings were compliant with those of Amihud and Mendelson. There is a significant relation between return and liquidity, even controlling other influencing factors. Further, testing the statement of Eleswarapu and Reinganum about January seasonality, the authors didn't find any different result after analyzing non-January month and complete year.[63]

In previous chapters the fund industry and notion of liquidity have been introduced. Later, the effect of liquidity on asset's return which has been investigated within several empirical analyses has been presented. Following work will serve as the basis of its thesis and it explores the liquidity of mutual funds and its impact on expected fund's return.

### 3.3.4. Liquidity as investment style

Currently there are assets' characteristics used in investment theory and asset allocation: Market, Size, Value/Growth, and Momentum. Sharpe, who first introduced the notion of investment style, defined criteria which must be fulfilled by style benchmark as:

- Identifiable before the fact
- Not easily beaten
- A viable alternative
- Low in cost

[62] Cf. Datar, V. T., Naik, N. Y., Radcliffe, R. (1998): *Liquidity and stock returns: An alternative test,* pp. 204-208

[63] Cf. Datar, V. T., Naik, N. Y., Radcliffe, R. (1998): *Liquidity and stock returns: An alternative test,* pp.208-216

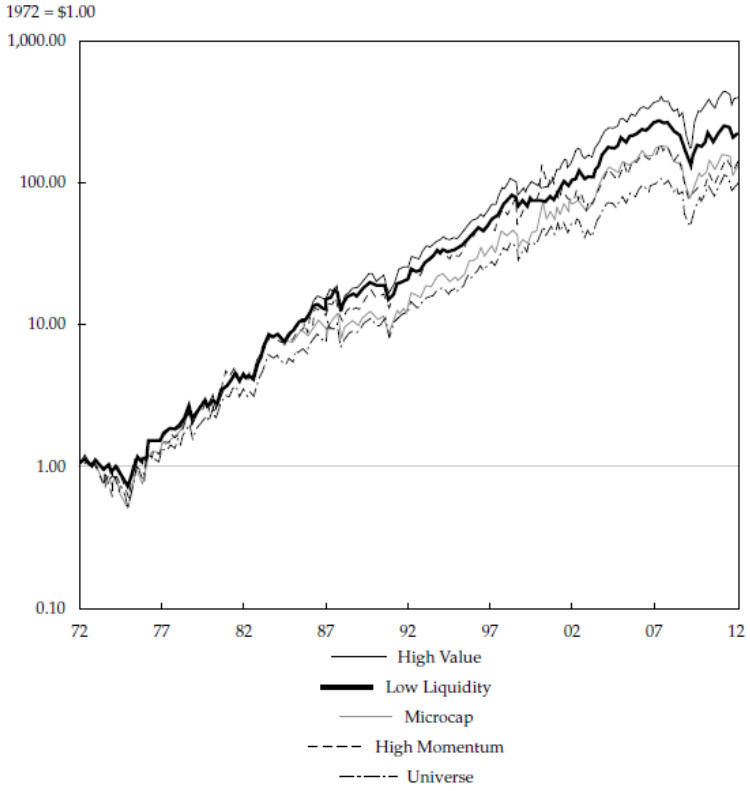
Based on previous researches and inspection of the stock level liquidity[64] for investment style criteria Ibbotson, Chen, Kim and Hu (2013) proposed liquidity as fifth style to the ubiquitous four-factor model. They proved all criteria to be met by style:

The liquidity was measured by turnover rate which is clearly measurable before the fact. As it is the simplest and the most available measure, if it mets all style criteria, the more sophisticated liquidity measure will be also considered as valid investment style.[65]

Ibbotson et al. collected information of 3,500 stocks from1971-2010, measured investment styles, ranked them for each style variable every year and grouped in sorted quartiles. For the subsequent years the performance has been measured. The results, long-term cumulative return, for the first quartile (where better performance is expected) are shown in Figure 7. Since the return lines of each style variable and proposed liquidity style lie above the average stock returns, they clearly outperform the benchmark and can be called as "hard to beat". Interestingly, the liquidity style lies above the microcap portfolio and high momentum portfolio which means that the style outperform the already accepted investment styles. In order to proof that liquidity style is a viable alternative, Ibbotson et al. tried to distinct disparities in size and liquidity, since the styles are considered as substitutes. The average of returns grouped by liquidity and size can be seen in Appendix c Table 7 Size and liquidity quartile portfoliosTable 7. One can recognize that liquidity effect is a stand-alone style which leads to risk premium regardless of size group. Same test has been carried out for other styles and liquidity has been proved as different from existing styles. This means, it can be used as blended investment strategy with other styles.[66]

[64] The liquidity was calculated using turnover ratio method
[65] Cf. Ibbotson, R. G., Chen, Z., Kim, D. Y.-J., Hu, W.J,(2012): *Liquidity as an Investment Style*, pp.1-2
[66] Cf. Ibbotson, R. G., Chen, Z., Kim, D. Y.-J., Hu, W.J,(2012): *Liquidity as an Investment Style*, pp.3-5

Figure 7 Top style quartile portfolio in comparison[67]




If one relies on the assumption that all four already widely accepted styles perfectly explain the return in excess of market return, regression of all these styles shouldn't have the intercept, $\alpha \approx 0$. However, after running regression for both, long-short portfolio and long-only portfolio, Ibbotson et al. noticed a positive and significant alpha. Following regressions have been done:

1) CAPM:

$$R_{it} = \alpha + \beta_{iM}(R_{Mt} - R_{ft}) + \varepsilon_{it} \quad (21)$$

2) Fama-French three-factor model:

$$R_{it} = \alpha + \beta_{i,M}(R_{Mt} - R_{ft}) + \beta_{i,SML}SML + \beta_{i,HML}HML + \varepsilon_{it} \quad (22)$$

3) The four-factor model which includes momentum factor:

$$(R_{it} = \alpha + \beta_{i,M}(R_{Mt} - R_{ft}) + \beta_{i,SML}SML + \beta_{i,HML}HML + \beta_{i,WML}WML + \varepsilon_{it} \quad (23)$$

[67] Source: Ibbotson, R. G., Chen, Z., Kim, D. Y.-J., Hu, W.J,(2012): *Liquidity as an Investment Style*, p.3

The detailed regression results can be viewed in Appendix Table 8. This means, that any of the existing style does fully capture liquidity and it must be entered as an autonomous factor.[68]

In order to proof that style detection can be done at "low cost", authors analyse how often the rebalancing should be done, to be more exact how frequent is the migration within liquidity quartiles happens. For comparison, Ibbotson et al. made the same test for other styles and came to conclusion, that liquidity is relatively stable asset's attribute compared to value and momentum.[69] The detailed migration matrix is listed in Appendix e) Table 9. Therefore, is can be considered as "low cost", since it is stable and the rebalancing can be carried out once a year.[70]

To conclude, liquidity fulfils all criteria to be an investment style and can be used as one of the indicators of asset's performance.

# *4.* Literature review: "The Liquidity Style of Mutual Funds"

Since several works have been made with the goal to indicate the relation between stock's return and its liquidity, Idzorek, Xiong and Ibbotson (IX&I) put their focus on the mutual funds and investigated the relation between performance and liquidity on fund level. In particular, they attempted to find out whether the performance of a fund is influenced by its asset's liquidities (liquidity style) among other factors.

The motivation for this study was the fact that no fund manager looks selectively for illiquid stocks for portfolio in order to increase its performance, despite the evidence of return-liquidity relationship. Idzorek et al. aimed to prevent unnecessarily excessive trade with illiquid stocks in case of existence of expected relation between liquidity and fund performance.[71]

## 4.1. Data

On the stock level the lower liquidity must be compensated by higher return[72], since investors prefer to hold liquid assets. Holding stock and holding share of a fund could differ in their liquidity derivation, as the liquidity of fund is composed of weighted single stock liquidities.

Idzorek et al. collected relevant individual stocks data base from investment analysis platform Morningstar for period 1994-2009[73] and calculated every single liquidity using turnover

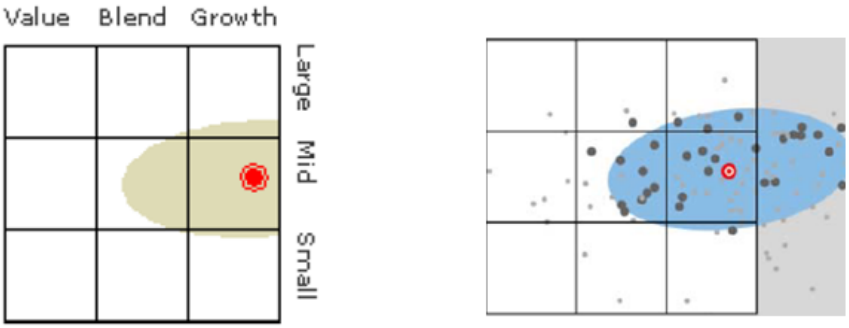
[68] Cf. Ibbotson, R. G., Chen, Z., Kim, D. Y.-J., Hu, W.J,(2012): *Liquidity as an Investment Style*, pp.5-9
[69] Approx. 63% of assets retain the same liquidity over one year, whereas only 52% have the same value characteristic and 30% momentum.
[70] Cf. Ibbotson, R. G., Chen, Z., Kim, D. Y.-J., Hu, W.J,(2012): *Liquidity as an Investment Style*, pp.10-11
[71] Cf. Idzorek, T. M., Xiong, J. X., Ibbotson, R. G. (2012): *The Liquidity Style of Mutual Funds*, p. 39
[72] The illiquidity premium is expected, but not guaranteed

measure, relation of the average daily traded shares over the last year and the number of outstanding shares. Another data set contained U.S.[74] open-end equity mutual funds over 1995-2009, their returns and holdings information throughout the same period. After the datasets were merged by stocks, the new composed data set incorporated funds' returns, funds' styles[75] and their holdings with respective liquidities.[76] The investment style which has been used within this work is described in next chapter.

## 4.2. Morningstar style box

A little attention must be devoted to Morningstar Style Box Methodology. Morningstar classifies funds into three size groups (large-cap, mid-cap and small-cap) and three valuation categories (value, blend/core or growth). The nine possible combinations of equity universe are represented by squares of Morningstar Style Box[77] as shown in Figure 8. Morningstar assign the x coordinates to valuation attribute and y coordinates to market capitalisation attributes of a stock and allocate every single stock inside of the Style box. On the left-hand side there is an example of a fund which is assigned to Growth Mid category. On the right-hand side one can see single equities assignment into the style box in an integrated system and the weighted average or "centroid" spot would be the fund itself.[78]

Figure 8 The Style Box[79]




The size style classification depends on geographic location (style zone), e.g. a stock which is classified to large-cap group in Europe could be classified to mid-cap group in the US. In general, stock's market capitalization is assigned using following approach: The largest stocks

[73] To be exact, 14 years and 11 month of U.S. and 9 years and 11 months on non-U.S. performance history, the granular data can be found in appendix g) Table 11
[74] Non-U.S. open-end mutual funds have been collected as well, but used for robustness checks.
[75] Idzorek et al. used two most common investment styles: valuation and size
[76] Cf. Idzorek, T. M., Xiong, J. X., Ibbotson, R. G. (2012): *The Liquidity Style of Mutual Funds*, p. 39
[77] Currently, an enhanced Style box with 10 categories is used which can be view in Appendix f Table 10
[78] Cf. Morningstar (2008): *Morningstar Style Box Methodology*, pp. 3-4
[79] Source: Morningstar (2008): *Morningstar Style Box Methodology*, p. 27

which make up 40% of style zone market are assigned to giant-cap, the largest remaining stocks which cumulatively account for 70% of the remaining total capitalization are assigned to large-cap. Usually, giant-cap and large cup are jointed to one group "large-cap". The next largest stocks which make up the 90% of remaining total capitalization belong to the "mid-cap" group and so on with 97% of cumulative remaining capitalization as "small-cap" and the rest as "micro-cap" which is often added to "small-cap" category.[80]

It is important to notice that valuation and growth are not represented by the same measure: Is the asset's price overvalued relative to anticipated per-share earnings, book value, revenues, cash flow and dividends, the value score is low. However, a low value score does not necessarily indicate growth equity. A high growth score is induced by a faster growth of per-share earnings, book value, revenues, cash flow relative to peer group. Both attributes can be combined and classified depending on the dominance to category accordingly. And if both characteristics have similar score, the equity is assigned to "core" style. For funds the nomenclature "blend" is used. The score for valuation and growth encompass both, the historic data and anticipated future data which equally contribute to the total score.[81]

The main purpose of Morningstar Style Box is the categorization and tracking of investment styles which should enable, simplify and accelerate the investment analysis and decision. The authors aimed to achieve two main objectives by adding funds style information to the data set. Firstly, the control for investment style on granular level and, secondly, the analysis of fund's performance relative to peer group average of category which is essential basis for manager's remuneration.[82]

## 4.3. Approach

Weighting single stock's liquidity with its percentage share on fund and to sum up all weighted liquidity of other constituent equities, the total fund's liquidity can be calculated. The liquidity calculation, rebalancing, is carried out monthly. Idzorek et al. ranked as next the funds on their liquidity within style classes and divided them into 5 equal groups. The group "L1" contained funds with lowest weighted-average liquidity, quintile "L2" comprised the next lowest weighted-average liquidity and so on until the more liquid funds were assigned to "L5".[83]

[80] Cf. Morningstar (2008): *Morningstar Style Box Methodology*, p. 10
[81] Cf. Morningstar (2008): *Morningstar Style Box Methodology*, p. 5-6
[82] Cf. Idzorek, T. M., Xiong, J. X., Ibbotson, R. G. (2012): *The Liquidity Style of Mutual Funds*, p. 39
[83] Cf. Idzorek, T. M., Xiong, J. X., Ibbotson, R. G. (2012): *The Liquidity Style of Mutual Funds*, p. 40

Following measures have been used to analyse the group's liquidity and performance relation: return's geometric mean of each group, arithmetic mean, standard deviation, Sharpe ratio, annualized alpha relative to category average, *t*-Statistic of alpha relative to category average, annualized alpha relative to Fama-French factors and *t*-Statistic of alpha relative to Fama-French factors.[84]

The arithmetic mean assumes the independence of returns within the group, whereas the geometric mean which denotes the typical value or central tendency is considered to be more appropriate and accurate in the finance world. In order to have a comprehensive analysis, both means are calculated and shown in the table.[85] Both, the a*rithmetic* $\mu^{arith} = \frac{1}{N}\sum_{n=1}^{N} x_n$ and the *geometric mean* $\mu^{geom} = (\prod_{n=1}^{N} x_n)^{1/N}$ are used to compare the average performance between all five groups.

*Standard deviation* is used to show how scattered are fund's returns within the group:

$$SD = \sqrt{\frac{1}{N}\sum_{n=1}^{N}(x_n - \mu)^2} \tag{24}$$

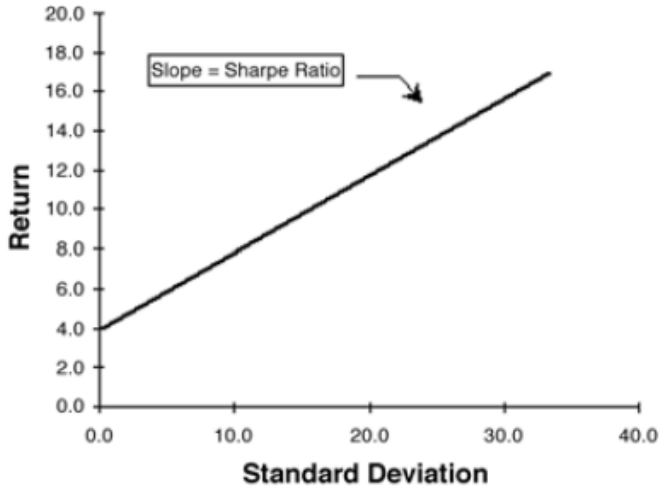
To make the liquidity quintiles more comparable among each other under risk consideration, the Sharpe ratio is used. It displays the risk/return efficiency of an asset. Different from simple risk adjusted measure, Sharpe argued that each risk-free return exceedance is connected to risk. Therefore, it measures the spread between equity's return and risk-free return, the excess return, in relation to its standard deviation. Dividing excess return by its annualized standard deviation enable to normalize and compare assets. It is also called the reward to variability ratio and calculated as follows:

$$Sharpe\ ratio = \frac{\mu - r_f}{SD \times \sqrt{N}} \tag{25}$$

Graphically, Sharpe ratio is represented by the slope of Capital Market Line as shown on the Figure 9.

[84] Cf. Idzorek, T. M., Xiong, J. X., Ibbotson, R. G. (2012): *The Liquidity Style of Mutual Funds*, pp. 41-43
[85] Cf. Investopedia.com (2015d): *What is the difference between arithmetic and geometric averages?*, retrieved from http://www.investopedia.com/ask/answers/06/geometricmean.asp

Figure 9 Capital Market Line and Sharpe Ratio[86]




The absolute term does not provide any information and they must be considered in relation to other assets/funds. A negative Sharpe Ratio indicates an underperformance of the equity with risk-free asset.[87]

The *annualized alpha relative to category average* is derived from a single factor regression of total returns of each fund against the total returns of the group average. The group average composite are equally weighted returns of all funds of a certain category through the time.

$$r_{Li} = \alpha + \beta \times r_{Benchmark} \tag{26}$$

The alpha exhibits the part of composite return which is not captured by the category-average composite, composite-specific liquidity premium. The statistical significance of the alpha is examined at 95% confidence level. T-statistic greater than 1.96 indicates a significant alpha.[88] As the regression involves monthly returns, the resulting alpha is annualized accordingly:

$$\alpha^{annual} = (1 + \alpha^{monthly})^{12} - 1 \tag{27}$$

And the last measure used for this analysis is the *annualized alpha relative to Fama-French factors.* It is derived using multiple regression of L-group excess-return[89] against the excess market return, Small Minus Large (SML) and High Minus Low (HML). A positive and statistically significant alpha would mean a return not being fully explained by the ubiquitous fac-

[86] Source: Feibel, B. J.(2003): *Investment Performance Measurement*, p. 186
[87] Cf. Feibel, B. J.(2003): *Investment Performance Measurement*, pp. 185-1891
[88] Cf. Idzorek, T. M., Xiong, J. X., Ibbotson, R. G. (2012): *The Liquidity Style of Mutual Funds*, p. 40
[89] Authors use T-Bill return as the risk-free return

tors. Like the alpha from univariate regression, the significance check is represented by t-statistics. Idzorek et al. controlled for styles size and valuation twice, as categories and as Fama-French based regression.[90]

## 4.4. Results

Detailed results of Idzorek, Xiong and Ibbotson's analysis can be seen in appendix h, Table 12. The table consist of 16 groups: small value, small core, small growth, mid value, mid core, mid growth, large value, large core, large growth, small, mid, large, growth, core, value and all. Each class incorporate above mentioned measures for all 5 L-groups, the category average and the difference between the L1 (lowest-liquidity quintile) and L5 ( the highest-quintile).

The most striking result is that in almost all categories the highest mean of return is in the L1 group which has the lowest liquidity. One can notice, that the returns and Sharpe ratio decrease throughout the groups with increasing liquidity. Another interesting finding is that the standard deviation is the smallest in the lowest-liquidity group and increases monotonically with the liquidity. The annualized alpha against category's composite average and the three Fama-French factors are also superior in the L1 group, which indicates a higher liquidity premium. The alpha is also statistically dominant at 95% confidence level, since t-statistic in majority of cases[91] exceeds 1.96 for L1 group. Another significant alpha can be detected in the difference between L1 and L5 for 11 of the 16 categories.[92]

Idzorek et al. draw the attention on the fact, that in all categories the alpha versus the categories-average composite for the differential between highest and lowest liquidity groups is higher than the geometric mean of this differential. The same relation holds for the majority of categories for alpha versus Fama-French[93] factors. This points out the lower standard deviation and a lower beta of L1 composite in comparison to the L5 group, the liquidity risk. Taking a closer look at alpha versus category average composite of the L1 and L5 differential, it becomes obvious which categories have a larger liquidity premium and are, therefore, more liquid. Small category depicts the largest difference in the amount of 727 bps and the large core category has the smallest difference of 274 bps. For the Fama-French factors regression the biggest alpha of L1-L5 was in the Small class (437 bps) and the smallest in the large growth (246 bps). Similar results provided studies done by Ibbotson et al (2012) using differ-

[90] Cf. Idzorek, T. M., Xiong, J. X., Ibbotson, R. G. (2012): *The Liquidity Style of Mutual Funds*, p. 40
[91] Except for growth category in univariate regression and seven categories in multifactorial regression (t-ststst<2.0)
[92] Cf. Idzorek, T. M., Xiong, J. X., Ibbotson, R. G. (2012): *The Liquidity Style of Mutual Funds*, p. 44
[93] To be exact it holds for 13 of 16 categories

ent data set. Regardless on the categories the overall results shown in Table 1 depict the same relation:

Table 1 Liquidity composites of total U.S. fund universe[94]

| | Geometric Mean (%) | Arithmetic Mean (%) | Standard Deviation (%) | Sharpe Ratio | Annualized Alpha Relative to Category Average (%) | *t*-Statistic of Alpha Relative to Category Average | Annualized Alpha Relative to Fama–French Factors (%) | *t*-Statistic of Alpha Relative to Fama–French Factors |
|---|---|---|---|---|---|---|---|---|
| All L1 | 9.09 | 10.16 | 15.25 | 0.43 | 2.95 | 2.04 | 2.18 | 2.44 |
| All L2 | 7.98 | 9.24 | 16.56 | 0.35 | 1.07 | 1.04 | 0.89 | 1.44 |
| All L3 | 7.15 | 8.58 | 17.58 | 0.29 | –0.29 | –0.54 | –0.18 | –0.30 |
| All L4 | 7.58 | 9.44 | 20.16 | 0.29 | –0.66 | –1.07 | –0.19 | –0.25 |
| All L5 | 6.44 | 9.22 | 24.83 | 0.23 | –2.54 | –1.37 | –1.43 | –1.16 |
| All average | 7.80 | 9.33 | 18.20 | 0.32 | — | — | 0.16 | 0.29 |
| L1 – L5 | 2.65 | 0.94 | –9.58 | 0.21 | 5.62 | 2.36 | 3.65 | 2.16 |

Here the means and Sharpe ratio for L1 is superior and decreases almost monotonically with liquidity. The standard deviation for less liquid funds is lower on average and increases with liquidity. Alpha which stands for liquidity premium is also positive and significant for the L1 composite and lower and insignificant in other groups.[95]

In order to make the results clearer and controlling for investment style, Idzorek et al. summarized the important liquidity performance results and illustrated them as a Style box (see Table 2). The numbers in each quadrate stands for annual geometric return. The upper number represents L1, the middle number is category's average, the lowest number represents L5 and the bold stands for L1-L5 geometric return. It is apparent that the highest difference liquidity premium between low liquidity funds and high liquidity funds are in the mid-size and small-size and value categories. The Value minus Growth value for large category amounts 0.67, for mid category 1.35 and for small 2.14.Values for small minus large in different categories can be seen below the table in bold.[96]

[94] Source: Idzorek, T. M., Xiong, J. X., Ibbotson, R. G. (2012): *The Liquidity Style of Mutual Funds*, 43
[95] Cf. Idzorek, T. M., Xiong, J. X., Ibbotson, R. G. (2012): *The Liquidity Style of Mutual Funds*, p. 44
[96] Cf. Idzorek, T. M., Xiong, J. X., Ibbotson, R. G. (2012): *The Liquidity Style of Mutual Funds*, p. 45

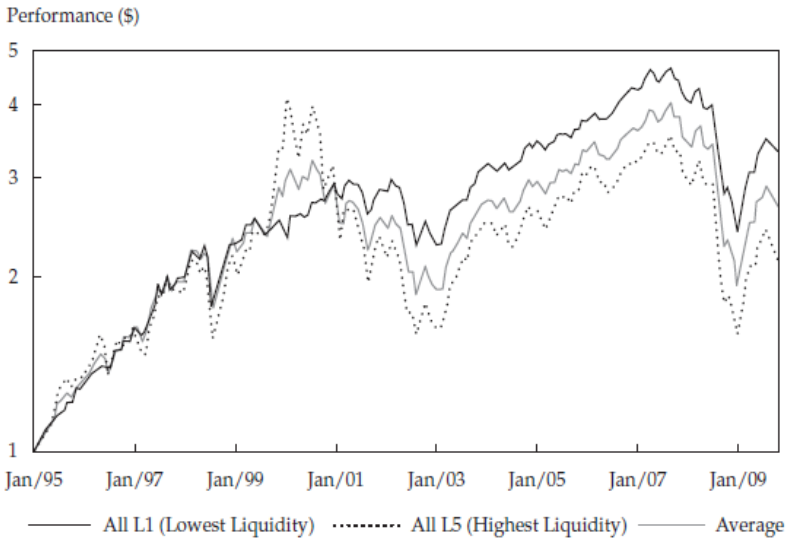
Table 2 Style Box Liquidity Performance[97]

| | Value | Core | Growth | Value minus Growth |
|---|---|---|---|---|
| | ← Valuation Spectrum → | | | |
| Large | 8.44 | 7.95 | 7.61 | |
| | 7.35 | 6.86 | 6.68 | 0.67 |
| | 6.11 | 6.30 | 5.87 | |
| | **2.33** | **1.65** | **1.75** | |
| Mid (Size Spectrum) | 11.06 | 10.66 | 9.82 | |
| | 9.73 | 9.61 | 8.38 | 1.35 |
| | 7.81 | 7.47 | 6.63 | |
| | **3.25** | **3.19** | **3.18** | |
| Small | 10.86 | 11.25 | 9.26 | |
| | 9.91 | 9.29 | 7.77 | 2.14 |
| | 8.09 | 7.94 | 6.26 | |
| | **2.77** | **3.32** | **3.00** | |
| **Small minus Large** | **2.56** | **2.43** | **1.09** | |

L1 Compound Return
Style Square's Compound Return
L5 Compound Return
**L1 – L5**

Another interesting finding has been gained from time series analysis of liquidity quintiles L1 to L5. Figure 10 illustrates the performance development of L1, L5 and average liquidity composites beginning with $1 over February 1995-December 2009.[98]

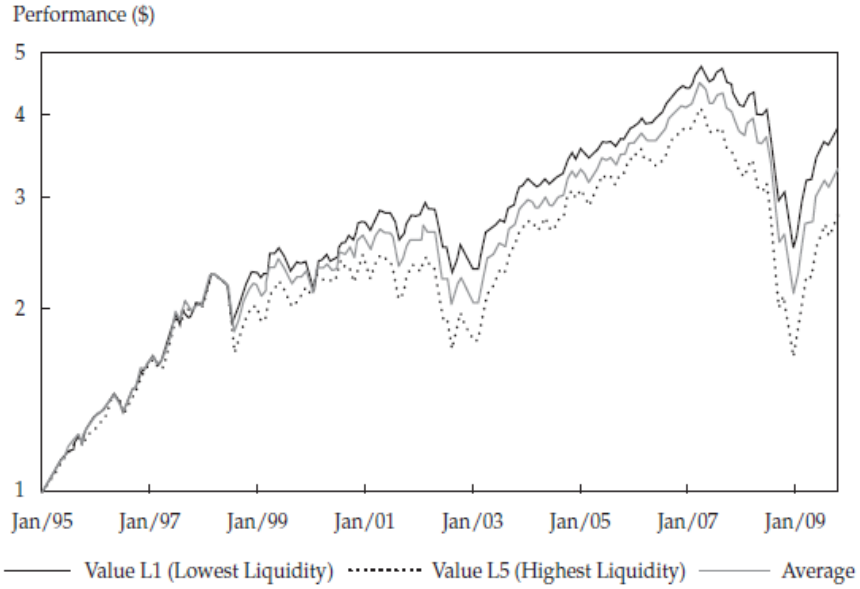
Figure 10 Performance development (of $1) over time[99]




[97] Source: Idzorek, T. M., Xiong, J. X., Ibbotson, R. G. (2012): *The Liquidity Style of Mutual Funds*, p. 45
[98] Cf. Idzorek, T. M., Xiong, J. X., Ibbotson, R. G. (2012): *The Liquidity Style of Mutual Funds*, pp. 44-45
[99] Source: Idzorek, T. M., Xiong, J. X., Ibbotson, R. G. (2012): *The Liquidity Style of Mutual Funds*, p. 45

The evidence is obvious that L1 outperformed L5 and the average returns most of the time. The period where the more liquid composite outperforms is explained by the excessive demand for liquid stocks in growth category (see Figure 11) during the technology bubble or dotcom bubble 1997-2000. The overinvestment in companies which focus primarily on the internet-based business, such as boo.com, Books-a-Million and broadcast.com, implies growth category investment. Therefore, this phenomenon was not prevailing in the value category, since value equity investors don't invest in technology stocks.[100]

Figure 11 Value Liquidity Quintile Performance[101]




Investors primarily buy stocks with high fundamentals and traded at bargain price. These are due to miscalculation or other errors undervalued assets which are expected to gain their true value soon.[102]

Contemplating the return behaviour of quintiles in up- and downmarket, the dependency on stock's liquidity was noticeable. Lou and Sadka (2011) acquired as result of their researches that price drop of stocks with higher liquidity level greater than of stocks with lower liquidity level during the financial crises 2008. The reason is the correlation between liquidity level and liquidity risk. More liquid stocks have higher $\beta^{Liq}$ sensitivity to market liquidity change and the price reaction is stronger.[103] These results were verified by Idzorek et al. in their studies when they examined the composites on the up-and down-market captures which evaluates the

[100] Cf. Idzorek, T. M., Xiong, J. X., Ibbotson, R. G. (2012): *The Liquidity Style of Mutual Funds*, p. 44
[101] Idzorek, T. M., Xiong, J. X., Ibbotson, R. G. (2012): *The Liquidity Style of Mutual Funds*, p. 46
[102] Cf. Investopedia.com (2016e):*Stock-Picking Strategies: Value Investing*, retrieved from http://www.investopedia.com/university/stockpicking/stockpicking3.asp
[103] Cf. Lou, X, Sadka, R (2011): *Liquidity Level or Liquidity Risk? Evidence from the Financial Crisis*, p. 56

fund's performance relative to the market's performance[104] on the up- market or down-market. There is an upmarket when the market index performance moves upward and the downward movements are referred to as down-market. Table 3 summarizes monthly statistics of the quintiles performance during the period February 1995 and December 2009:

Table 3 Monthly Up- and Down-Market Capture Statistics[105]

| | Up Periods | Down Periods | Average Up-Market Return | Average Down-Market Return | Up-Market Capture | Down-Market Capture | Up-Market/Down-Market Capture Ratio | Loss from Apr. 2000 to Dec. 2001 | Loss from Sep. 2008 to Feb. 2009 |
|---|---|---|---|---|---|---|---|---|---|
| All L1 | 117 | 62 | 3.03% | –3.09% | 86.31 | 75.93 | 1.14 | 11.0% | –40.3% |
| All L2 | 112 | 67 | 3.3 | –3.75 | 93.91 | 91.88 | 1.02 | –5.9 | –42.3 |
| All L3 | 109 | 70 | 3.47 | –4.19 | 98.73 | 102.57 | 0.96 | –17.4 | –43.5 |
| All L4 | 107 | 72 | 3.89 | –4.75 | 110.45 | 116.32 | 0.95 | –24.5 | –43.5 |
| All L5 | 106 | 73 | 4.37 | –5.63 | 123.01 | 138.71 | 0.89 | –39.6 | –45.1 |
| All average | 109 | 70 | 3.61 | –4.28 | 102.78 | 104.85 | 0.98 | –17.7 | –42.8 |

The Up and Down periods columns indicate the number of days with positive and negative market index performance during the mentioned above period. It is evident that the Down-Market capture for composites with high liquidity is greater than 100 which implies a higher sensitivity compared to the market. It is important to notice that in the up-market, the capture of L4 and L5 is also higher than 100. The Up-Market/Down-Market Capture Ratio shows the relation between the both captures. If it is greater than 1, the composite's performance reacts stronger in up-markets than in down-markets and vice versa. As it can be seen on the able, less liquid composites are more sensitive in up markets, whereas liquid equities have a stronger performance reaction in the down markets. This might seem to be odd at the first glance, but the authors explain this phenomenon with high holdings turnover of liquid stocks. Investment strategy of managers who buy primarily liquid stocks is often based on frequent trading. Indeed, looking on the turnover statistics, the assumption could be confirmed by 59% average annual holding turnover for L1 quintile and 124% for L5 (for detailed results see Table 13 in Appendix i).[106]

The most interesting down-market periods are 2000-2001, recession after the dot-com bubble busted, and 2008-2009, the financial crisis. Comparing the L-groups one can see that more liquid quintiles suffered greater loss. Moreover, after the technology bubble, L1 quintile exhibited gains and not losses. This phenomenon can be explained with higher demand on tech-

[104] In this case as index the Russell 3000 Index is used
[105] Source: Idzorek, T. M., Xiong, J. X., Ibbotson, R. G. (2012): *The Liquidity Style of Mutual Funds*, p. 47
[106] Cf. Idzorek, T. M., Xiong, J. X., Ibbotson, R. G. (2012): *The Liquidity Style of Mutual Funds*, pp. 46-47

nology-business stocks which makes them more liquid and other stocks which are not related to internet lost the liquidity and were hardly affected by bubble burst.

The negative relation between fund's liquidity and performance seems to be evident and statistically partial significant for chosen data set. In order to check the robustness of results, Idzorek et al. changed several settings successively and compared the results. In the next chapter these tests will be introduced.

## 4.5. Robustness Checks

The first test examines whether data implemented with one quarter delay changes the results significantly. The not subdivided in styles results can be view in Table 14 Appendix j. The outcome, again, proves the assumption of negative relationship between liquidity and performance. Although, the number of observation has been reduced, the t-statistics of both alphas in L1 group still remains significant and even greater. Furthermore, the difference between L1 and L5 has also increased, but this finding was not commented by authors.[107]

Another test incorporated annual rebalancing of composites. In the principal analysis authors rebalance monthly in order to have more accurate results. As the robustness and stability of the liquidity has been already mentioned in previous chapters, the rebalancing composites should lead to the same results. Indeed, in the average 70% of the funds didn't migrate to any other liquidity group in the subsequent months. As expected, the results don't show any remarkable differences to the main results (see Table 15 in Appendix k): again the less liquid composites show a better performance. However, the t-statistic of alpha against the category average is smaller than (but close to) the critical value.[108]

As next, a different liquidity definition, the Amihud measure, has been used in order to proof the robustness of relation. As described in the liquidity chapters, its simplicity and data availability makes it to another popular liquidity indicator. Idzorek et al. used formula (4) to calculate the liquidity level[109] for each stock and add up the weighted the stock's liquidities in order to obtain fund's liquidity level. The remaining analysis is the same as described in previous chapters. Only stocks with non-missing data for at least 10 days have been considered in the analysis. It is important to note that in turnover rate measure both, numerator and denominator, included fund's size (volume) and were, thus, adjusted for market capitalization. In the Amihud measure, in contrast, only denominator contains fund's volume, but not the numera-

[107] Cf. Idzorek, T. M., Xiong, J. X., Ibbotson, R. G. (2012): *The Liquidity Style of Mutual Funds*, p. 48
[108] Cf. Idzorek, T. M., Xiong, J. X., Ibbotson, R. G. (2012): *The Liquidity Style of Mutual Funds*, pp. 48-49
[109] Note that Amihud approach measures illiquidity, therefore, the lower is the measure the higher the liquidity and vice versa. It must be noted by assigning funds to liquidity quintiles.

tor. The measure will be, therefore, affected by the fund's size. Therefore, considering the fact that less liquid funds hold mainly small size stocks, a large standard deviation is expected. As it can be seen in the resulting Table 16 in appendix l, the less liquid quantiles have, indeed, a larger scatter. The rest correspond with the previous results, besides the t-statistics which are much lower that the critical value and point out that alpha might not be significant. This shows how different the measures are, however, the main result is still consistent.[110]

The last test was carried out with non U.S. mutual funds universe. Due to large number of missing holdings information the data set was relative small and covered period from February 1995 to February 2000 (see Table 17 in appendix m). Surprisingly, the geometric mean of returns is smaller than even geometric mean of L3 composites and the arithmetic mean does not exceed the arithmetic mean of L2 returns. Despite this fact, the rest means of return decrease monotonically with increasing liquidity level. No relation or monotonicity could be ascertained in standard deviation. The highest volatility showed L5 composite followed by L1 composite. The authors used turnover measure and a high volatility in L1 cannot be explained with small-cap stocks. Sharpe ratio shows the same behaviour as arithmetic mean, there is monotonic decline from L2 to L5, but L1 is lower than L2. The alpha versus category's average and Fama-French factors show neither ordered relation nor significance. L5 holds the highest alpha versus Fama-French factors and the second lowest alpha is in L1. The t-statistics for L1 groups are extremely small. These findings contradict all previous analysis made with U.S. mutual funds universe and authors don't provide any explanation for this outcome. It might be, however, explained by small sample which could be collected due to not available information.[111]

## 4.6. Conclusion

The overall results for U.S mutual funds universe confirm the assumption that fund which holds less liquid stocks outperforms the peer with more liquid stocks. Even varying analysis characteristics in order to check the robustness of the outcome, the premise could be proved.

Especially, during the down-market less liquid funds outperformed the liquid funds considerably. This phenomenon could be explained by holding less liquid stocks manager don't have propensity to trade them. Therefore, trading more liquid stock during the down-market leads to steeper decline in their performance and to larger losses. A deviated conclusion could be made after testing the same assumption with non U.S. mutual funds. No monotonic perfor-

[110] Cf. Idzorek, T. M., Xiong, J. X., Ibbotson, R. G. (2012): *The Liquidity Style of Mutual Funds*, p. 50
[111] Cf. Idzorek, T. M., Xiong, J. X., Ibbotson, R. G. (2012): *The Liquidity Style of Mutual Funds*, pp. 51-52

mance behavior throughout the L-groups could be established. This outcome can be attributed to small sample which could be obtained due to the lack of availability of large data set.[112]
Controlling twice for valuation and size, the authors omitted another common style, the momentum. This analysis is captured by the study of Idzorek, Xiong and Ibbotson in their working paper "Combining Liquidity and Momentum to Pick Top-Performing Mutual Funds". Following similar approach, but using momentum instead of liquidity, they found out that high-momentum composite's arithmetic and geometric means, Sharpe ratio and alpha versus category's average outperform other quintiles. They also combined momentum with liquidity and could and came to the same conclusion. Therefore, controlling for all existing styles, liquidity remains significant performance determinant.[113]

# 5. Empirical part

In the practical part of this work the UK open-end mutual funds will be analysed. Since the non-U.S. results from Idzorek et al. were not consistent with the U.S. results, the new analysis will be carried out. However, this research will focus not on the composition of several different markets, but only one market. Therewith we want to exclude heterogeneity of country-specifics and it is simpler to extract stocks data set from one market. The goal of this work is to test whether this liquidity return relation is valid for the UK market, the largest fund market in the European Union. In the next chapter the data set and its extraction will be introduced.

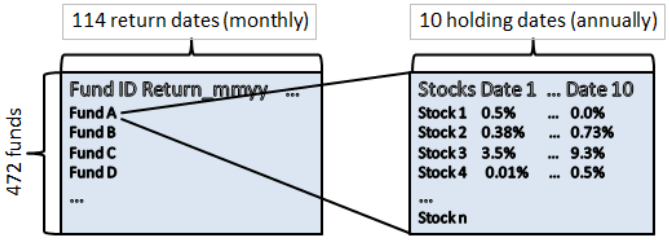
## 5.1. Data

As already mentioned the focus of this work is placed on the UK market. The UK mutual funds form the largest mutual funds universe among European markets and has been chosen for sample size reasons. As in Idzorek et al.'s work, two datasets have been extracted: the equity mutual funds with UK as primary investment area and the UK stock data sets.
The mutual funds data set has been extracted from Morningstar Direct, cloud-based investment analysis platform. After applying filter regarding investment area and investment type (equity) and removing duplicates a dataset with 472 funds has been formed. For each fund the historical holdings data set must be extracted separately. Therefore, as shown in Figure 12 472 data sets with historical holding have been retrieved. As the oldest available holdings can be traced back to 10 years which means our analysis data will cover the period of 10 years,

[112] Idzorek, T. M., Xiong, J. X., Ibbotson, R. G. (2012): *The Liquidity Style of Mutual Funds*, p. 52
[113] Cf. Idzorek, T., Xiong, J. X., Ibbotson, G. (2011): *Combining Liquidity and Momentum to Pick Top-Performing Mutual Funds*, retrieved from https://www.researchgate.net/publication/267366002_Combining_Liquidity_and_Momentum_to_Pick_Top-Performing_Mutual_Funds

from January 2007 to May 2016. This is a very short period 9 years and 6 months is a little shorter than in analysis of Idzorek et al. and the sample size might not be large enough to represent the population. For this reason, the results might be similar to non-U.S. dataset results in Idzorek et al (2012).

Figure 12 Fund's data and holdings[114]




As next the funds data (historical monthly returns, size style, valuation style, FundID) is to be merged with all holdings tables.

The UK stock information has been retrieved from Thomson Reuters Datastream, a database with financial and macroeconomic information. Due to liquidity stability, we can assume that only small part of stocks will migrate to other liquidity group and we can rebalance annually. As in Idzorek et al. the turnover measure is used as liquidity proxy. Therefore, annual trading volume and number of stocks outstanding must be extracted. Note, that the turnover rate of the previous year is needed to represent the liquidity of the subsequent year. Therefore, the liquidity data from January 2006 to December 2015 is to be obtained. After calculating liquidity both, stocks' liquidity and funds data sets have been merged by stock ticker and as output a table with UK mutual funds, returns, styles, fund's holdings and liquidity of fund's holdings has been obtained. The funds have been sorted on their liquidity and have been divided into 5 equal groups L1 (lowest liquidity quintile) to L5 (highest liquidity quintile) generally and within various style categories. The analysis has been carried out using SAS Enterprise Guide 7.1 statistic software. And the SAS macro for assigning composite can be seen in Appendix m. As in Idzorek et al., the funds with missing liquidity for more than 40% of its holding have been removed from the data set and the resulting number of fuds has become 461. Also funds with missing return information during observation period have been eliminated. After this step the data used for further analysis has been reduced and the final data set size is represented in Table 4. It is evident that large value funds account for the biggest part in the UK mutual funds universe, whereas small value poses the smallest amount of funds. We can assume that

[114] Source: own illustration

regardless of fund's valuation characteristic, investors prefer to invest in large UK funds. However, as many funds have been removed due to the lack of liquidity or return information, we cannot entirely rely on the representativeness of this sample.

Table 4 Number of Mutual Funds with Required Data[115]

| Morningstar Category | Start Date No. of Funds (January 2007) | End Date No. of Funds (May 2007) |
|---|---|---|
| Small Value | 4 | 7 |
| Small Blend | 12 | 19 |
| Small Growth | 30 | 40 |
| Mid Value | 15 | 29 |
| Mid Blend | 23 | 31 |
| Mid Growth | 17 | 24 |
| Large Value | 111 | 161 |
| Large Blend | 73 | 118 |
| Large Growth | 13 | 20 |
| Small | 46 | 66 |
| Mid | 55 | 84 |
| Large | 197 | 299 |
| Value | 130 | 197 |
| Blend | 108 | 168 |
| Growth | 60 | 84 |
| All | 298 | 449 |

As next, the same investigation as in Idzorek et al. has been carried out, calculating geometric and arithmetic means, standard deviation, Sharpe ration, alpha against category average and against Fama-French factors and corresponding t-statistics. The results will be presented in the following chapter

## 5.2. Results

Joining UK mutual funds with UK stocks data set, non-UK stocks were ignored. Although, funds invest heavily in UK area, there might be some ignored non-UK stocks the absence of which in the analysis could lead to wrong liquidity quintile assignment. Neglecting some stocks in liquidity data set which, however, are captured by fund's return could lead to discrepancies and wrong results. The number of non-UK stock is assumed to be very small and should have no large impact, unless the stock's liquidity is too high or too low and could change the fund's liquidity level significantly. As in primary literature, the calculated alphas have been annualized using the formula (27). For calculation of alpha versus Fama-French

[115] Source: own calculation, data retrieved from Morningstar Direct and Data Stream

Factors, European three Fama-French factors from 2007 to 2016 have been used.[116] Following results reported in Table 5 have been obtained by carrying out the analysis described by Idzorek et al. Comparing analysis of UK funds with US funds results, two interesting evidences can be noted:

First, there is no obvious relation between smaller liquidity and higher return. In any categories L1 composite does not outperform other quintiles, neither in return means nor in alphas.[117] There is also no monotonicity in performance evident within any of categories. In the largest category "large value" the L2 quintile is superior to the others in almost all measures, whereas in second largest group, "large blend", the less liquid composite L5 exhibits the best performance. Looking at the rougher segmentation, the middle liquidity composite, L2, L3 or L4, outperform and there is no relation in valuation categories traceable. A higher attention must be paid on the size categories. In Large category, which is over-represented, L2 quintile is superior, whereas in Small category a more liquid from "middle" composites, L4 outperforms. In the overall analysis different quintiles show the top results in different measures.[118]

It is also interesting that the standard deviation does not change significantly for any of composites and varies between 4.64 and 7.18. This fact is also reflected by the alphas differentials between the lowest and the highest liquidity quintiles. In contrast to U.S. mutual funds universe, where all L1-L5 alpha versus category's average exceeds the L1-L5 geometric mean in each category, only in 6 categories out of 16 it is the case in UK mutual funds universe. Regarding differential alpha versus Fama-French Factors, it is greater in only one case analysing UK funds, whereas U.S. funds exhibit a larger number 13.

Another striking result is the low level of returns comparing to US data. This can be explained by a large number of negative stocks' returns, especially during the financial crisis. The average return throughout the analysed funds is shown in Figure 13.

Emphasizing on overall results, it can be seen that the highest average returns are offered by middle liquidity composites, L2 and L3. Geometric (as well as arithmetic) mean of highest liquidity and lowest liquidity composites amount 0.24% and 0.20% (0.27% and 0.32%) respectively and are lower than the average 0.20% (0.34). Similar situation can be seen in Sharpe Ratio results. Surprisingly, the highest standard deviation is shown by L1 composite.

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[116] Monthly European Fama-French factors have been retrieved from: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html. Publicly available UK Fama-French factors were not complete to be used for analysis data.

[117] Exceptions are the smallest standard deviations in Small Value and Large Blend categories exhibited by L1. But since these groups have different sizes and no common characteristics, this observation cannot be explained by any fund's features/characteristics.

[118] L2 and L3 have a greater geometric mean, L2 exhibits the greatest arithmetic mean, L4 has the smallest standard deviation, L2& L3 outperform in Sharpe Ratio measure and L2 shows the greatest alphas.

Table 5 Mutual Fund Liquidity Quintiles, UK Equity Universe, January 2007- Mai 2016[119]

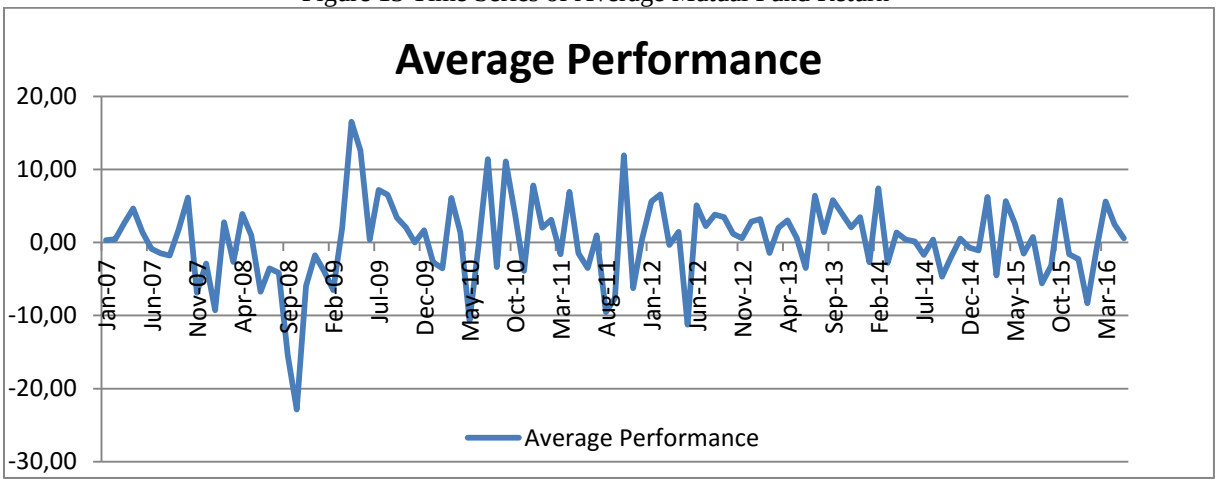
| | Geometric Mean (%) | Arithmetic Mean (%) | Standard Deviation (%) | Sharpe Ratio | Annualized Alpha Relative to Category Average (%) | *t*-Statistic of Alpha Relative to Category Average | Annualized Alpha Relative to Fama-French Factors (%) | *t*-Statistic of Alpha Relative to Fama-French Factors |
|---|---|---|---|---|---|---|---|---|
| Small Value L1 | 0,29 | 0,46 | 5,16 | 0,08 | -0,96 | -1,09 | -0,99 | -0,94 |
| Small Value L2 | 0,12 | 0,32 | 6,23 | 0,04 | -0,59 | -0,45 | -0,87 | -0,72 |
| Small Value L3 | 0,23 | 0,45 | 6,53 | 0,06 | 0,42 | 0,22 | -0,39 | -0,25 |
| Small Value L4 | 0,23 | 0,50 | 6,97 | 0,06 | 2,53 | 0,68 | 3,73 | 0,54 |
| Small Value L5 | 0,48 | 0,76 | 6,63 | 0,11 | 18,65 | 1,50 | 11,08 | 0,69 |
| Small Value Average | 0,21 | 0,39 | -0,92 | -0,36 | - | - | -0,71 | -0,47 |
| L1-L5 | -0,77 | -0,92 | 3,27 | -0,30 | -1,00 | 0,34 | -1,00 | -2,13 |
| | | | | | | | | |
| Small Blend L1 | 0,36 | 0,61 | 6,91 | 0,08 | -0,20 | -0,13 | 0,16 | 0,04 |
| Small Blend L2 | 0,45 | 0,70 | 6,92 | 0,09 | 0,97 | 0,61 | 4,15 | 0,55 |
| Small Blend L3 | 0,33 | 0,54 | 6,37 | 0,07 | -0,41 | -0,39 | 0,13 | 0,05 |
| Small Blend L4 | 0,45 | 0,66 | 6,37 | 0,09 | 1,34 | 0,76 | 3,98 | 0,66 |
| Small Blend L5 | 0,31 | 0,55 | 6,80 | 0,07 | -0,59 | -0,64 | 0,17 | 0,06 |
| Small Blend Average | 0,39 | 0,61 | 6,58 | 0,08 | - | - | 1,13 | 0,30 |
| L1-L5 | 0,04 | 0,06 | 2,12 | 0,00 | 0,86 | 0,25 | -0,58 | -0,34 |
| | | | | | | | | |
| Small Growth L1 | 0,46 | 0,67 | 6,49 | 0,09 | -0,56 | -0,73 | 1,91 | 0,37 |
| Small Growth L2 | 0,43 | 0,64 | 6,46 | 0,09 | -0,71 | -1,75 | 1,43 | 0,35 |
| Small Growth L3 | 0,44 | 0,64 | 6,20 | 0,09 | -0,59 | -1,13 | 2,61 | 0,53 |
| Small Growth L4 | 0,59 | 0,79 | 6,18 | 0,12 | 1,55 | 1,25 | 14,12 | 1,19 |
| Small Growth L5 | 0,65 | 0,83 | 5,93 | 0,13 | 4,51 | 2,02 | 17,92 | 1,30 |
| Small Growth Average | 0,51 | 0,71 | 6,21 | 0,10 | - | - | 5,12 | 0,77 |
| L1-L5 | -0,17 | -0,16 | 1,42 | -0,16 | -0,95 | -1,65 | -0,97 | -1,84 |
| | | | | | | | | |
| Mid Value L1 | 0,16 | 0,34 | 5,90 | 0,05 | -0,57 | -0,92 | -0,80 | -0,73 |
| Mid Value L2 | 0,22 | 0,39 | 5,87 | 0,06 | -0,20 | -0,27 | -0,07 | -0,03 |
| Mid Value L3 | 0,33 | 0,59 | 7,18 | 0,07 | 1,85 | 1,12 | 2,37 | 0,46 |
| Mid Value L4 | 0,24 | 0,42 | 5,96 | 0,06 | 0,06 | 0,08 | -0,31 | -0,18 |
| Mid Value L5 | -0,04 | -0,12 | 5,03 | -0,04 | -0,32 | -0,16 | -1,00 | -1,09 |
| Mid Value Average | 0,24 | 0,43 | -24,23 | -0,02 | - | - | -0,17 | -0,08 |
| L1-L5 | 0,01 | 0,07 | -2,98 | 0,00 | 0,96 | 0,18 | -0,08 | -0,02 |
| | | | | | | | | |
| Mid Blend L1 | 0,17 | 0,37 | 6,22 | 0,05 | -0,75 | -1,24 | -0,89 | -0,88 |
| Mid Blend L2 | 0,24 | 0,43 | 6,01 | 0,06 | -0,31 | -0,43 | -0,57 | -0,40 |
| Mid Blend L3 | 0,38 | 0,58 | 6,33 | 0,08 | 2,08 | 1,47 | 0,69 | 0,24 |
| Mid Blend L4 | 0,26 | 0,44 | 5,95 | 0,06 | -0,13 | -0,21 | -0,39 | -0,21 |
| Mid Blend L5 | 0,33 | 0,53 | 6,23 | 0,07 | 0,84 | 0,67 | 0,76 | 0,24 |
| Mid Blend Average | 0,28 | 0,47 | 6,10 | 0,07 | - | - | -0,36 | -0,21 |
| L1-L5 | -0,17 | -0,16 | 1,42 | -0,16 | -0,88 | -1,12 | -0,98 | -2,00 |
| | | | | | | | | |
| Mid Growth L1 | 0,30 | 0,51 | 6,28 | 0,07 | -0,49 | -0,55 | -0,29 | -0,13 |
| Mid Growth L2 | 0,47 | 0,65 | 5,92 | 0,10 | 3,08 | 1,38 | 4,50 | 0,85 |
| Mid Growth L3 | 0,50 | 0,70 | 6,26 | 0,10 | 3,90 | 1,24 | 4,83 | 0,70 |
| Mid Growth L4 | 0,15 | 0,33 | 5,96 | 0,04 | -0,93 | -2,24 | -0,84 | -0,72 |
| Mid Growth L5 | 0,34 | 0,52 | 5,93 | 0,08 | -0,10 | -0,09 | 0,07 | 0,03 |
| Mid Growth Average | 0,36 | 0,54 | 5,99 | 0,08 | - | - | 0,41 | 0,16 |
| L1-L5 | -0,03 | -0,01 | 5,93 | -0,01 | -0,43 | -0,3 | -0,72 | -0,64 |
| | | | | | | | | |
| Large Value L1 | 0,16 | 0,35 | 6,05 | 0,05 | 0,08 | 0,1 | -0,79 | -0,67 |
| Large Value L2 | 0,23 | 0,40 | 5,68 | 0,06 | 1,39 | 2,81 | -0,32 | -0,18 |
| Large Value L3 | 0,15 | 0,31 | 5,66 | 0,04 | -0,13 | -0,36 | -0,77 | -0,65 |
| Large Value L4 | 0,10 | 0,27 | 5,78 | 0,04 | -0,49 | -1,4 | -0,91 | -1,03 |
| Large Value L5 | 0,14 | 0,31 | 5,82 | 0,04 | -0,18 | -0,55 | -0,85 | -0,89 |
| Large Value Average | 0,16 | 0,33 | 5,79 | 0,05 | - | - | -0,78 | -0,70 |
| L1-L5 | 0,03 | 0,03 | 5,80 | -0,01 | 0,31 | 0,27 | -0,41 | -0,58 |
| | | | | | | | | |
| Large Blend L1 | 0,18 | 0,33 | 5,55 | 0,05 | -0,27 | -0,64 | -0,81 | -0,81 |
| Large Blend L2 | 0,18 | 0,36 | 5,83 | 0,05 | -0,23 | -0,73 | -0,82 | -0,83 |
| Large Blend L3 | 0,22 | 0,39 | 5,62 | 0,06 | 0,29 | 0,93 | -0,67 | -0,57 |
| Large Blend L4 | 0,19 | 0,35 | 5,59 | 0,05 | -0,17 | -0,59 | -0,81 | -0,80 |
| Large Blend L5 | 0,24 | 0,41 | 5,72 | 0,06 | 0,63 | 1,09 | -0,54 | -0,38 |
| Large Blend Average | 0,20 | 0,37 | 5,65 | 0,05 | - | - | -0,75 | -0,69 |
| L1-L5 | -0,08 | -0,08 | 0,71 | -0,20 | -0,57 | -0,97 | -0,83 | -1,99 |
| | | | | | | | | |
| Large Growth L1 | 0,23 | 0,37 | 5,18 | 0,06 | -0,22 | -0,18 | -0,56 | -0,36 |
| Large Growth L2 | 0,24 | 0,39 | 5,54 | 0,06 | -0,31 | -0,45 | -0,70 | -0,63 |
| Large Growth L3 | 0,23 | 0,39 | 5,68 | 0,06 | -0,39 | -0,74 | -0,60 | -0,48 |
| Large Growth L4 | 0,37 | 0,54 | 5,79 | 0,08 | 2,13 | 1,46 | 1,24 | 0,41 |
| Large Growth L5 | 0,01 | 0,14 | 4,64 | 0,02 | -0,40 | -0,2 | -1,00 | -1,63 |
| Large Growth Average | 0,27 | 0,42 | 5,50 | 0,06 | - | - | -0,42 | -0,30 |
| L1-L5 | -0,01 | -0,06 | 2,50 | -0,05 | -0,34 | -0,06 | 1276,97 | 0,82 |

[119] Source: own calculation, data extracted from Morningstar Direct and Datastream

| | Geometric Mean (%) | Arithmetic Mean (%) | Standard Deviation (%) | Sharpe Ratio | Annualized Alpha Relative to Category Average (%) | *t*-Statistic of Alpha Relative to Category Average | Annualized Alpha Relative to Fama-French Factors (%) | *t*-Statistic of Alpha Relative to Fama-French Factors |
|---|---|---|---|---|---|---|---|---|
| Small L1 | 0,32 | 0,54 | 6,48 | 0,07 | -0,79 | -1,21 | -0,44 | -0,19 |
| Small L2 | 0,38 | 0,60 | 6,52 | 0,08 | -0,56 | -1,29 | 0,69 | 0,2 |
| Small L3 | 0,43 | 0,63 | 6,17 | 0,09 | -0,05 | -0,09 | 2,38 | 0,52 |
| Small L4 | 0,58 | 0,77 | 6,20 | 0,11 | 3,79 | 2,35 | 13,16 | 1,18 |
| Small L5 | 0,49 | 0,69 | 6,27 | 0,10 | 0,87 | 0,84 | 4,63 | 0,78 |
| Small Average | 0,44 | 0,65 | 6,29 | 0,09 | - | - | 2,19 | 0,49 |
| L1-L5 | -0,17 | -0,16 | 1,47 | -0,15 | -0,90 | -1,19 | -0,98 | -1,87 |
| | | | | | | | | |
| Mid L1 | -0,02 | 0,20 | 6,41 | 0,02 | -0,98 | -2,7 | -0,99 | -1,7 |
| Mid L2 | 0,30 | 0,48 | 6,01 | 0,07 | 0,59 | 0,74 | 0,14 | 0,06 |
| Mid L3 | 0,42 | 0,61 | 6,07 | 0,09 | 4,99 | 2,92 | 2,51 | 0,62 |
| Mid L4 | 0,31 | 0,52 | 6,26 | 0,07 | 0,86 | 1,34 | 0,15 | 0,06 |
| Mid L5 | 0,27 | 0,46 | 6,02 | 0,07 | 0,22 | 0,24 | -0,17 | -0,08 |
| Mid Average | 0,26 | 0,45 | 6,12 | 0,06 | - | - | -0,40 | -0,24 |
| L1-L5 | -0,27 | -0,26 | 1,49 | -0,22 | -0,98 | -1,98 | -1,00 | -2,72 |
| | | | | | | | | |
| Large L1 | 0,18 | 0,34 | 5,71 | 0,05 | -0,06 | -0,14 | -1,00 | -0,77 |
| Large L2 | 0,20 | 0,37 | 5,73 | 0,05 | 0,30 | 1,02 | -0,70 | -0,61 |
| Large L3 | 0,18 | 0,34 | 5,59 | 0,05 | -0,04 | -0,13 | -0,73 | -0,61 |
| Large L4 | 0,19 | 0,35 | 5,72 | 0,05 | 0,07 | 0,26 | -0,73 | -0,61 |
| Large L5 | 0,16 | 0,33 | 5,79 | 0,05 | -0,21 | -0,78 | -0,81 | -0,79 |
| Large Average | 0,18 | 0,35 | 5,70 | 0,05 | - | - | -0,76 | -0,69 |
| L1-L5 | 0,01 | 0,01 | 0,57 | -0,10 | 0,18 | 0,24 | -0,54 | -1,22 |
| | | | | | | | | |
| Value L1 | 0,10 | 0,29 | 6,12 | 0,04 | -0,48 | -0,58 | -0,93 | -1,12 |
| Value L2 | 0,24 | 0,41 | 5,91 | 0,06 | 1,41 | 2,09 | -0,28 | -0,15 |
| Value L3 | 0,19 | 0,36 | 5,69 | 0,05 | 0,46 | 0,84 | -0,53 | -0,35 |
| Value L4 | 0,14 | 0,30 | 5,76 | 0,04 | -0,25 | -0,45 | -0,85 | -0,84 |
| Value L5 | 0,13 | 0,30 | 5,86 | 0,04 | -0,32 | -0,70 | -0,87 | -0,93 |
| Value Average | 0,16 | 0,33 | 5,84 | 0,05 | - | - | -0,78 | -0,70 |
| L1-L5 | -0,02 | -0,01 | 1,31 | -0,06 | -0,23 | -0,16 | -0,77 | -1,23 |
| | | | | | | | | |
| Blend L1 | 0,24 | 0,46 | 6,56 | 0,06 | -0,06 | -0,04 | -0,71 | -0,46 |
| Blend L2 | 0,24 | 0,42 | 5,86 | 0,06 | -0,08 | -0,22 | -0,61 | -0,45 |
| Blend L3 | 0,26 | 0,44 | 5,88 | 0,06 | 0,19 | 0,38 | -0,53 | -0,39 |
| Blend L4 | 0,23 | 0,39 | 5,62 | 0,06 | -0,11 | -0,17 | -0,66 | -0,53 |
| Blend L5 | 0,25 | 0,43 | 5,83 | 0,06 | 0,10 | 0,14 | -0,43 | -0,27 |
| Blend Average | 0,25 | 0,43 | 5,91 | 0,06 | - | - | -0,79 | -0,89 |
| L1-L5 | 0,02 | 0,03 | 1,85 | -0,02 | -0,15 | -0,08 | -0,60 | -0,44 |
| | | | | | | | | |
| Growth L1 | 0,40 | 0,58 | 5,93 | 0,09 | -0,21 | -0,21 | 0,44 | 0,15 |
| Growth L2 | 0,41 | 0,61 | 6,26 | 0,09 | -0,24 | -0,32 | 1,14 | 0,31 |
| Growth L3 | 0,52 | 0,71 | 6,01 | 0,11 | 2,06 | 1,49 | 6,85 | 0,96 |
| Growth L4 | 0,48 | 0,65 | 5,82 | 0,10 | 1,04 | 0,81 | 2,91 | 0,70 |
| Growth L5 | 0,29 | 0,46 | 5,78 | 0,07 | -0,77 | -1,21 | -0,18 | -0,10 |
| Growth Average | 0,42 | 0,60 | 5,90 | 0,09 | - | - | 1,45 | 0,44 |
| L1-L5 | 0,10 | 0,11 | 1,73 | 0,03 | 2,00 | 0,55 | -0,22 | -0,14 |
| | | | | | | | | |
| All L1 | 0,20 | 0,32 | 6,00 | 0,04 | -0,34 | -0,31 | -0,75 | -0,58 |
| All L2 | 0,35 | 0,42 | 5,67 | 0,06 | 1,50 | 2 | 0,31 | 0,15 |
| All L3 | 0,35 | 0,39 | 5,58 | 0,06 | 1,05 | 1,92 | 0,20 | 0,10 |
| All L4 | 0,26 | 0,28 | 5,48 | 0,04 | -0,45 | -0,91 | -0,68 | -0,60 |
| All L5 | 0,24 | 0,27 | 5,59 | 0,04 | -0,51 | -0,93 | -0,73 | -0,66 |
| All Average | 0,28 | 0,34 | 5,62 | 0,05 | - | - | -0,48 | -0,34 |
| L1-L5 | -0,03 | 0,04 | 1,82 | -0,01 | 0,33 | 0,14 | -0,57 | -0,59 |

This is nor compliant with results of Idzorek et al. nor is expected within this analysis, since the middle liquidity quintiles exhibit superior results in other measures.

Figure 13 Time Series of Average Mutual Fund Return[120]



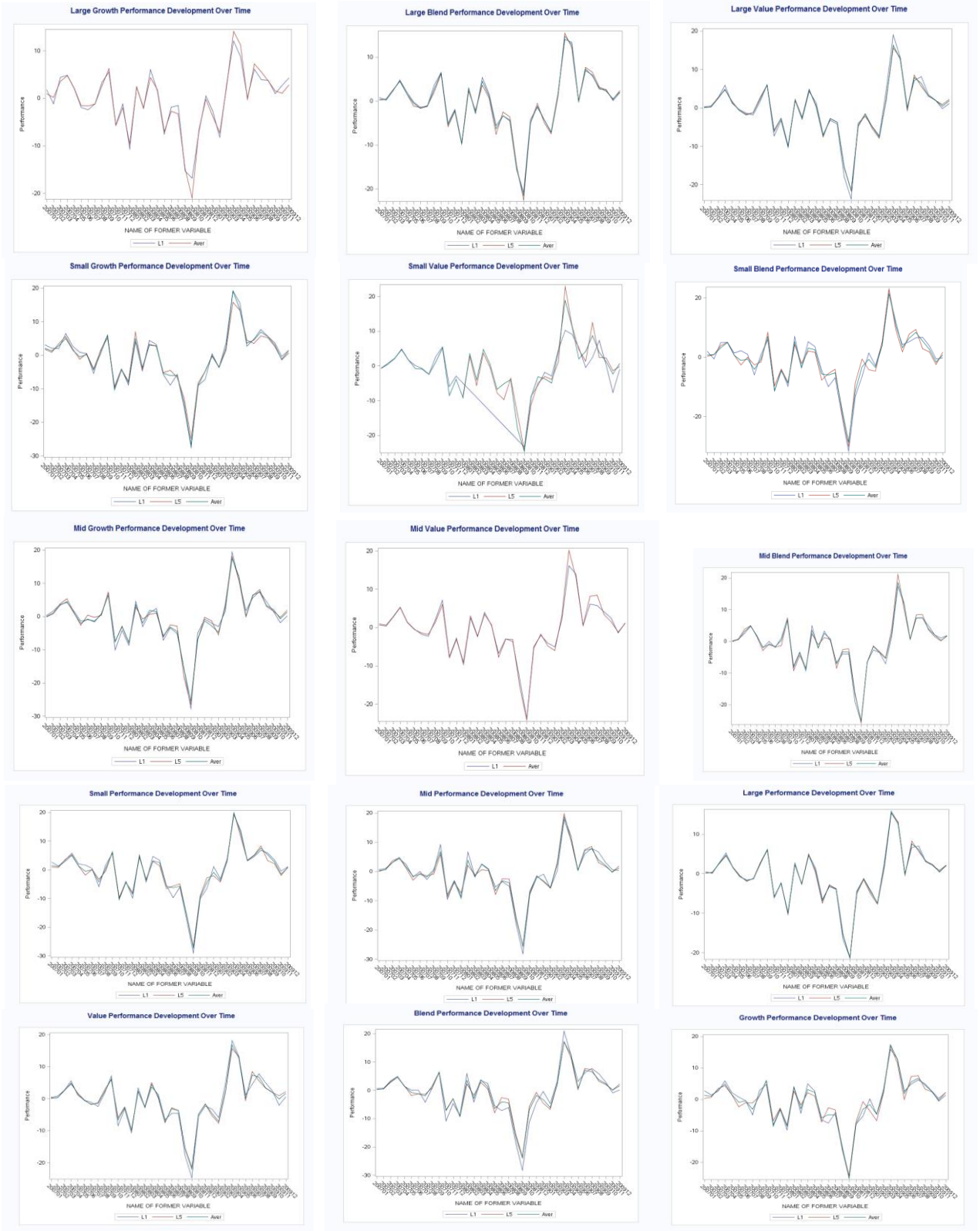

No closer look could be taken on the data during the technology bubble due to short recent period covered by available data. But it is interesting to look at the performance behaviour during the financial crisis (see Figure 14). The average performance of L1, L5 composites and average performance throughout all liquidities in certain category are presented as time series during the recent financial crisis. In all categories the dicrepanies between highest liquidity composite's performance and lowest liquidity composite's performance are very small. Especially, in largest groups, such as large, large value, value, the performances ran very close and did not diverge throughout the time drastically. An interesting finding is the time right before and after the drastical fall in late 2008: in the most of figures, the low liquid quintile, L5 outperform the L1 and average performance, whereas during the recession is wasn't the case. As this phenomenon is illustrated for all categories, it can be assumed as entire market phenomenon, regardless on stock's characteristics. The pre-recession high demand for liquid funds can be explained with anticipation of bear market and the desire to stay liquid and lack of trust in less liquid investments. After returning to the same level after the depression, investors might still untrust the well functioning of market institution and starting their investment again in more liquid assets.

The general performance line structure is the same for categories. The investors in the UK market did not concentrate their investment on specific style or change their investment

[120] Own calculation, row data retrieved from Morningstar Direct

allocation due to financial crisis. However, as it has been seen, the liquidiuty played a special role in their investment decision and triggered some chages in their portfolios.[121]

Figure 14 Liquidity Quintile Performance during the Financial Crisis, 2007-2009[122]




[121] Investors cannot change easily their funds components, but they do demand more for certain sort of stocks which return increase affect the fund's performance as well (if the stock is held in funds)

[122] Source: own creation, data retrieved from Morningstar Direct and Data Stream

As robustness check only liquidity measure will be changed and the results will be compared to the prior ones. Liquidity quintiles have been assigned based on another popular illiquidity proxy, Amihud measure expressed in formula (2). Here the quintile assignment has been made reversely, the 20% of the funds with highest Amihud measure make up the less liquid group L1.Despite the new liquidity measure, the results obtained (see Table 6) are similar, the second liquid group outperform the rest in all measures and the alpha against category average is significant. However, the performance moves slightly upwards: L1 composite has a higher means, Sharpe ratio and alphas[123], but also a higher standard deviation, than in analysis with turnover as liquidity proxy. More liquid quintiles exhibit a lower performance than in turnover liquidity.

Table 6 Mutual Fund Liquidity Quintiles using Amihud Measure[124]

| | Geometric Mean (%) | Arithmetic Mean (%) | Standard Deviation (%) | Sharpe Ratio | Annualized Alpha Relative to Category Average (%) | *t*-Statistic of Alpha Relative to Category Average | Annualized Alpha Relative to Fama-French Factors (%) | *t*-Statistic of Alpha Relative to Fama-French Factors |
|---|---|---|---|---|---|---|---|---|
| ALL L1 | 0,25 | 0,45 | 6,21 | 0,06 | 0,01 | 0,04 | -0,09 | -0,47 |
| ALL L2 | 0,39 | 0,57 | 5,99 | 0,08 | 0,14 | 2,58 | 0,06 | 0,36 |
| ALL L3 | 0,25 | 0,43 | 5,85 | 0,06 | 0,00 | 0,11 | -0,04 | -0,26 |
| ALL L4 | 0,22 | 0,38 | 5,67 | 0,06 | -0,03 | -0,49 | -0,07 | -0,44 |
| ALL L5 | 0,13 | 0,29 | 5,77 | 0,04 | -0,12 | -1,43 | -0,16 | -0,97 |
| ALL Average | 0,25 | 0,42 | 5,85 | 0,06 | - | - | -0,06 | -0,37 |
| L1-L5 | 0,13 | 0,15 | 2,10 | 0,04 | 0,12 | 0,60 | 0,00 | 0,01 |

In general, no significant difference could be established and the analysis can be seen as robust regarding liquidity measure. No further robustness tests have been implemented to check the accuracy of the study.

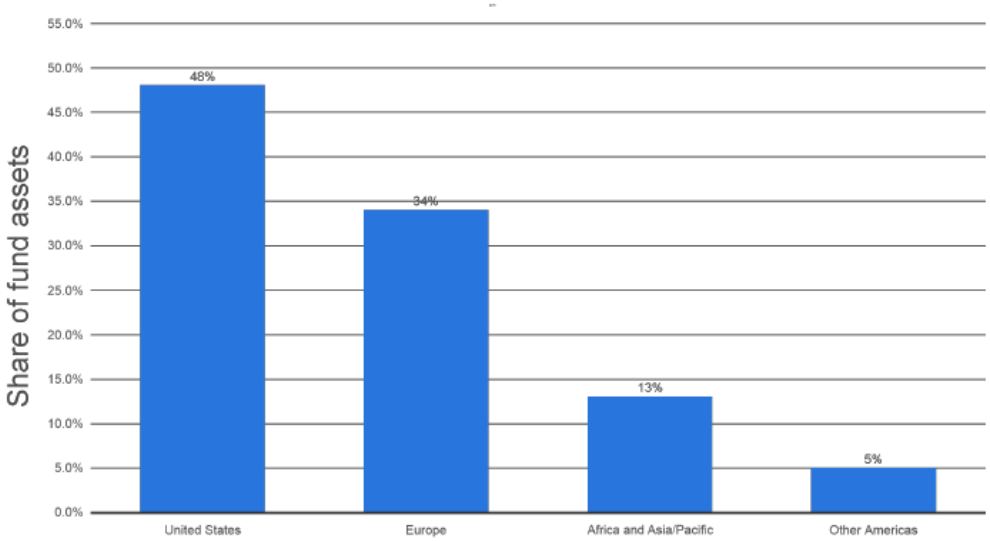
# *6.* Problems and criticism

Contrary to U.S. results, the UK mutual fund market does not demonstrate any consistent relationship between fund's liquidity and its performance. Fund's liquidity does not turn out to be a significant explanatory factor for fund's returns as other investment styles, such as size, valuation and momentum, do. However, it must be taken into account, that the number of mutual funds with UK as investment area has been strongly reduced due to lack of information. While Idzorek et al. analyzed 1,294 funds for year 1995 and 5,198 funds for 2009, the amount of UK funds at one's disposal accounted for 298 at the beginning if observation period and

[123] The t-statistics for less liquid composites increased as well
[124] Source: own calculation using data from Morningstar Direct and Data Stream

449 in the current year. This number is much smaller than the sample of non-U.S. funds used by Idzorek et al. which also didn't provide the expected results. In general, the number of U.S. funds is much higher than in any other region (see Figure 15), therefore, it is not possible to get country-specific data with the size comparable to U.S. mutual funds market.

Figure 15 Number of mutual funds worldwide[125]



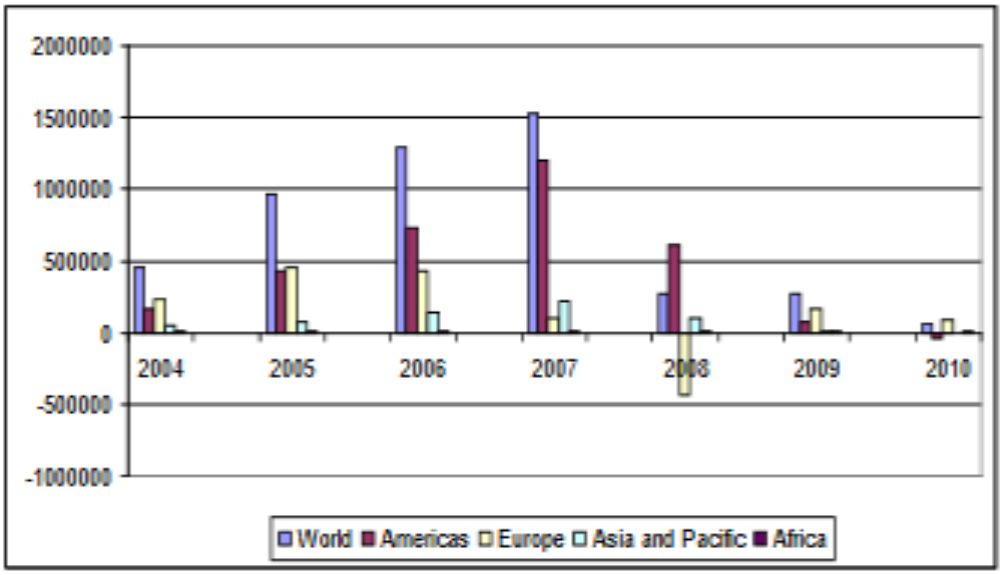

Despite of the fact that the number of mutual funds investing in the UK assets is small compared to US market, a big part of the funds has been eliminated from the analysis data set due to missing information. First of all, the maximum available holding history provided by Morningstar was 10 years, what reduced our sample significantly. Furthermore, for some funds no historic holdings were available and they must be removed from the sample as well. Missing values of traded volume or outstanding number of stocks made the fund's liquidity calculation impossible and led also to their removal. Another important information needed for the calculation were the historical returns. Although, forming the average return within composites alleviates this problem, missing values could lead to biased performance result. As it is described in the previous chapter, non-UK stocks contained in the funds are ignored. In case their performance and liquidity would change the fund's performance or its assignment to liquidity composite, the results can be considered as biased as well.

The fact that the observation period heavily covers the period of financial crisis cannot be ignored. The situation on financial market during the crisis drastically deviates from the usual state and cannot reflect the economical relation adequately. The market is not stable and the investors' responses don't correspond to the usual ones. Regardless of funds' liquidity, investors tried to get rid of assets and to ensure thereby the liquidity. Especially, the European mu-

[125] Statista.com (2016): Mutual funds- Statista dossier, p. 7

tual funds market was affected by financial crisis (see Figure 16) which resulted in negative net sales in the mutual funds market.

Figure 16 Worldwide Net Sales of Mutual (in US $ bn)[126]




Despite everything mentioned before, we cannot deny the possibility of non-validity of the performance-liquidity relation on the UK market. Note that all investigations described in chapter 3.3 have been carried with U.S. assets.[127] The established statement of liquidity and performance relation might not apply for other markets. In order to check the possible reasons, some thorough and extensive researches must be carried out which include country and market specifics, investors' strategies, regulatory aspects and more.

Using OLS to analyze the influence and significance of investment factors is straightforward, but is more suitable to evaluate cross-sectional data. It requires the data to be iid to represent a random sample. The panel data, such as returns we use in our study, exhibit the autocorrelation and violate thereby one of the OLS conditions. As a result of the analysis provides contains auto correlated error term and, therefore, biased factors. If we cannot rely on the accuracy of factors, the intercept (alpha) might be also biased. Consequential, it is required to find a more appropriate model to investigate liquidity influence on return on panel data.

[126] Source: Barna, F., Nachescu, M., Mihart, L. L. (2011) : Mutual Funds and the Impact of Financial Crises, p.69

[127] To be more exact, the data has been extracted from NYSE

# 7. Conclusion

Various studies which investigate the explanatory factors for assets' returns indicate liquidity as one of the missing and not less important investment style. While a lot of studies concentrated on the relation between stock's liquidity and its performance, Idzorek et al. scrutinized the U.S. mutual funds market. The results exhibit a significant negative relation and should be encouraging manager to invest in less liquid funds in order to obtain higher returns. However, this is not the case observed in the market and fund managers continue prefer more liquid investments. Another interesting finding was the deviating results for the same analysis, but with non-U.S funds. The less liquid funds did not outperform the more liquid ones. In this study, one particular market has been choses and examined carefully. This thesis focused on the UK as one of the biggest mutual funds market worldwide and tried to analyze the existence of such relation outside of U.S. market.

First, the funds market and its trait and recent development were shed more light on. Currently existing types of funds have been introduced as next and their advantages and disadvantages have been described. Subsequent chapter dealt with the notion of liquidity, different types of liquidity and its measures. Despite of the large variety of liquidity proxy measures, a majority of works use only two of them, turnover and Amihud liquidity measure, due to their simplicity and data availability. This topic is followed by the three main works on the relation of asset's liquidity and its performance. The same relationship was discovered on the fund-level by Idzorek, Xiong and Ibbotson which is comprehensively described in Chapter 4.

The practical part of this thesis incorporated the same analyses carried out on UK mutual funds data. The funds and stocks data has been collected from Morningstar Direct and Data Stream and joined using the filter for equity mutual funds and UK as investment area. Calculating the fund's liquidity by adding up the weighted stock's liquidities and group all funds into 5 composites based on their liquidity enables to derive statements about the investigated relation. Surprisingly, the results didn't comply with the U.S. ones: There is no evidence of a better performance in the composite of less liquid funds. Furthermore, there is no monotonic behavior which allows reference to any relation between liquidity and performance.

The small sample reduced by missing data or instabilities caused by financial crisis could be the reason for biased results which are not consistent with theoretical statements. However, these results can also be explained by invalidity of the model on the non-U.S. market, which requires further researches on the possible causes.

# V. References

## a. Books

Ang, A. (2014): *Asset Management. A systematic approach to factor investing*., New York

Connor, G., Woo, M.: *An Introduction to Hedge Funds. Introductory Guide*,

Fabozzi, F.J (2002): *The Handbook of financial instruments*, Wiley finance series, New Jersey

Feibel, B. J.(2003): *Investment Performance Measurement*, John Wiley & Sons Inc., New Jersey

Hull, C. F., (2015): Risk Management and Financial Institutions, 4th edition, Wiley finance series, New Jersey

Lhabitant, F.-S., Gregoriou, G. N. (2008): Stock Market Liquidity. Implication for Market Microstructure and Asset Pricing, Wiley finance series, New Jersey

## b. Scientific papers

Amihud, Y (2002): *Illiquidity and stock returns: Cross-section and time-series effects*, Journal of Financial Markets 5, New York, pp. 31–56

Amihud, Y., Mendelson, H. (1986): *Asset pricing and the bid-ask spread*, Journal of Financial Economics 17, pp. 223-249

Baks, K. P., Metrick, A., Wachter, J. (2001): *Should Investors Avoid All Actively Managed Mutual Funds*? A Study in Bayesian Performance Evaluation, The Journal of Finance, Vol. LVI, No. 1, Febrary 2001

Barber, B. M., Odean, T. (2000): *Trading is hazardous to your wealth. The common stock investment performance of individual investors*, Journal of Finance, 55, 773–806.

Barna, F., Nachescu, M., Mihart, L. L. (2011) : Mutual Funds and the Impact of Financial Crises, "Ovidius" University Annals, Economic Sciences Series Volume XI, Issue 2 /2011, Timisoara

Brennan, M. J., Subrahmanyam, A. (1996): *Market microstructure and asset pricing: On the compensation for illiquidity in stock returns*, Journal of Financial Economics 41, pp. 441-464

Danyliv, O, Bland, B, Nicholass, D (2014*): Convenient liquidity measure for financial markets,* Journal of Financial Markets 00 (2014) 1–1, sciencedirect.com

Danyliv, O., Bland, B, Nicholass, D. (2014): *Convenient liquidity measure for financial markets*, Cornell University Library, retrieved from https://arxiv.org/abs/1412.5072

Datar, V. T., Naik, N.Y., Radcliffe, R.(1998): *Liquidity and stock returns: An alternative test*, Journal of Financial Markets 1, pp. 203-219

Eleswarapu, V., Reinganum, M. (1993): *The seasonal behavior of the liquidity premium in asset pricing*, Journal of Financial Economics 34, pp.281-305

Gabrielsen, A., Marzo, M., Zagag, P.(2011): *Measuring market liquidity: An introductory survey,* Quaderni DSE Working Paper No. 802

Hasbrouck, J.(1999): *The dynamics of discrete bid and ask quotes*, The Journal of Finance, Vol LIV, No. 6

Ibbotson, R. G., Chen, Z., Kim, D. Y.-J., Hu, W.J,(2012): *Liquidity as an Investment Style*, Financial Analysts Journal, Vol. 69, Nr. 3

Idzorek, T. M., Xiong, J. X., Ibbotson, R. G. (2012): *The Liquidity Style of Mutual Funds*, Financial Analysis Journal, Vol. 68, Nr. 6, pp.38-53

Idzorek, T., Xiong, J. X., Ibbotson, G. (2011): *Combining Liquidity and Momentum to Pick Top-Performing Mutual Funds*, retrieved from https://www.researchgate.net/publication/267366002_Combining_Liquidity_and_Momentum_to_Pick_Top-Performing_Mutual_Funds

Lee, C. (1993): *Market fragmentation and price-execution in NYSE-listed securities*, Journal of Finance 48, pp. 733-746

Lou, X, Sadka, R (2011): *Liquidity Level or Liquidity Risk? Evidence from the Financial Crisis,* Financial Analysts Journal, Volume 67, Number 3

Müller, S., Weber, M. (2010): *Financial Literacy and Mutual Fund Investments: Who Buys actively managed funds*?,Schmalenbach Business Review, Vol. 62, pp. 126-153, April 2010, Mannheim

Odean, T. (1999): *Do investors trade too much*? American Economic Review, 89, 1279–1298

Petersen, M., Fialkowski, D. (1993): *Posted versus effective spreads. Good prices or bad quotes?*, Journal of Financial Economics 35, pp. 269-292

Sarr, A., Lybek, T. (2002): *Measuring Liquidity in Financial Markets*, IMF Working paper, WP 02/232

## c. Non-scientific papers

IMA (2012), *Enhanced disclosure of fund charges and costs*, September, retrieved from http://www.theinvestmentassociation.org/assets/files/industry-guidance/20120920-enhanceddisclosureoffundchargesandcosts.pdf

IMA (2012), *Enhanced disclosure of fund charges and costs*, September

Morningstar (2008): *Morningstar Style Box Methodology*, Morningstar Methodology Paper

Statista.com (2016): Mutual funds- Statista dossier, retrieved from https://www.statista.com/study/14528/mutual-funds-statista-dossier/

The Investment Association (2015): Asset Management in the UK 2014-2015. The Investment Association Annual Survey, London

## d. Websites

French, K. R.(2016): Fama/French European 3 Factors from Data Library, Retrieved from http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

Investopedia.com (2016a): *Fund Management Issues*, Author: Richard Loth, retrieved from http://www.investopedia.com/university/quality-mutual-fund/chp6-fund-mgmt/

Investopedia.com (2016b): Unit Trust – UT, retrieved from http://www.investopedia.com/terms/u/unittrust.asp

Investopedia.com (2016c): *Crossed market*, retrieved from : http://www.investopedia.com/terms/c/crossedmarket.asp

Investopedia.com (2016d): *What is the difference between arithmetic and geometric averages?*, retrieved from http://www.investopedia.com/ask/answers/06/geometricmean.asp

Investopedia.com (2016e):*Stock-Picking Strategies: Value Investing*, retrieved from http://www.investopedia.com/university/stockpicking/stockpicking3.asp

J.P.Morgan (2016): *What is an Investment Trust?*, retrieved from http://am.jpmorgan.co.uk/investment-trusts/explained/what-is-an-investment-trust.aspx

Morningstar: Fund ABCs: Types of Funds, retrieved from http://www.morningstar.co.uk/uk/news/62085/fund-abcs-types-of-funds.aspx

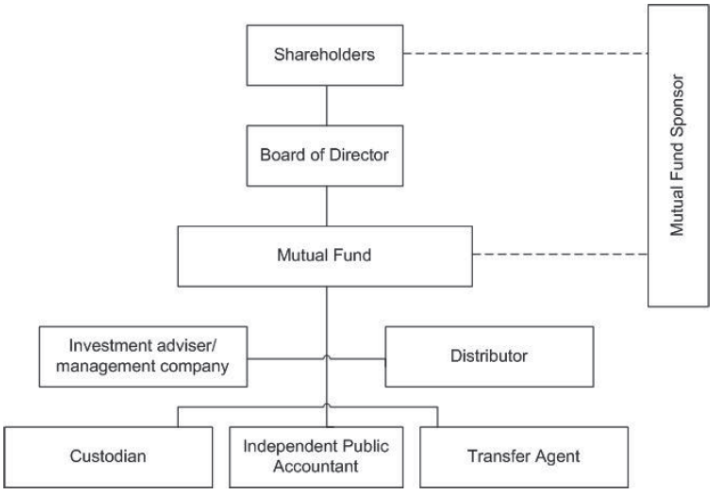
Statista.com (2016c): *Assets managed by hedge funds worldwide from 1997 to 2015*, retrieved from http://www.statista.com/statistics/271771/assets-of-the-hedge-funds-worldwide/

Statista.com(2016a): *Statistics and facts on mutual funds*, retrieved from http://www.statista.com/topics/1441/mutual-funds/

Statista.com(2016b): *Development of assets of global Exchange Traded Funds (ETFs) from 2003 to 2015*, retrieved from http://www.statista.com/statistics/224579/worldwide-etf-assets-under-management-since-1997/

# VI. Appendix

## a) The mutual fund complex[128]




## b) Amihud and Mendelson maximization problem

There are i=1,2,…M investor types and j=0,1,…,N assets which generate positive perpetual cash flows $d_j > 0$ per unit time and has a relative spread $S_j$ which is the difference between ask price vector $\boldsymbol{V_j}$ or $(V_0, V_1, \dots, V_N)$ and bid price vector $\boldsymbol{V_j(1 - S_j)}$ or $(V_0, V_1(1 - S_1, \dots, V_N(1 - S_N))$. Each investor I, endowed with an initial wealth $W_i$, purchases assets and holds them within random exponentially distributed time $T_i$with a mean $E(T_i) = \frac{1}{\mu_i}$.

The expected present value of portfolio is therefore:

$$E_{T_i}\left\{\int_0^{T_i} e^{-\rho y}\left[\sum_{j=0}^{N} x_{ij} d_j\right] dy\right\} + E_{T_i}\left\{e^{-\rho T_i}\sum_{j=0}^{N} x_{ij} V_j(1 - S_j)\right\}$$

$$= (\mu_i + \rho)^{-1}\sum_{j=0}^{N} x_{ij}\left[d_j + \mu_i V_j(1 - S_j)\right].$$

And for a given vector of bid and ask prices, a type I investor solves following problem

$$max \sum_{j=0}^{N} x_{ij}\left[d_j + \mu_i V_j(1 - S_j)\right]$$

[128] Source: Mattig, A. (2009): Industrial Dynamics and the Evolution of Markets in the mutual funds industry, p.22

subject to $\sum_{j=0}^{N} x_{ij}V_j \leq W_i$ and $x_{ij} \geq 0$ for all j=0,1,…, N. The market clearing condition implies $\sum_{m=1}^{M} m_i x_{ij} = 1$ for j=1,2,…N, where $m_i$ is the expected number of type i agents in the market. Given spread adjusted return $r_{ij} = \frac{d_j}{V_j} - \mu_i S_j$ the investors chose their portfolio which has a maximal spread adjusted (net) returns $r_i^* = \max_{j=0,1,2,\ldots,N} r_{ij}$ and in equilibrium the observed market return equals the gross the minimal required gross return of portfolio i:

$\frac{d_j}{V_j^*} = \min_{i=1,2,\ldots,M}\{r_i^* + \mu_i S_j\}$ or $V_j^* = \max_{i=1,2,\ldots,M}\left\{\frac{d_j}{(r_i^* + \mu_i S_j)}\right\}$

If the available amount of assets are held by investor's type I than holds:

$$V_j^* = \frac{d_j}{r_j^*} - \mu_i V_j^* S_j / r_i^*$$

## c) Size and Liquidity Quartile Portfolios, 1972-2011

Table 7 Size and liquidity quartile portfolios[129]

| Quartile | Low Liquidity | Mid-Low Liquidity | Mid-High Liquidity | High Liquidity |
|---|---|---|---|---|
| *Microcap* | | | | |
| Geometric mean | 15.36% | 16.21% | 9.94% | 1.32% |
| Arithmetic mean | 17.92% | 20.00% | 15.40% | 6.78% |
| Standard deviation | 23.77% | 29.41% | 35.34% | 34.20% |
| Average no. of stocks | 323 | 185 | 132 | 103 |
| *Small cap* | | | | |
| Geometric mean | 15.30% | 14.09% | 11.80% | 5.48% |
| Arithmetic mean | 17.07% | 16.82% | 15.38% | 9.89% |
| Standard deviation | 20.15% | 24.63% | 28.22% | 31.21% |
| Average no. of stocks | 196 | 193 | 175 | 179 |
| *Midcap* | | | | |
| Geometric mean | 13.61% | 13.57% | 12.24% | 7.85% |
| Arithmetic mean | 15.01% | 15.34% | 14.51% | 11.66% |
| Standard deviation | 17.91% | 20.10% | 22.41% | 28.71% |
| Average no. of stocks | 141 | 171 | 197 | 233 |
| *Large cap* | | | | |
| Geometric mean | 11.53% | 11.66% | 11.19% | 8.37% |
| Arithmetic mean | 12.83% | 12.86% | 12.81% | 11.58% |
| Standard deviation | 16.68% | 15.99% | 18.34% | 25.75% |
| Average no. of stocks | 83 | 194 | 238 | 227 |

[129] Source: Ibbotson, R. G., Chen, Z., Kim, D. Y.-J., Hu, W.J,(2012):*Liquidity as an Investment Style*, p. 4

# d) Regression Analyses of Liquidity Factor

Table 8 Regression Analyses of Dollar-Neutral Liquidity Factor and Low-Liquidity Long Portfolios with (t-stat)[130]

| | Monthly Alpha (%) | Market Beta | Size | Value | Momentum | Adjusted $R^2$ (%) | $N$ |
|---|---|---|---|---|---|---|---|
| *Liquidity factor* | | | | | | | |
| CAPM | 0.66 | –0.66 | | | | 48.0 | 480 |
| | (4.52) | (–21.06) | | | | | |
| Fama–French | 0.44 | –0.47 | –0.39 | 0.54 | | 70.4 | 480 |
| | (3.93) | (–18.55) | (–10.53) | (14.05) | | | |
| Four factor | 0.31 | –0.45 | –0.39 | 0.58 | 0.14 | 72.2 | 480 |
| | (2.80) | (–17.66) | (–10.87) | (15.33) | (5.54) | | |
| *Low-liquidity long* | | | | | | | |
| CAPM | 0.45 | 0.75 | | | | 67.4 | 480 |
| | (3.97) | (31.47) | | | | | |
| Fama–French | 0.16 | 0.73 | 0.56 | 0.44 | | 88.2 | 480 |
| | (2.41) | (47.32) | (24.98) | (18.63) | | | |
| Four factor | 0.16 | 0.74 | 0.56 | 0.44 | 0.00 | 88.2 | 480 |
| | (2.30) | (46.40) | (24.95) | (18.24) | (0.25) | | |

# e) Migration of Stocks' Style Quartiles

Table 9 Migration of Stocks' Style Quartiles One Year after Portfolio Formation[131]

| | Year $t$ + 1 Liquidity | | | |
|---|---|---|---|---|
| | 1 (low) | 2 | 3 | 4 (high) |
| *A. Liquidity migration (62.93% stay in the same quartile)* | | | | |
| Year $t$ Liquidity | | | | |
| 1 (low) | **77.28%** | 18.06% | 3.54% | 1.11% |
| 2 | 18.80 | **53.11** | 22.29 | 5.80 |
| 3 | 2.96 | 24.26 | **49.99** | 22.79 |
| 4 (high) | 0.77 | 4.19 | 23.70 | **71.33** |
| | Year $t$ + 1 Market Cap | | | |
| *B. Size migration (78.73% stay in the same quartile)* | | | | |
| Year $t$ Market Cap | | | | |
| 1 (micro) | **83.46%** | 15.65% | 0.87% | 0.02% |
| 2 | 19.85 | **64.75** | 15.19 | 0.21 |
| 3 | 1.20 | 13.89 | **74.66** | 10.25 |
| 4 (large) | 0.07 | 0.22 | 7.67 | **92.03** |
| | Year $t$ + 1 Value | | | |
| *C. Value migration (51.63% stay in the same quartile)* | | | | |
| Year $t$ Value | | | | |
| 1 (low) | **65.22%** | 18.46% | 7.55% | 8.77% |
| 2 | 21.01 | **44.47** | 23.85 | 10.68 |
| 3 | 9.92 | 23.07 | **43.41** | 23.61 |
| 4 (high) | 12.73 | 10.75 | 23.09 | **53.43** |
| | Year $t$ + 1 Momentum | | | |
| *D. Momentum migration (29.03% stay in the same quartile)* | | | | |
| Year $t$ Momentum | | | | |
| 1 (low) | **37.29%** | 21.49% | 19.63% | 21.60% |
| 2 | 23.97 | **27.20** | 28.01 | 20.82 |
| 3 | 22.35 | 27.86 | **28.23** | 21.56 |
| 4 (high) | 30.73 | 23.50 | 22.36 | **23.42** |

*Note:* All rows sum (within rounding error) to 100%.

[130] Source: Ibbotson, R. G., Chen, Z., Kim, D. Y.-J., Hu, W.J,(2012):*Liquidity as an Investment Style*, p. 8
[131] Source: Ibbotson, R. G., Chen, Z., Kim, D. Y.-J., Hu, W.J,(2012):*Liquidity as an Investment Style*, p. 12

# f) Morningstar 10 Style factors

Table 10 Morningstar's 10 Style factors[132]

| Value Score Components and Weights | Growth Score Components and Weights |
|---|---|
| Forward Looking | Forward Looking |
| 1. Price-to-Projected Earnings* | 1. Long-Term Projected Earnings Growth |
| Historical-based measures: | Historical-based measures: |
| 2. Price-to-Book* | 2. Book Value Growth |
| 3. Price-to-Sales* | 3. Sales Growth |
| 4. Price-to-Cash Flow* | 4. Cash Flow Growth |
| 5. Dividend Yield | 5. Historical Earnings Growth |

# g) The summarized analysis data

Table 11 The analysis data[133]

| Morningstar Category | Start Date No. of Funds (February 1995) | End Date No. of Funds (December 2009)[a] |
|---|---|---|
| Small value | 42 | 238 |
| Small core | 73 | 369 |
| Small growth | 123 | 494 |
| Mid value | 45 | 229 |
| Mid core | 84 | 314 |
| Mid growth | 131 | 527 |
| Large value | 212 | 719 |
| Large core | 322 | 1,260 |
| Large growth | 262 | 1,048 |
| Small | 238 | 1,101 |
| Mid | 260 | 1,070 |
| Large | 796 | 3,027 |
| Value | 299 | 1,186 |
| Core | 479 | 1,943 |
| Growth | 516 | 2,069 |
| All U.S. | 1,294 | 5,198 |
| All non-U.S.[b] | 634 | 815 |

[a]Including defunct funds.
[b]Non-U.S. mutual fund data start in February 2000.

[132] Source: Morningstar (2008): *Morningstar Style Box Methodology*, p. 4
[133] Soure: Idzorek, T. M., Xiong, J. X., Ibbotson, R. G. (2012): *The Liquidity Style of Mutual Funds*, p. 40

# h) Mutual Funds Liquidity Quintiles

Table 12 Mutual Funds Liquidity Quintiles, U.S. Equity Universe, Feb95–Dec09[134]

| | Geometric Mean (%) | Arithmetic Mean (%) | Standard Deviation (%) | Sharpe Ratio | Annualized Alpha Relative to Category Average (%) | *t*-Statistic of Alpha Relative to Category Average | Annualized Alpha Relative to Fama–French Factors (%) | *t*-Statistic of Alpha Relative to Fama–French Factors |
|---|---|---|---|---|---|---|---|---|
| Small value L1 | 10.86 | 12.26 | 17.61 | 0.50 | 1.68 | 2.69 | 2.50 | 1.71 |
| Small value L2 | 10.79 | 12.50 | 19.55 | 0.46 | 0.77 | 1.46 | 2.10 | 1.33 |
| Small value L3 | 10.17 | 11.91 | 19.63 | 0.43 | 0.14 | 0.26 | 1.58 | 0.96 |
| Small value L4 | 9.48 | 11.26 | 19.81 | 0.39 | –0.61 | –1.17 | 0.84 | 0.52 |
| Small value L5 | 8.09 | 10.05 | 20.75 | 0.31 | –2.17 | –2.20 | –0.86 | –0.67 |
| Small value average | 9.91 | 11.59 | 19.27 | 0.42 | — | — | 1.26 | 0.90 |
| L1 – L5 | 2.77 | 2.21 | –3.15 | 0.18 | 3.93 | 3.21 | 3.39 | 2.98 |
| Small core L1 | 11.25 | 12.67 | 17.74 | 0.51 | 2.93 | 3.21 | 2.87 | 1.98 |
| Small core L2 | 9.48 | 11.14 | 19.09 | 0.40 | 0.59 | 0.88 | 1.00 | 0.67 |
| Small core L3 | 8.81 | 10.71 | 20.43 | 0.35 | –0.61 | –1.35 | 0.18 | 0.12 |
| Small core L4 | 8.73 | 10.93 | 22.07 | 0.34 | –1.19 | –1.76 | –0.11 | –0.08 |
| Small core L5 | 7.94 | 10.13 | 21.98 | 0.30 | –1.87 | –2.09 | –0.73 | –0.57 |
| Small core average | 9.29 | 11.11 | 20.02 | 0.38 | — | — | 0.67 | 0.52 |
| L1 – L5 | 3.32 | 2.54 | –4.24 | 0.21 | 4.88 | 3.19 | 3.62 | 3.35 |
| Small growth L1 | 9.26 | 11.15 | 20.44 | 0.37 | 2.81 | 2.15 | 0.82 | 0.70 |
| Small growth L2 | 7.88 | 10.43 | 23.91 | 0.29 | 0.47 | 0.81 | –0.40 | –0.31 |
| Small growth L3 | 6.87 | 9.87 | 25.93 | 0.24 | –0.90 | –1.77 | –1.21 | –0.88 |
| Small growth L4 | 8.13 | 11.50 | 27.84 | 0.29 | 0.01 | 0.01 | 0.02 | 0.01 |
| Small growth L5 | 6.26 | 10.04 | 29.30 | 0.22 | –1.98 | –2.58 | –1.76 | –1.14 |
| Small growth average | 7.77 | 10.60 | 25.22 | 0.28 | — | — | –0.50 | –0.41 |
| L1 – L5 | 3.00 | 1.10 | –8.86 | 0.15 | 4.88 | 2.59 | 2.62 | 1.83 |
| Mid value L1 | 11.06 | 12.15 | 15.52 | 0.56 | 2.31 | 3.66 | 3.74 | 2.88 |
| Mid value L2 | 9.95 | 11.28 | 17.13 | 0.45 | 0.49 | 0.69 | 2.55 | 1.53 |
| Mid value L3 | 9.76 | 11.11 | 17.23 | 0.44 | 0.20 | 0.35 | 2.23 | 1.54 |
| Mid value L4 | 9.82 | 11.45 | 18.92 | 0.42 | –0.46 | –0.75 | 1.87 | 1.29 |
| Mid value L5 | 7.81 | 9.72 | 20.39 | 0.30 | –2.83 | –2.52 | –0.54 | –0.40 |
| Mid value average | 9.73 | 11.14 | 17.56 | 0.43 | — | — | 2.00 | 1.54 |
| L1 – L5 | 3.25 | 2.42 | –4.87 | 0.25 | 5.27 | 3.92 | 4.30 | 3.73 |
| Mid core L1 | 10.66 | 11.81 | 15.87 | 0.52 | 2.71 | 2.32 | 3.22 | 2.48 |
| Mid core L2 | 10.06 | 11.58 | 18.29 | 0.44 | 0.81 | 1.13 | 2.17 | 1.76 |
| Mid core L3 | 10.24 | 12.02 | 19.86 | 0.43 | 0.33 | 0.54 | 2.14 | 1.68 |
| Mid core L4 | 9.22 | 11.12 | 20.49 | 0.37 | –0.91 | –1.38 | 1.03 | 0.75 |
| Mid core L5 | 7.47 | 9.65 | 21.86 | 0.28 | –2.85 | –2.24 | –0.51 | –0.40 |
| Mid core average | 9.61 | 11.23 | 18.87 | 0.41 | — | — | 1.60 | 1.50 |
| L1 – L5 | 3.19 | 2.16 | –5.99 | 0.24 | 5.71 | 2.90 | 3.74 | 2.48 |

[134] Source:Idzorek, T. M., Xiong, J. X., Ibbotson, R. G. (2012): *The Liquidity Style of Mutual Funds*, pp. 41-43

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Mid growth L1 | 9.82 | 11.27 | 17.94 | 0.43 | 3.36 | 2.36 | 2.22 | 2.10 |
| Mid growth L2 | 9.14 | 11.26 | 21.82 | 0.35 | 1.27 | 1.87 | 1.52 | 1.17 |
| Mid growth L3 | 8.38 | 11.01 | 24.38 | 0.31 | –0.13 | –0.30 | 0.85 | 0.57 |
| Mid growth L4 | 7.35 | 10.39 | 26.15 | 0.26 | –1.47 | –2.32 | –0.04 | –0.02 |
| Mid growth L5 | 6.63 | 10.19 | 28.46 | 0.23 | –2.54 | –2.40 | –0.58 | –0.29 |
| Mid growth average | 8.38 | 10.82 | 23.39 | 0.31 | — | — | 0.78 | 0.58 |
| L1 – L5 | 3.18 | 1.08 | –10.52 | 0.20 | 6.04 | 2.72 | 2.82 | 1.42 |
| Large value L1 | 8.44 | 9.41 | 14.49 | 0.41 | 1.61 | 3.67 | 2.07 | 2.02 |
| Large value L2 | 7.65 | 8.75 | 15.38 | 0.34 | 0.46 | 1.59 | 1.09 | 1.12 |
| Large value L3 | 7.42 | 8.61 | 16.04 | 0.32 | –0.03 | –0.15 | 0.65 | 0.71 |
| Large value L4 | 7.07 | 8.34 | 16.53 | 0.29 | –0.55 | –2.29 | 0.19 | 0.20 |
| Large value L5 | 6.11 | 7.52 | 17.32 | 0.23 | –1.71 | –2.98 | –1.11 | –1.33 |
| Large value average | 7.35 | 8.52 | 15.88 | 0.31 | — | — | 0.62 | 0.69 |
| L1 – L5 | 2.33 | 1.89 | –2.83 | 0.18 | 3.37 | 3.76 | 3.21 | 4.58 |
| Large core L1 | 7.95 | 8.95 | 14.69 | 0.37 | 1.70 | 2.88 | 1.50 | 2.39 |
| Large core L2 | 6.91 | 8.10 | 15.98 | 0.29 | 0.16 | 0.70 | 0.25 | 0.61 |
| Large core L3 | 6.66 | 7.97 | 16.76 | 0.27 | –0.33 | –1.21 | 0.01 | 0.02 |
| Large core L4 | 6.35 | 7.63 | 16.56 | 0.25 | –0.59 | –2.66 | –0.43 | –1.05 |
| Large core L5 | 6.30 | 7.84 | 18.12 | 0.24 | –1.01 | –1.39 | –0.97 | –2.06 |
| Large core average | 6.86 | 8.10 | 16.31 | 0.28 | — | — | 0.08 | 0.24 |
| L1 – L5 | 1.65 | 1.11 | –3.42 | 0.13 | 2.74 | 2.55 | 2.48 | 3.18 |
| Large growth L1 | 7.61 | 8.80 | 16.04 | 0.33 | 1.99 | 2.01 | 1.21 | 1.86 |
| Large growth L2 | 6.92 | 8.36 | 17.64 | 0.27 | 0.72 | 1.24 | 0.31 | 0.47 |
| Large growth L3 | 5.86 | 7.48 | 18.62 | 0.21 | –0.61 | –2.01 | –0.82 | –1.10 |
| Large growth L4 | 6.74 | 8.63 | 20.30 | 0.25 | –0.16 | –0.44 | –0.18 | –0.20 |
| Large growth L5 | 5.87 | 8.60 | 24.52 | 0.21 | –1.70 | –1.38 | –1.21 | –0.83 |
| Large growth average | 6.68 | 8.38 | 19.15 | 0.25 | — | — | –0.18 | –0.25 |
| L1 – L5 | 1.75 | 0.20 | –8.48 | 0.12 | 3.74 | 2.23 | 2.46 | 1.50 |
| Small L1 | 11.12 | 12.61 | 18.19 | 0.50 | 4.17 | 2.45 | 2.66 | 1.87 |
| Small L2 | 9.36 | 11.19 | 20.06 | 0.38 | 1.45 | 1.25 | 0.74 | 0.54 |
| Small L3 | 8.40 | 10.72 | 22.74 | 0.32 | –0.53 | –1.42 | –0.23 | –0.19 |
| Small L4 | 7.76 | 10.59 | 25.28 | 0.28 | –1.67 | –1.68 | –0.59 | –0.47 |
| Small L5 | 6.75 | 9.91 | 26.62 | 0.24 | –2.90 | –2.48 | –1.63 | –1.24 |
| Small average | 8.82 | 11.00 | 22.01 | 0.34 | — | — | 0.19 | 0.18 |
| L1 – L5 | 4.37 | 2.70 | –8.42 | 0.26 | 7.27 | 2.84 | 4.36 | 2.51 |
| Mid L1 | 10.24 | 11.42 | 16.08 | 0.49 | 3.90 | 2.13 | 2.75 | 2.30 |
| Mid L2 | 10.00 | 11.58 | 18.70 | 0.43 | 2.06 | 1.91 | 2.14 | 2.04 |
| Mid L3 | 9.25 | 11.28 | 21.29 | 0.36 | 0.25 | 0.54 | 1.33 | 1.10 |
| Mid L4 | 7.75 | 10.34 | 24.07 | 0.28 | –1.97 | –2.63 | –0.01 | –0.01 |
| Mid L5 | 6.91 | 10.08 | 26.70 | 0.25 | –3.23 | –2.24 | –0.63 | –0.37 |
| Mid average | 9.01 | 10.94 | 20.69 | 0.36 | — | — | 1.05 | 0.99 |
| L1 – L5 | 3.33 | 1.34 | –10.62 | 0.25 | 7.34 | 2.62 | 3.40 | 1.53 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Large L1 | 8.34 | 9.35 | 14.81 | 0.39 | 2.42 | 2.10 | 1.90 | 1.71 |
| Large L2 | 7.49 | 8.66 | 15.92 | 0.32 | 0.94 | 1.46 | 2.10 | 1.33 |
| Large L3 | 6.41 | 7.71 | 16.72 | 0.25 | –0.45 | –1.29 | 1.58 | 0.96 |
| Large L4 | 6.01 | 7.44 | 17.46 | 0.22 | –1.07 | –2.84 | 0.84 | 0.52 |
| Large L5 | 6.03 | 8.11 | 21.23 | 0.22 | –1.76 | –1.21 | –0.86 | –0.67 |
| Large average | 6.93 | 8.25 | 16.83 | 0.28 | — | — | 1.26 | 0.90 |
| L1 – L5 | 2.30 | 1.24 | –6.42 | 0.18 | 4.24 | 2.23 | 3.39 | 2.98 |
| Growth L1 | 8.10 | 9.38 | 16.67 | 0.35 | 2.38 | 1.72 | 1.26 | 1.84 |
| Growth L2 | 7.18 | 8.78 | 18.61 | 0.28 | 0.65 | 0.80 | 0.04 | 0.05 |
| Growth L3 | 7.34 | 9.36 | 21.02 | 0.28 | 0.09 | 0.30 | –0.13 | –0.15 |
| Growth L4 | 7.83 | 10.50 | 24.46 | 0.28 | –0.13 | –1.18 | 0.19 | 0.16 |
| Growth L5 | 5.85 | 9.18 | 27.34 | 0.21 | –2.44 | –1.88 | –1.68 | –1.09 |
| Growth average | 7.40 | 9.44 | 21.17 | 0.28 | — | — | –0.14 | –0.17 |
| L1 – L5 | 2.26 | 0.20 | –10.67 | 0.14 | 4.93 | 2.12 | 2.99 | 1.74 |
| Core L1 | 9.12 | 10.15 | 15.04 | 0.44 | 2.14 | 2.86 | 2.14 | 2.68 |
| Core L2 | 7.84 | 9.10 | 16.54 | 0.34 | 0.25 | 0.42 | 0.79 | 1.40 |
| Core L3 | 7.21 | 8.57 | 17.09 | 0.29 | –0.61 | –1.28 | 0.06 | 0.11 |
| Core L4 | 7.43 | 8.90 | 17.81 | 0.30 | –0.65 | –1.44 | –0.21 | –0.29 |
| Core L5 | 7.48 | 9.39 | 20.37 | 0.29 | –1.14 | –0.89 | –0.72 | –0.79 |
| Core average | 7.87 | 9.22 | 17.08 | 0.33 | — | — | 0.40 | 0.69 |
| L1 – L5 | 1.63 | 0.76 | –5.33 | 0.15 | 3.32 | 2.38 | 2.88 | 2.98 |
| Value L1 | 9.29 | 10.30 | 14.86 | 0.46 | 1.76 | 3.28 | 2.49 | 2.48 |
| Value L2 | 8.40 | 9.56 | 15.87 | 0.38 | 0.42 | 1.09 | 1.40 | 1.37 |
| Value L3 | 8.27 | 9.55 | 16.68 | 0.36 | –0.06 | –0.22 | 1.06 | 0.96 |
| Value L4 | 7.92 | 9.26 | 17.03 | 0.34 | –0.54 | –1.91 | 0.53 | 0.49 |
| Value L5 | 7.01 | 8.59 | 18.39 | 0.27 | –1.76 | –1.96 | –0.99 | –0.97 |
| Value average | 8.20 | 9.45 | 16.43 | 0.36 | — | — | 0.92 | 0.94 |
| L1 – L5 | 2.28 | 1.71 | –3.53 | 0.18 | 3.58 | 3.08 | 3.52 | 4.20 |

# i) Annual Average Stock Turnover

Table 13 Annual average stock turnover within fund categories[135]

| | Annual Stock Turnover | | | | |
|---|---|---|---|---|---|
| Category | L1 | L2 | L3 | L4 | L5 |
| Small value | 108% | 143% | 168% | 208% | 545% |
| Small core | 118 | 163 | 200 | 263 | 793 |
| Small growth | 163 | 228 | 290 | 380 | 1,095 |
| Mid value | 110 | 138 | 163 | 203 | 493 |
| Mid core | 118 | 165 | 208 | 260 | 610 |
| Mid growth | 158 | 218 | 273 | 355 | 808 |
| Large value | 93 | 113 | 130 | 150 | 220 |
| Large core | 105 | 135 | 150 | 168 | 270 |
| Large growth | 128 | 160 | 188 | 230 | 450 |
| Small | 125 | 180 | 233 | 315 | 928 |
| Mid | 128 | 183 | 233 | 308 | 728 |
| Large | 105 | 135 | 155 | 185 | 343 |
| Value | 95 | 120 | 138 | 163 | 328 |
| Core | 110 | 140 | 160 | 195 | 455 |
| Growth | 135 | 178 | 223 | 295 | 725 |
| All U.S. | 110 | 145 | 175 | 230 | 573 |

[135] Source: Cf. Idzorek, T. M., Xiong, J. X., Ibbotson, R. G. (2012): *The Liquidity Style of Mutual Funds*, p. 47

# j) Robustness test: Implementation Delay

Table 14 Mutual Fund Liquidity Quintiles with a Quarterly Implementation Delay[136]

| | Geometric Mean (%) | Arithmetic Mean (%) | Standard Deviation (%) | Sharpe Ratio | Annualized Alpha Relative to Category Average (%) | *t*-Statistic of Alpha Relative to Category Average | Annualized Alpha Relative to Fama–French Factors (%) | *t*-Statistic of Alpha Relative to Fama–French Factors |
|---|---|---|---|---|---|---|---|---|
| All L1 | 8.83 | 9.89 | 15.17 | 0.42 | 3.05 | 2.19 | 2.39 | 2.66 |
| All L2 | 7.74 | 9.00 | 16.48 | 0.33 | 1.26 | 1.29 | 1.16 | 1.92 |
| All L3 | 6.68 | 8.14 | 17.7 | 0.26 | –0.32 | –0.61 | –0.18 | –0.30 |
| All L4 | 6.76 | 8.66 | 20.28 | 0.25 | –0.97 | –1.59 | –0.48 | –0.61 |
| All L5 | 5.58 | 8.34 | 24.69 | 0.2 | –2.75 | –1.48 | –1.72 | –1.37 |
| All average | 7.26 | 8.80 | 18.24 | 0.29 | — | — | 0.18 | 0.32 |
| L1 – L5 | 3.26 | 1.55 | –9.52 | 0.23 | 5.95 | 2.44* | 4.17 | 2.42 |

# k) Robustness test: Annual rebalancing

Table 15 Annually rebalanced composites[137]

| | Geometric Mean (%) | Arithmetic Mean (%) | Standard Deviation (%) | Sharpe Ratio | Annualized Alpha Relative to Category Average (%) | *t*-Statistic of Alpha Relative to Category Average | Annualized Alpha Relative to Fama–French Factors (%) | *t*-Statistic of Alpha Relative to Fama–French Factors |
|---|---|---|---|---|---|---|---|---|
| All L1 | 7.86 | 8.92 | 15.17 | 0.36 | 2.39 | 1.84 | 2.31 | 2.77 |
| All L2 | 6.61 | 7.86 | 16.33 | 0.27 | 0.62 | 0.64 | 1.04 | 1.85 |
| All L3 | 6.39 | 7.83 | 17.57 | 0.25 | –0.10 | –0.18 | 0.60 | 0.93 |
| All L4 | 6.53 | 8.42 | 20.28 | 0.25 | –0.66 | –1.07 | 0.39 | 0.45 |
| All L5 | 5.81 | 8.42 | 24.03 | 0.21 | –1.79 | –0.97 | –0.40 | –0.32 |
| All average | 6.77 | 8.29 | 18.09 | 0.27 | — | — | 0.69 | 1.18 |
| L1 – L5 | 2.05 | 0.50 | –8.87 | 0.16 | 4.25 | 1.96* | 2.72 | 1.68 |

# l) Robustness test: Alternative Liquidity Measure

Table 16 Analysis with Amihud Measure[138]

| | Geometric Mean (%) | Arithmetic Mean (%) | Standard Deviation (%) | Sharpe Ratio | Annualized Alpha Relative to Category Average (%) | *t*-Statistic of Alpha Relative to Category Average | Annualized Alpha Relative to Fama–French Factors (%) | *t*-Statistic of Alpha Relative to Fama–French Factors |
|---|---|---|---|---|---|---|---|---|
| All L1 | 9.03 | 11.06 | 21.20 | 0.35 | 0.82 | 0.54 | 0.31 | 0.27 |
| All L2 | 9.07 | 10.94 | 20.28 | 0.37 | 0.80 | 1.00 | 1.10 | 1.03 |
| All L3 | 7.49 | 8.87 | 17.26 | 0.31 | 0.14 | 0.25 | 0.23 | 0.31 |
| All L4 | 6.52 | 7.86 | 16.94 | 0.26 | –0.65 | –0.87 | –0.33 | –0.89 |
| All L5 | 6.35 | 7.85 | 17.95 | 0.24 | –0.92 | –0.73 | –0.19 | –0.34 |
| All average | 7.78 | 9.31 | 18.21 | 0.32 | — | — | 0.20 | 0.34 |
| L1 – L5 | 2.67 | 3.21 | 3.25 | 0.11 | 1.75 | 1.19* | 0.49 | 0.34 |

[136] Idzorek, T. M., Xiong, J. X., Ibbotson, R. G. (2012): *The Liquidity Style of Mutual Funds*, p. 47
[137] Source: Idzorek, T. M., Xiong, J. X., Ibbotson, R. G. (2012): *The Liquidity Style of Mutual Funds*, p. 48
[138] Source: Idzorek, T. M., Xiong, J. X., Ibbotson, R. G. (2012): *The Liquidity Style of Mutual Funds*, p. 50

# m) Robustness test: Non-US mutual funds

Table 17 Non U.S. mutual funds[139]

| | Geometric Mean (%) | Arithmetic Mean (%) | Standard Deviation (%) | Sharpe Ratio | Annualized Alpha Relative to Category Average (%) | *t*-Statistic of Alpha Relative to Category Average | Annualized Alpha Relative to Fama–French Factors (%) | *t*-Statistic of Alpha Relative to Fama–French Factors |
|---|---|---|---|---|---|---|---|---|
| All L1 | 1.5 | 3.28 | 19.16 | 0.03 | 0.54 | 0.40 | 0.13 | 0.09 |
| All L2 | 2.69 | 4.07 | 16.9 | 0.08 | 1.66 | 1.28 | 1.00 | 0.65 |
| All L3 | 1.58 | 2.97 | 16.92 | 0.01 | 0.60 | 0.37 | –1.15 | –0.72 |
| All L4 | 0.74 | 2.37 | 18.27 | –0.02 | –0.22 | –0.15 | 1.12 | 0.61 |
| All L5 | –1.63 | 1.13 | 23.84 | –0.07 | –2.10 | –0.77 | 3.95 | 1.43 |
| All average | 1.15 | 2.76 | 18.19 | 0 | — | — | 0.88 | 0.99 |
| L1 – L5 | 3.13 | 2.15 | –4.69 | 0.1 | 2.69 | 0.85* | –3.69 | –1.16 |

# n) SAS Macro for Quintile Classification

```
%macro groups(style1=, style2=, year=);
data &style1._&style2._&year.;
set thesis.funds_complete(keep=liq&year. FundID r_&year._01-r_&year._12 Style_box_1
Style_box_2);
where Style_box_1="&style1." and Style_box_2="&style2.";
run;
```
(creates data set with concrete style category)

```
proc univariate data=thesis.&style1._&style2._&year. noprint;
var liq&year.;
output out=thesis.quantile pctlpts=20 40 60 80 pctlpre=pct;
run;
```
(calculates quintiles binnings for category's liquidity)

```
data _null_;
set thesis.quantile;
call symput('q1',pct20) ;
call symput('q2',pct40) ;
call symput('q3',pct60) ;
call symput('q4',pct80) ;
run;
```
(Creates macro variables and assigns quintile binnings)

```
data thesis.&style1._&style2._&year.;
set thesis.&style1._&style2._&year.;
if liq&year. =. or liq&year. =0 then delete;
```
(only data with liquidity information considered)

```
else if liq&year. < &q1. or liq&year.= &q1. then L=1;
else if &q1. < liq&year. <= &q2. then L=2;
else if &q2. < liq&year. <= &q3. then L=3;
else if &q3. < liq&year. <= &q4. then L=4;
else L=5;
run;
```
(assigning L composites)

```
proc means data=thesis.&style1._&style2._&year. noprint nway;
class l;
Var r_&year._01-r_&year._12;
output out=thesis.&style1._&style2._&year.;
run;
```
(summarizing return information per composite)

```
data thesis.&style1._&style2._&year.;
```

[139] Source: Idzorek, T. M., Xiong, J. X., Ibbotson, R. G. (2012): *The Liquidity Style of Mutual Funds*, p. 51

```
set thesis.&style1._&style2._&year.(keep=L r_&year._01-r_&year._12 _STAT_);
where _STAT_="MEAN";
drop _STAT_ L;
run;

proc transpose data=thesis.&style1._&style2._&year. name= Date prefix=L
out=thesis.&style1._&style2._&year._transposed;
run;

%mend;
```