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LIQUIDITY STYLE IN EUROPEAN STOCK MARKET

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ABSTRACT

Sami Aho: Liquidity style in European stock market
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Liquidity, the ability to trade assets quickly without significant trading cost or price impact, has a compelling economic intuition for explaining an excess premium: investor want liquidity for the ability to exit positions quickly and are willing to pay for it and thus, long-term investors of illiquid stocks should be rewarded with a premium. But still, even though the cross-sectional relation between stock's liquidity and future returns, the liquidity style, has been researched extensively in the past 30 years, no consensus has been reached on whether a liquidity premium exists.

Most studies have been conducted in the U.S. stock market using only a single measure of liquidity as the style characteristic. This study replicates the analysis framework of a study conducted by Ibbotson, et al. (2013) to find out if a liquidity premium exists in the European stock market using a composite liquidity measure consisting of four different academic liquidity measures. Additionally, it answers the open questions on how estimated transaction costs affect the liquidity premium and whether liquidity premiums can be attributed to certain market regimes.

The scope of the study is the primary European exchanges from January 2000 to December 2020. The liquidity style is compared against size, value, and momentum styles through various analysis, where each style is split in quartile portfolios based on their respective ranking variables. Estimated transaction costs are analysed using a simple model based on portfolio turnover and bid-ask spread. Monthly liquidity style returns are examined against market returns, volatility and maximum drawdown to find out if liquidity premium stems from a specific market regime.

The study finds that the most illiquid quartile portfolio return is similar to other style top quartile portfolio returns and overperforms the market return. Portfolio turnover ratios among the style portfolios are similar, except for momentum having the highest turnover. In terms of portfolio composition, liquidity style is clearly different from value and momentum styles but shares similarities with the size style. Liquidity effect (higher returns for more illiquid stocks) was present across different size quartiles, but this was not true the other way around, indicating that size could be a proxy for liquidity. The long-short liquidity factor premium was positive but insignificant after controlling risk for market, size, value, and momentum factors. The removal of size risk control from the regression model made the liquidity premium positive and significant. The liquidity premium is observed to dissipate after applying estimated transaction costs, which implies that the liquidity effect could be hard to exploit in a practical setting. The liquidity style is found to resemble low beta strategies, hence overperforming the market in downturns.

Keywords: Liquidity style, Liquidity factor, Style investing, Factor investing

The originality of this thesis has been checked using the Turnitin OriginalityCheck service.

TIIVISTELMÄ

Sami Aho: Likviditeettisijoitustyyli Euroopan osakemarkkinoilla
Diplomityö
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Likviditeetillä tarkoitetaan kykyä käydä kauppaa sijoitusinstrumentilla nopeasti ilman merkittäviä kuluja tai vaikutusta instrumentin hintaan. Likviditeettiin liittyvä ansaintamalli on houkutteleva: sijoittajat ovat valmiit maksamaan paremmasta likviditeetistä, koska pystyvät irtaantumaan positioista nopeammin. Tästä syystä pitkäjänteisten epälikvidien osakkeiden omistajien tulisi ansaita alhaisemmasta likviditeetistä johtuva preemio. Vaikka osakkeiden likviditeetin ja tulevien tuottojen välistä suhdetta, likviditeettisijoitustyyliä, on tutkittu perusteellisesti viimeisten 30 vuoden aikana, akateeminen yhteisö ei ole saavuttavat yhteisymmärrystä siitä, onko likviditeettipreemio olemassa.

Suurin osa tutkimuksista on suoritettu Yhdysvaltain osakemarkkinoilla käyttäen vain yhtä likviditeettimittaria tyylin määrittävänä tekijänä. Tämä tutkimus toistaa Ibbotson et al. (2013) tutkimuksen viitekehyksen selvittääkseen, onko Euroopan osakemarkkinoilla havaittavaa likviditeettipreemiota, käyttämällä yhdistettyä likviditeettimittaria, joka koostuu neljästä erilaisesta akateemisesta likviditeettimittarista. Lisäksi tutkitaan kuinka estimoidut transaktiokustannukset vaikuttavat likviditeettipreemioon ja että syntyykö likviditeettipreemio pääosin tietyissä markkinaolosuhteissa.

Työssä tutkitaan Euroopan keskeisiä pörssejä tammikuusta 2000 joulukuuhun 2020. Likviditeettisijoitustyyliä verrataan koko-, arvostus- ja momentum-sijoitustyyleihin erilaisissa analyyseissa. Kaikista sijoitustyyleistä on muodostettu neljännesportfolioita kunkin tyylin järjestysmuuttajan perusteella. Estimoidut transaktiokustannukset analysoidaan yksinkertaisella mallilla, jossa muuttujina ovat portfolion kiertonopeus sekä myynti- ja ostokurssin erotus. Likviditeettisijoitustyylin kuukausituottoja verrataan saman hetken markkinan tuottoihin, volatiliteettiin ja suhteelliseen maksimitappioon. Tarkoituksena arvioida syntyykö merkittävä osa likviditeettisijoitustyylin preemiosta tietyissä markkinaolosuhteissa.

Tutkimuksessa todetaan epälikvideimmän neljännesportfolion tuoton olevan yhtä hyvä kuin muiden sijoitustyylien parhaiden neljännesportfolioiden sekä päihittävän markkinatuoton. Portfolioiden kiertonopeudet ovat samankaltaisia pois lukien korkean kiertonopeuden momentum-sijoitustyyli. Likviditeettisijoitustyylin portfolioihin valikoituvat osakkeet ovat selkeästi erilaisia arvostus- ja momentum-sijoitustyylien portfolioihin verrattuna, mutta koko- ja likviditeettisijoitustyylin välillä on huomattavia samankaltaisuuksia. Epälikvidiosakkeet tuottivat enemmän kuin likvidit osakkeet kun tätä tarkasteltiin eri kokosijoitustyylin neljänneksissä, mutta pienen koon yhtiöt eivät tuottaneet paremmin kuin ison koon yhtiöt eri likviditeettisijoitustyylin neljänneksissä. Tämä antaa olettaa, että kokosijoitustyyli vain mallintaa likviditeettisijoitustyyliä, mutta ei ole aito preemion lähde. Likviditeettifaktorin (epälikvidein neljännes ostettu portfolioon ja likvidein neljännes myyty lyhyeksi) preemio oli positiivinen, mutta tilastollisesti merkityksetön kun regressiomallin selittävinä tekijöinä oli markkinaportfolio sekä koko-, arvostus- ja momentumfaktori. Kun kokofaktori poistettiin mallista, likviditeettifaktorin preemiosta tuli positiivinen ja tilastollisesti merkitsevä. Estimoitujen transaktiokustannusten huomioon ottaminen laski preemion lähelle nollaa. Likviditeettisijoitustyylin todetaan muistuttavan alhaisen beta-kertoimen strategioita, jotka tuottavat markkinoita enemmän laskukausissa.

Avainsanat: Likviditeettisijoitustyyli, Likviditeettifaktori, Faktorisijoittaminen

Tämän julkaisun alkuperäisyys on tarkastettu Turnitin OriginalityCheck –ohjelmalla.

PREFACE

The idea for this researched stemmed from my passion towards investing. The notion that stock market returns are, to some level, deterministic and logical is soothing. I want to contribute to research advancing this notion.

I could have not accomplished this work without a strong support group. I am very grateful to my spouse and employer for all the support and understanding. I would also like to thank my thesis supervisor for his valuable guidance and his patience.

Helsinki, 27 April 2021

Sami Aho

CONTENTS

LIST OF SYMBOLS AND ABBREVIATIONS

AMEX	American Stock Exchange
APT	Arbitrage Pricing Theory
BPS	Basis points (1 per 10 000)
CAPM	Capital Asset Pricing Model
CRSP	Centre for Research in Security Prices
GICS	Global Industry Classification Standard
NYSE	The New York Stock Exchange
OLS	Ordinary Least Squares
TC	Transaction cost

1. INTRODUCTION

Style investing is the process of classifying assets based on a common characteristic (Barberis & Shleifer, 2003). Over the recent decades style investing has grown to be the foremost investing approach. Styles such as value and size proposed by Fama & French (1993) and momentum by Carhart (1997) have dominated the space.

Liquidity is the ability to buy and sell securities quickly at low cost without significant price impact. The liquidity style may have the most convincing economic intuition even when compared to the style investing giants size, value and momentum: Investors want liquidity for the ability to exit positions quickly and are willing to pay for it. Two stocks with identical cash flows which only differ in terms of liquidity, the stock with less liquidity should trade on a discount, since the cost of trading it is higher, and the trading horizon is longer. For an investor able and willing to keep the stocks for longer periods, a (liquidity) premium should exist.

Yet, even though the liquidity style has been investigated by academic scholars for over 30 years, the results over whether a liquidity premium, which is the cross-sectional relation between stock's liquidity and future returns, exists have been divided and thus it has not been accepted as a mainstream style (Subrahmanyam, 2010; Ibbotson, et al., 2013; Drienko, et al., 2019). Most studies have been conducted in the highly liquid and efficient U.S. stock market. Liquidity is inherited from the underlying market structure and may vary between markets (Bernstein, 1987). The European stock market is fragmented and generally not seen as efficient as the U.S. stock market, hence it is an interesting market for testing if less liquid stocks produce excess returns compared to liquid stocks. Researchers have built and analyzed the liquidity style using different variables that describe liquidity, but usually only one variable is used (Amihud & Mendelson, 1986; Datar, et al., 1998; Amihud, 2002). Liu (2006) suggests that liquidity consist four dimensions so using more than one variable may be needed to capture the true nature of a stock's liquidity. The studies on liquidity style discuss transaction costs extensively as they are a key reason for the existence of liquidity premium but fail to incorporate them when interpreting the return results in their analysis. Liquidity style has been associated with low volatility and low beta, but the market conditions in which it produces excess returns has not been examined (Ibbotson, et al., 2013; Ibbotson & Idzorek, 2014).

These are clear gaps in the research of liquidity style and this work sets to fill in the blanks. I construct a liquidity factor using a composite liquidity variable which consists of four pre-established liquidity metrics. Using this new factor, the analysis framework of the study “Liquidity as an Investment Style” by Ibbotson, et al. (2013) is replicated in the European stock market to see if a liquidity premium exists and whether aspects of liquidity style is already being captured by the well-established styles. Later on, estimated transaction costs are applied to see whether the premium ceases to exist. Liquidity style return association to market return and risk metrics is also analyzed.

This study has the following structure. The next chapter introduces a brief history of style investing and the key styles that this work refers to. Then the concept of liquidity is defined. After this a literary review of liquidity style research follows with the formulation of research objectives. Chapter three gives a broad overview on the used dataset for reproducibility. The set of rules which define the investment universe along with summary data is introduced. In chapter four, the composite variable for liquidity is defined. The liquidity style, based on the new variable, is compared to size, value and momentum styles as the Ibbotson, et al. (2013) study is replicated. The results are scrutinized with estimated transaction costs. Finally, the liquidity style returns are compared to market returns and risk metrics. Chapter five summarizes the findings.

2. THEORETICAL BACKGROUND

2.1 Style and Factor investing

The linchpin of modern finance, Capital Asset Pricing Model (CAPM), founded in the 1960s independently by Sharpe (1964) and Lintner (1965), was the first model to answer the question of what drives investment returns. The CAPM breaks it down to two drivers: idiosyncratic and systematic risk. Idiosyncratic risk is the investment specific risk which can be mitigated through diversification. Systematic risk is the market risk of the investment and it cannot be diversified. Systematic risk is described by beta: the relationship between a security's volatility relative to the market volatility. The idea is that investors are compensated with returns for holding this risk. The higher the beta the higher the expected returns.

A decade later the Arbitrage Pricing Theory (APT) was proposed by Ross (1976). Unlike in the CAPM, which has just one explanatory variable (systematic risk), the APT models expected returns of securities with multiple explanatory variables. These variables are called "factors". The APT did not define what these factors are, but noted that they could fluctuate throughout time and markets. This lead to the everlasting hunt for different factors.

In the academic literature, the words "style" and "factor" are sometimes used interchangebly. In this paper style refers to the general idea of the relation between expected returns and a characteristics variable, and factor refers to this exposure via a specific variable. For example, the value style premium could be captured with a low book to price -ratio or a low price to earnings -ratio factor portfolio.

2.2 Benchmark styles

Throughout this work the liquidity style is compared to the three well-established styles: size, value and momentum. In this chapter, the characteristic variables of the benchmark styles (factors) are defined.

The **Size** effect, first proposed by Banz (1981), is the phenomenon of smaller companies, measured by market capitalization, having higher returns than larger companies in average over time. The idea is that smaller companies have greater risk associated with them, and thus investors are compensated for holding this risk. **Value** effect, on the other hand, is an observation where securities that are cheap, measured by e.g. the price to earnings ratio, generate higher returns than securities that are expensive. Cheaper companies are thought to be riskier, thus the holders of the securities of these companies are rewarded with higher returns. Basu (1977) was the first to show that value ratios did not live up to the CAPM efficient market hypothesis. The breakthrough research of Fama & French (1993) brought these two factors together along with the market beta factor of CAPM to form the three-factor model. They used market capitalization and book to market -ratio as variables for the size and value factors, respectively. The benchmark factors in this work use these same measures. In the following chapters of this work when the results are compared to result of Ibbotson, et al. (2013), it should be noted that they use the price to earnings -ratio instead of the book to market -ratio, but argue that the resulting portfolios are very similar.

Momentum investing strategies seek to generate returns by investing in stocks based on their past return trend. The idea is that the past good performance will continue in the short-term. Momentum was first proposed by Jagadeesh & Titman (1993) and later by Carhart (1997) as an addition to the three-factor model to create the four-factor model. There are multiple different implementations of momentum where the length of the return horizon varies and recent months being omitted from return calculations (Moskowitz, et al., 2012). This work uses the original definition of momentum style: past 12-month return.

Additional information on the characteristics and returns for the size, value, momentum styles in the European investment universe of this work are supplied in **Appendix B**, **Appendix C** and **Appendix D**, respectively.

2.3 Liquidity definition

Liquidity is an elusive concept that does not have an exact definition among scholars. (Keynes, 1930) was one of the first to claim that the relative liquidity between assets can be determined by which one is “more certainly realizable at short notice without loss”. Decades later, many authors refer to liquidity as the ability to trade significant quantities of an asset, quickly, at low cost, and without meaningfully affecting the price (Pástor & Stambaugh, 2003; Harris, 2003; Brennan, et al., 2012).

Liu (2006) breaks liquidity down to four components: trading quantity, trading cost, price impact and trading speed. **Trading quantity** can be thought as the amount of trades that take place. This can be a relative measure (volume compared to outstanding shares) or an absolute measure (volume multiplied by price, traded value). **Trading cost** and **price impact** are related to the broader concept of execution cost (Perold, 1988). Trading costs are composed of the brokerage commissions, different taxes and the bid-ask spread. Bid-ask spread is an explicit cost of the difference between bid and ask price. It can be thought as a trading cost since if an investor, in theory, were to immediately buy and sell a stock, the cost of doing this would be the bid-ask spread (Amihud & Mendelson, 1986). Roll (1984) contradicts this by arguing that most of the trades happen inside the spread, not at the actual bid and ask prices. Price impact is an implicit cost that incurs when an investor interacts with the current order book state and causes it to change. In a theoretical context, an investor will drive up the price if executing a buy order or drive it down if executing a sell order when no other orders are placed (Perold, 1988). **Trading speed** is related to the notion of market thickness described by Lippman & McCall (1986). They find that an increase in the offer frequency decreases the time of a trade to take place, thus improving liquidity. Liu (2006) states that the trading speed dimension of liquidity has little research compared to other dimensions. He then creates a new measure, trading discontinuity ratio, which mainly focuses on trading speed dimensions, but should also capture trading quantity and cost dimensions.

2.4 Liquidity style research

The relation of stock liquidity and returns was initially investigated by Amihud & Mendelson (1986). The Amihud-Mendelson model shows that the expected return of a security increases as the related trading costs increase. When buying two securities with identical future cash flows and risks, but different trading costs, rational investors would demand a lower price (thus higher expected return) for the security with higher trading costs. The increase in the expected returns is not linear, but decreases as trading costs increase, making the relation concave. They argue that this is due to some investors having longer investment horizons and thus requiring less compensation for the paid trading costs. The model was tested with data from NYSE (New York Stock Exchange) from 1961 to 1980 using bid-ask spread as a proxy for trading costs. The results supported the model, showing an 8 percent per annum return premium between the highest and lowest bid-ask spread (7^{th}-tile) portfolios.

Eleswarapu & Reinganum (1993) argue that the results of Amihud & Mendelson (1986) are due to a seasonal phenomenon. They report finding a reliable liquidity premium only during January and that size premium was meaningful even after controlling for bid-ask spread and market beta.

Brennan & Subrahmanyam (1996) took the Amihud-Mendelson model further by extending the model with market impact (trade-size-dependent) variable in addition to the bid-ask spread (fixed) variable. This was enabled by new trade-by-trade data that was not previously available. They argue that bid-ask spread is not a very good measure as it is, since many large trades happen outside the spread and many small ones happen inside the spread. They adjust returns for risk using the Fama & French (1993) three factor model, unlike Amihud & Mendelson (1986) and Eleswarapu & Reinganum (1993) who use the single factor capital asset pricing model (CAPM). They report finding a significant return premium for both the variable and fixed components of their model. However, concave relation between trading costs and returns are only found on the variable component, thus questioning the Amihud & Mendelson (1986) investment horizon hypothesis. They admit this can be caused by incomplete data or a missing risk factor in the Fama & French (1993) three factor model. Contrary to Eleswarapu & Reinganum (1993), no meaningful seasonality was found.

Datar, et al. (1998) propose turnover rate is a better proxy for liquidity arguing that it is hard to acquire bid-ask spread data for longer periods and that previous research has shown that the bid-ask spread itself does not very well reflect on the transaction costs paid by investors. Turnover rate is defined as dividing the average transaction volume over three previous months by the number of shares outstanding. Stocks with splits are omitted for three months. To achieve a robust study, they create three datasets: full, trimmed and non-January. The full dataset accounts for all of the CRSP (Centre for Research in Security Prices) data from 1962 to 1991. In the trimmed dataset outliers are removed from the full dataset by omitting the stocks that are in the highest and lowest 1 percent based on turnover rate each month. The non-January dataset is built by excluding every January from the full dataset. In the study they examine the relation of monthly turnover rates to asset returns after controlling risks for size, value and market premium. They find a decreasing negative relation between returns and turnover supporting the predictions of the Amihud & Mendelson (1986) model. The reported January effect of Eleswarapu & Reinganum (1993) was not found. They go even further with robustness of the study by dividing the data in two time periods, the first one from 1963 to 1977 and the second from 1997 to 1991, and confirm the relation is stable over time.

Chordia, et al. (2001) examine the relation between the standard deviation of liquidity and asset returns. The hypothesis is that variability in liquidity would demand higher expected assets returns, since the available liquidity would be more uncertain. They choose dollar trading volume (share price multiplied with volume) and the turnover rate of Datar, et al. (1998) as their liquidity proxies. They use monthly data of companies listed on NYSE and AMEX (American Stock Exchange) from 1966 to 1995. After controlling risk for size, value and momentum premium, they find that greater standard deviation of volume, contrary to their hypothesis, is observed to decrease the expected return. This negative relation of asset return and volatility of liquidity was found to be significant.

Amihud (2002) extends his previous research (Amihud & Mendelson, 1986) of cross-sectional illiquidity premium to examine the relationship of illiquidity and returns over time. Following the research of Brennan & Subrahmanyam (1996) he suggests an alternative measure for market impact and liquidity. The measure, denoted as ILLIQ, is defined as the mean over one month of daily liquidity ratios: absolute returns divided by daily dollar trading volume. The study argues that the market impact measure provided by Brennan & Subrahmanyam (1996) is a finer measure, but it requires detailed trade-by-trade data, which is hard to access and not available for all markets especially for long periods of time. Hence, a measure with better accessibility is required. The study uses data of NYSE stocks from 1963 to 1997. He proposes that a higher expected illiquidity for period $t+1$ raises expected returns for period $t+1$, inline with the theory of Amihud-Mendelson model. Additionally, a higher unexpected liquidity for period t should decrease expected returns for period $t+1$. This is due to the unexpected illiquidity being realized to expected liquidity, which in turn decreases the stock price (raises expected returns). The results were as assumed, expected liquidity has positive effect on asset returns and unexpected liquidity has negative effect on asset returns. These effects were reported to be more significant for small companies.

Liu (2006) suggest that liquidity has four dimensions (described in chapter 2.3), and states that the final dimension, trading speed, has gone unnoticed from the scientific community. He proposes a new liquidity measure, the standardized turnover-adjusted number of zero daily trading volumes over the prior 12 months, which is to simulate the trading speed dimension. The study reports that the new measure captures also the trading quantity and cost dimensions. Using this measure, a significant and robust monthly liquidity premium of 0.68% is recorded. He proposes a two-factor model, where CAPM is augmented by the liquidity factor, and states that this new model captures the size and value effect from the Fama & French (1993) three-factor model. The study uses data from NYSE, AMEX and NASDAQ between 1963 to 2003.

Ibbotson, et al. (2013) propose that liquidity, measured as stock turnover, should be considered as an investment style equal to size, value and momentum styles. They show that the liquidity style satisfies the style criteria set by Sharpe (1992): The illiquid portfolio returns are similar to other style portfolios and overperform the market; Liquidity quartile portfolios are clearly different from other style portfolios and the long-short liquidity factor returns are not captured by the size, value and momentum factors; The liquidity portfolios have low turnover relative to other style portfolios. This work replicates the analysis framework created by Ibbotson, et al. (2013) in chapter 4.2.

Ben-Rephael, et al. (2015) study the liquidity ratio by Amihud (2002) and two other liquidity measures. The study reports that the liquidity premium is mainly concentrated to small stocks using data from NYSE, AMEX and NASDAQ between 1964 to 2011. The premium is larger before mid-1980s and then diminishes. For large and medium capitalization stocks a liquidity premium cannot be identified, even for earlier periods of the data set. They suggest that the liquidity premium could be significant in less liquid markets than the U.S. stock market.

Drienko, et al. (2019) replicate the Amihud (2002) analysis and report that the results only hold in-sample. In the out-of-sample results, using data from 1997 to 2015, the liquidity premium is statistically insignificant. They argue that this due to the development of equity trading in the past two decades.

2.5 Research objectives

Majority of liquidity premium related studies have been conducted using the US stock market data. Bernstein (1987) states that liquidity may vary between markets, thus it is not clear what is the manifestation of liquidity style in different markets. In their conclusion, Ben-Rephael, et al. (2015) agree with this. Amihud, et al. (2015) investigated emerging and developed markets with promising results. Moreover, most studies are conducted using a single or multiple liquidity measure, but separetely. Liu (2006) argues liquidity has four dimensions, thus a factor with multiple liquidity measures combined should be studied. Past research papers have not analyzed the effect of estimated transaction costs on the liquidity premium, which are essential if any pratical application were to be considered. Liquidity style has previously been linked to low beta and low volatily styles, but these relations have not been researched further (Ibbotson, et al., 2013; Ibbotson & Idzorek, 2014). This work aims to expand existing research by examining the following questions:

1) Can a liquidity premium be observed in the European stock market using a factor based on a new composite liquidity variable combining the four dimensions?
2) How do estimated transaction costs affect the liquidity premium?
3) Does the liquidity style overperform in certain market regimes?

3. RESEARCH MATERIALS

3.1 Data overview

S&P Capital IQ Fundamentals and Market dataset serves as the main the data for the study. It is a point-in-time representation of company financials and market data with a complete revision history served as a SQL database. The point-in-time feature allows the analysis to be conducted in "as it were" fashion, so that new revisions do not cause forward bias. The data for this analysis is from January 3rd, 2000 to December 31st, 2020. Since a year of data to construct the portfolios is needed, the subsequent results are calculated from January 3rd, 2001 onwards. **Table 1** shows the used variables and other information.

Table 1. *Data description, reasoning and source table for the variables used in the study.*

Data Description	Reasoning	Source table
Market capitalization	Restriction for universe Size factor	ciqMarketCap
Country	Restriction for universe	ciqCompany
Exchange	Restriction for universe	ciqTradingItem
Dividend adjusted price at market close	Return and risk calculation Liquidity ratio	ciqPriceEquity
Price at market close	Momentum factor Value factor Liquidity ratio	ciqPriceEquity
Bid price at market close	Relative bid-ask spread	ciqPriceEquity
Ask price at market close	Relative bid-ask spread	ciqPriceEquity
Daily trade volume	Turnover ratio Trading discontinuity ratio Liquidity ratio	ciqPriceEquity
Number of outstanding shares	Turnover ratio	ciqMarketCap
Book value per share	Value factor	ciqFinCollectionData

The description column reports which variable is in question. The reasoning column points to what end the variable is used and the source table column shows the SQL table name where the data is obtained. Detailed data queries are available upon request.

3.2 Investment Universe

The scope of the research is the European stock market. To achieve this, companies are required to domicile in the developed European countries and underlying stocks are required to trade in the exchanges listed in **Table 2**. We exclude the emerging and frontier European countries and markets for the possibility of having market structures that might affect the result of study and lack of data. The list of stocks is further limited by only allowing ones that trade in primary exchanges.

Table 2. *Investment universe rule set.*

Include **developed European countries**: *Austria, Belgium, Denmark, Finland, France, Germany, Ireland, Italy, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, United Kingdom*
Include **main European exchanges**: *Deutsche Boerse AG, SIX Swiss Exchange, BATS 'Chi-X Europe', XETRA Trading Platform, OMX Nordic Exchange Stockholm, London Stock Exchange AIM Market, Aktietorget, Dusseldorf Stock Exchange, Nordic Growth Market, Oslo Bors, London Stock Exchange, OMX Nordic Exchange Helsinki, Bourse de Luxembourg, Boerse-Stuttgart, Euronext Paris, Bolsas y Mercados Espanoles, Boerse Muenchen, Borsa Italiana, OMX Nordic Exchange Copenhagen, Wiener Boerse AG, Euronext Am-sterdam, Euronext Brussels, SWX Europe Limited, Hamburg Stock Exchange, Berne Stock Exchange, SIBE - Spanish Stock Exchange Interconnection System, Euronext Lisbon, Bolsa de Madrid, Barcelona Stock Exchange, Obsolete - formerly Paris, Bol-sa de Valencia, Bilbao Stock Exchange, Boerse Muenchen - Freiverkehr*
Include only **primary securities and listings**
Include companies with **market capitalization greater than 10 million EUR**
Include companies that have a **turnover ratio greater than zero**
Include companies that have **more than 60 daily observations of bid-ask spread for the previous year**
Include companies that have **more than 60 daily observations for price impact for the previous year**

The data quality with very small companies varies over time. Working with missing values makes the results more unreliable, which is why the lower limit of market capitalization has been set to 10 million Euros. The process of updating the universe or a portfolio to comply with the rules is called **rebalancing**. The universe rebalancing happens once a year on the first business day of the year. The list of exact rebalancing dates and number of companies with market capitalization summaries can be found in **Table 3**.

Table 3. *Investment universe rebalancing dates with summary data, 2001-2020.*

		Market Capitalization (million EUR)			
Rebalancing Date	Number of stocks	Mean	Median	Maximum	Minimum
Wednesday, January 03, 2001	2 604	2 115	173	195 597	10
Thursday, January 03, 2002	2 735	1 966	152	138 889	10
Friday, January 03, 2003	2 591	1 597	135	100 615	10
Monday, January 05, 2004	3 111	1 885	160	144 955	10
Monday, January 03, 2005	3 187	2 016	174	158 814	10
Tuesday, January 03, 2006	3 348	2 450	204	199 093	10
Wednesday, January 03, 2007	3 558	2 723	223	176 470	10
Thursday, January 03, 2008	3 881	2 431	185	184 865	10
Monday, January 05, 2009	3 341	1 641	108	121 180	10
Monday, January 04, 2010	3 441	2 044	141	139 597	10
Monday, January 03, 2011	3 472	2 237	160	153 746	10
Tuesday, January 03, 2012	3 339	2 087	141	181 480	10
Thursday, January 03, 2013	3 256	2 465	163	168 365	10
Friday, January 03, 2014	3 347	2 817	186	173 096	10
Monday, January 05, 2015	3 414	2 851	208	194 623	10
Monday, January 04, 2016	3 540	3 010	230	216 162	10
Tuesday, January 03, 2017	3 713	2 991	237	221 099	10
Wednesday, January 03, 2018	3 870	3 164	256	236 077	10
Thursday, January 03, 2019	3 876	2 710	214	220 694	10
Friday, January 03, 2020	3 875	3 368	252	282 989	10
Whole sample	**67 499**	**2 429**	**180**	**282 989**	**10**

3.3 Portfolio construction

The objective of the portfolio construction is to split the stocks in the investment universe into four equal sized portfolios by some variable. The output portfolios are called **quartile portfolios**. Why split in four portfolios? Fama & French (1993) split stocks in five portfolios and a few years later they, Fama & French (2015), split stocks in five portfolios as Liu (2006) split stocks in ten portfolios. The selection of the resolution is therefore maybe a bit more of an art than science and it should not meaningfully affect the outcome. This work opts for grouping stocks in four portfolios so that results are comparable to the work of Ibbotson, et al. (2013). I mentioned that stocks are divided into four equal size portfolios. This is not true, when the number of the stocks in the universe is not divisible by four. Most quartile functions drop observations with some logic so that they can be truly set in four equal parts. That kind of behavior is unwanted, since stocks would be randomly excluded on the edges of the quartiles. **Program 1** is a pseudo code algorithm for the logic of dividing stock into four fuzzy equal parts.

```
# x: a numeric vector that needs to be split into 4 ~equal parts
# e.g. market capitalization per stock at one time point

# create a vector [0, 1] that has the quartile thresholds
p <- c(0.00, 0.25, 0.50, 0.75, 1.00)

# get length of vector x (number of observations)
len <- length(x)

# helper parameter for solving ties
eps <- 10^-6

# create empty vector where position information is saved
pos <- integer(length(p))

# get position of the values on the quartile thresholds and save to pos
for(i in 1:length(p))
  pos[i] <- round(len * (p[i] – eps))

# rank of values, ties solved so that first tied value gets smaller rank
r <- rank(x, ties.method = "first")

# create empty vector where quartile number is stored
q <- integer(len)

# for each element in x, deduce in which quartile it belongs to
for(i in 1:(length(pos) - 1))
  q[r > pos[i] & r <= pos[i + 1]] <- i

# vector q holds the quartile portfolio number for each number in x
return(q)
```

Program 1. *Pseudo code for dividing variables into four almost equal size buckets. Uses notations and base function from R language.*

The algorithm above is run for all the styles one by one using the selected variable for each style. This process is repeated for every rebalancing date using the latest available data. Each stock in a quartile portfolio has an equal weight so that the sum of weights equals to one.

In the analysis that follows, two different benchmarks are used commonly. The **universe portfolio** is the equal weighted portfolio (every stock has the same weight) of all the stocks that comply with the universe rule set. The **market portfolio** has the same constituents than the universe portfolio, but the stocks are weighted respective to their market capitalization. All quartile (and factor) portfolios are weighted equally.

4. ANALYSIS OF LIQUIDITY STYLE

4.1 Composite variable for Liquidity style

Liu (2006) proposes that liquidity has four dimensions. A new composite variable for liquidity style is created by combining metrics from previous academic literature that simulate these four dimensions. **Table 4** shows how the dimensions are linked to the different variables.

Table 4. *The four dimensions of liquidity with related measures Liu (2006).*

Dimension	Measure
Trading Quantity	Turnover Ratio (Datar, et al., 1998)
Trading Cost	Relative Bid-Ask Spread (Amihud & Mendelson, 1986)
Price Impact	Liquidity Ratio (Amihud, 2002)
Trading Speed	Trading Discontinuity Ratio (Liu, 2006)

The **turnover ratio**, which was first examined by Datar, et al. (1998), is defined as the total volume over the last year divided by the average number of shares outstanding over the same period. Formally,

$$\frac{\sum_{t=-1}^{-T} v_t}{\frac{1}{T}\sum_{t=-1}^{-T} so_t} \tag{1}$$

where T is the number of trading dates in the period, v_t is volume and so_t is shares outstanding at time t. Index t denotes trading days from the rebalancing date such that $t = 0$ is the rebalancing date, $t = -1$ is the previous trading day before rebalancing and $t = -252$ is approximately the rebalancing date year ago. The measure is slightly modified from the original measure by using the average of shares outstanding over the period instead of only using the final value. A lower value translates to the stock being less liquid.

The **relative bid-ask spread**, which was first examined by Amihud & Mendelson (1986), is defined as bid-ask spread divided by the average of bid and ask price. These values are averaged over the period T. Formally,

$$\frac{1}{T}\sum_{t=-1}^{-T} \frac{2\,(bid_t - ask_t)}{bid_t + ask_t} \tag{2}$$

where T is the number of trading dates in the period, bid_t is the bid price and ask_t is the ask price at time t. A higher value translates to the stock being less liquid.

The **liquidity ratio** was introduced by Amihud (2002) and closely relates to the measure employed by Cooper, et al. (1985). It is defined as the average ratio of daily absolute return divided by the daily euro volume (volume multiplied by close price). Formally,

$$\frac{1}{T}\sum_{t=-1}^{-T}\frac{|r_t|}{v_t * p_t} \tag{3}$$

where T is the number of trading dates in the period, v_t is the volume, r_t is the daily total return in local currency and p_t is the euro nominated close price at time t. A higher value translates to the stock being less liquid.

The **trading discontinuity ratio** was introduced by Liu (2006), which is the standardized turnover-adjusted number of zero daily trading volumes over the past 12 months. Formally,

$$(z - pt) * \frac{252}{T} \tag{4}$$

where T is the number of trading dates in the period, z is the number of trading days the stock has no trades within period T and pt is the cross-section percentile rank of the stock in terms of turnover ratio in the current period scaled from zero to one. In essence, this measure sets stocks in order based on the number of no trade days and resolves cases where stocks have same number of no trade days by penalizing stocks that have high turnover more. A higher value translates to the stock being less liquid.

Liu (2006) stated the trading discontinuity ratio is highly correlated with the bid-ask spread, turnover and liquidity ratio variables. This does not seem to hold, since **Table 5** shows the Kendall rank correlations between different variables are positive but low. Bid-ask spread and liquidity ratio have the highest correlation of 0.63. The lowest correlation is between the trading discontinuity ratio and the bid-ask spread (0.28).

Table 5. *Average rank correlation between liquidity composite variables, 2000-2020.*

	Bid-Ask spread	Liquidity ratio	Turnover ratio	Trading discontinuity ratio
Bid-Ask spread	1.000	0.613	0.325	0.283
Liquidity ratio	0.613	1.000	0.440	0.400
Turnover ratio	0.325	0.440	1.000	0.339
Trading discontinuity ratio	0.283	0.400	0.339	1.000

Since the rank correlations are low, information is being left out if just one variable would be used. The new composite liquidity variable is created by first standardizing all four metrics (equations 1-4) one by one so that each has a uniform distribution from zero to one. Before doing this, the turnover ratio is multiplied by minus one, since it's logic is counter to the other measures: a low value is less liquid. The standardized variables are then added together. The maximum value a stock can have in the liquid composite variable is four (score of one from all variables) and the minimum value is zero (score of zero from all variables). The higher the stock's score, the less liquid the stock is. Additional information on the characteristics and returns for the liquidity style is supplied in **Appendix A**.

4.2 Liquidity as an investment style

To examine the existence of liquidity premium in the European stock market, I replicate the analysis from the study *"Liquidity as an Investment Style"* done by Ibbotson, et al. (2013) and compare the results. In the study, using data between 1971 – 2011 of the top 3500 U.S. stocks ranked by market capitalization, the researchers set out to show that liquidity should be recognized as an investment style just as the well-established size, value and momentum styles are. To accomplish this, they define a set of criteria created by Sharpe (1992) which a style candidate needs to satisfy to be considered a legitimate investment style:

1) Identifiable before the fact
2) Not easily beaten
3) A viable alternative
4) Low in cost

Identifiable before the fact means that the style portfolios must be constructed in a way that there is no forward bias and that an economic intuition pre-exists. A style portfolio can be described as **not easily beaten** if it produces returns similar to other style portfolios and greater than the market portfolio. For a style portfolio to be **a viable alternative** it should meaningfully differ from other style portfolios. This can be verified by constructing double-sorted portfolios respective to the other styles and by then comparing the return characteristics in these to showcase that a style is not contained within a style. Combining the top style portfolios should yield greater returns as new not overlapping information value is added. Another way is to build long-short factor portfolios and study whether the return timeseries of a factor portfolio is fully explained by the other factor portfolios via regression analysis. If the alpha intercept is positive and significant, the set of regression coefficients (betas) from the dependent factors can't be presented in a way that makes up an efficient portfolio. A style portfolio is **low in cost** if the year-on-year turnover is low relative to other style portfolios.

At the start of each year stocks are ranked in the universe using the variable introduced in the previous chapters. The size portfolios are ranked using market capitalization, value using price to book -ratio, and momentum using the past years total return. Liquidity portfolio uses the composite variable build from the four measures of liquidity. This process fulfills the "**identifiable before the fact**" criteria. The ranked portfolios are split in four equal parts to create 16 portfolios, four for each style. Stocks are weighted equally in the portfolios. This process in described in more detail in chapter three. A first quartile portfolio (or Q1) is noted as a top quartile portfolio and fourth quartile portfolio (or Q4) is noted as a bottom quartile portfolio. **Figure 1** shows the indexed total return timeseries for the top quartile style portfolios. Each Q1 style portfolio overperforms the universe portfolio confirming that none of the portfolios **are easily beaten**. The illiquid quartile portfolio overperforms both micro-cap and high-value quartile portfolios. Ibbotson, et al. (2013) show that all top style portfolios beat the universe portfolio, but in their analysis (in U.S. stock market and between years 1972 to 2011) value performed best with liquidity, size and momentum ranked in the respective order in terms of performance.

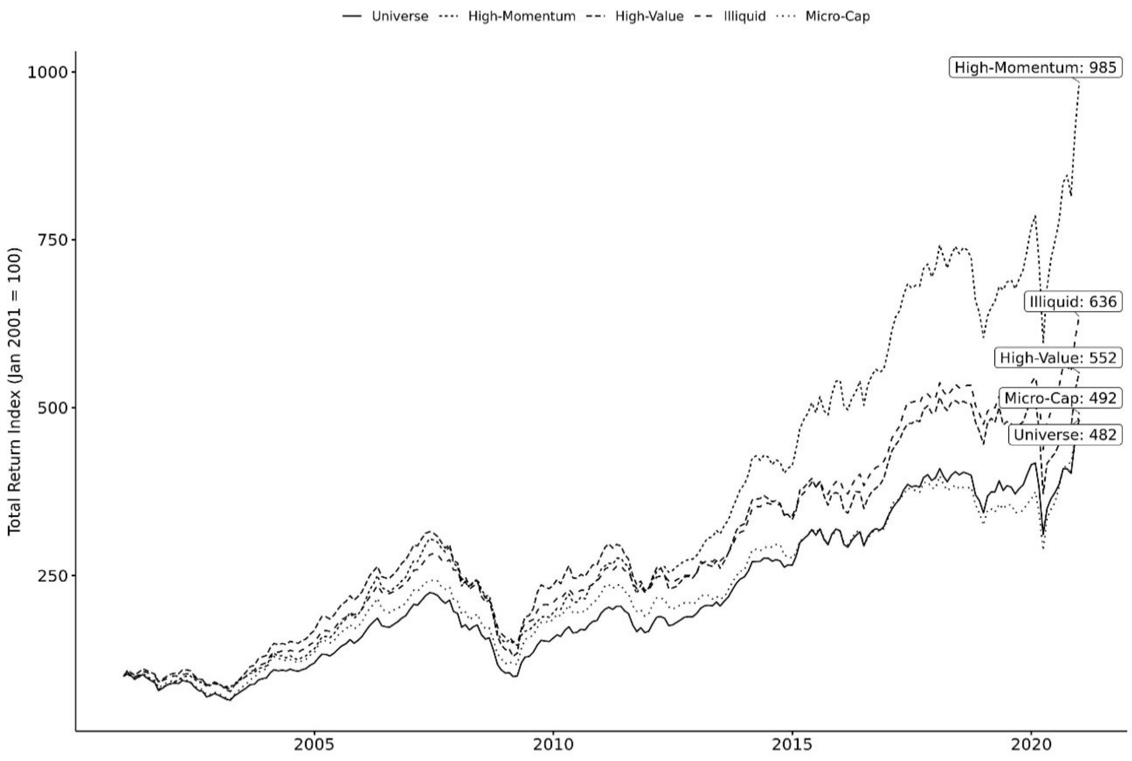

Figure 1. *Top quartile style portfolio total returns, 2001-2020.*

The geometric mean returns, arithmetic mean returns and return standard deviations of the cross-sectional quartile portfolios are shown in **Table 6**. For a risk premium to exists one should see a positive return spread between Q1 and Q4 portfolios, meaning that the desired style characteristics yields more than the anti-characteristics. All style portfolios have a positive spread with momentum being the clear winner with a spread of 9.4%, liquidity 4.1%, value 2.7% and finally size with a spread of 1.2%. Moreover, momentum and liquidity exhibit a monotonic increase between the quartile returns (Q1 > Q2 > Q3 > Q4) as value and size struggle to produce this resolution. Size Q3 has a greater return than size Q1 and Q2 and value Q3 has a greater return than value Q2. An interesting aspect is that the liquidity and momentum styles are not related risk (measured as standard deviation) as their top quartiles have a smaller standard deviation than the bottom quartiles. Size is the only style that shows increasing risk going from Q4 to Q1. Similar findings are seen in the original work of Ibbotson, et al. (2013). They find that liquidity, momentum and value all have diminishing standard deviations. The spreads shown are higher with both returns and standard deviations compared to the results in this study. They summarize this effect perfectly: "the fact we can make risk factors does not mean there is a payoff for risk; rather, there is a payoff for a factor that fluctuates, which is associated with the underlying characteristics".

Table 6. *Cross-sectional quartile portfolio returns for each style, 2001-2020*

Cross-Section	Result	Q1	Q2	Q3	Q4
Liquidity					
Q1 = Illiquid, Q4 = Liquid	Geometric mean	9.69%	9.24%	7.85%	5.59%
	Arithmetic mean	11.30%	11.72%	11.00%	8.31%
	Standard deviation	17.98%	22.43%	25.06%	23.37%
Size					
Q1 = Micro-Cap, Q4 = Large-Cap	Geometric mean	8.30%	7.98%	8.72%	7.41%
	Arithmetic mean	10.88%	10.54%	11.40%	9.51%
	Standard deviation	23.44%	22.43%	23.20%	20.56%
Value					
Q1 = High-Value, Q4 = High-Growth	Geometric mean	8.92%	8.31%	8.71%	6.25%
	Arithmetic mean	11.70%	10.48%	11.00%	9.16%
	Standard deviation	24.35%	20.80%	21.40%	23.71%
Momentum					
Q1 = High-Momentum, Q4 = Low-Momentum	Geometric mean	12.12%	9.28%	7.79%	2.71%
	Arithmetic mean	14.39%	11.20%	9.99%	6.75%
	Standard deviation	21.50%	19.53%	21.00%	29.36%
Universe					
	Geometric mean	8.18%	—	—	—
	Arithmetic mean	10.58%	—	—	—
	Standard deviation	21.92%	—	—	—

I evaluate whether liquidity is **a viable alternative** style compared to the other styles by creating double-sorted quartile portfolios and examining the return characteristics. The double-sorted portfolios are constructed out of the overlapping stocks in each quartile for each style pair. The style pairs of interest are liquidity – size, liquidity – value and liquidity

– momentum. Let us denominate a style quartile portfolio as $p_{i,q}$, where i is the style name and q is the quartile number. A double-sorted portfolio is the intersection of two quartile portfolios that are from different styles, mathematically

$$p_{i,q} \cap p_{j,q} \tag{5}$$

where $i = \{liquidity\}$, $j = \{size, value, momentum\}$ and $q = \{1, 2, 3, 4\}$. For each style pair, I generate double-sorted portfolios for all quartile permutations giving us 16 double-sorted portfolios. For each of these portfolios a geometric mean return, arithmetic mean return, return standard deviation and the average number of stocks over time in the portfolio is calculated.

Table 7 reports the double-sorted portfolio analysis for liquidity and size. The liquidity spread, the difference of geometric returns between illiquid and liquid quartile portfolios, is positive in all size quartiles and diminishes in order: micro-cap quartile has a spread of 18.72%, small-cap quartile 10.95%, mid-cap quartile 3.92% and large-cap quartile 1.9%. This is counter to the Ben-Rephael, et al. (2015) results, as a premium clearly exist in all size quartiles. The standard deviation spreads also diminish in similar fashion. The fact that the liquidity premium is present within all size quartiles implies that the liquidity premium is not captured by size. Ibbotson, et al. (2013) come to the same conclusion stating that "the liquidity premium holds regardless of size group". They also report that size spread is not positive in all liquidity quartiles. The same behavior can be seen in this analysis as well. The size spread is positive in illiquid quartile (1.83%), but negative in mid-illiquid (-1.36%), mid-liquid (-6.15%) and liquid (-14.99%) quartiles. This would suggest that size could be captured by liquidity, not the other way around. Indeed, other researchers have also suggested this (Brennan & Subrahmanyam, 1996; Amihud, 2002; Hou & Moskowitz, 2005; Sadka, 2006; Alquist, et al., 2018). I examine this aspect in the factor regression analysis section below. A discrepancy between this analysis and the analysis of Ibbotson, et al. (2013) is that the diagonal double-sorted quartile portfolios are much larger in terms of number of stocks compared to the portfolios that are not on the diagonal. This means that the liquid and size portfolios have more overlap and thus have much of the same stocks in them amplifying the suspicion that they are related which contradicts the findings of Ibbotson, et al. (2013). This diagonal effect also makes the calculations less reliable for portfolios like the liquid micro-cap and illiquid large-cap since the measures are calculated based on a small basket of stocks.

Table 7. *Liquidity and Size double-sorted quartile portfolios, 2001-2020*

Quartile	Illiquid	Mid-Illiquid	Mid-Liquid	Liquid
Micro-Cap				
Geometric mean	10.38%	7.74%	2.75%	−8.34%
Arithmetic mean	12.19%	10.94%	8.47%	−0.89%
Standard deviation	19.46%	26.59%	35.94%	40.32%
Average no. of stocks	452	264	114	15
Small-Cap				
Geometric mean	8.88%	9.97%	5.92%	−2.07%
Arithmetic mean	10.60%	12.47%	9.49%	3.50%
Standard deviation	18.37%	22.14%	26.74%	33.90%
Average no. of stocks	264	312	221	47
Mid-Cap				
Geometric mean	8.93%	9.50%	9.67%	5.01%
Arithmetic mean	10.17%	11.82%	12.79%	8.78%
Standard deviation	15.69%	21.45%	24.98%	27.93%
Average no. of stocks	101	217	345	180
Large-Cap				
Geometric mean	8.55%	9.06%	8.90%	6.65%
Arithmetic mean	9.45%	10.58%	11.07%	8.95%
Standard deviation	13.85%	17.93%	20.65%	21.55%
Average no. of stocks	27	50	164	602

Liquidity and value double-sorted quartile portfolio analysis is shown in **Table 8**. The liquidity spreads are again positive but much smaller than seen with size: high-value portfolio has a spread of 4.55%, mid-value 5.28%, mid-growth 3.84% and high-growth has a spread of 1.04%. The same effect can be seen with the results of Ibbotson, et al. (2013). Unlike in the size spread analysis of this study, the value spreads hold throughout the liquidity quartiles, meaning that the difference between high-value and high-growth portfolios is positive in all liquidity quartile portfolios. This suggest that liquidity and value do not capture the same risk premium. The number of shares in double-sorted portfolios are also more evenly distributed as a result of liquidity and value being different ways of selecting stocks although there is a slight concentration of stock mass around the diagonal. If examined closely, it can be seen that the largest average portfolio sizes with high- and mid-value rows are in the illiquid column and the largest average portfolio sizes with the mid- and high-growth rows are in the liquid column. The value stocks thus tend to be less liquid and growth stocks more liquid. This can be explained by value stocks not being generally popular and growth stocks are (Ibbotson & Idzorek, 2014). Another explanation might be that the illiquid stocks tend to be less inefficiently priced (Arbel, et al., 1983; Roulstone, 2003). Liu (2006) suggests that less liquid stocks could be a proxy for small value stocks.

Table 8. *Liquidity and Value double-sorted quartile portfolios, 2001-2020*

Quartile	Illiquid	Mid-Illiquid	Mid-Liquid	Liquid
High-Value				
Geometric mean	10.19%	9.29%	7.91%	5.64%
Arithmetic mean	12.05%	12.25%	11.54%	9.56%
Standard deviation	19.50%	25.65%	27.99%	29.05%
Average no. of stocks	274	237	192	141
Mid-Value				
Geometric mean	10.33%	9.85%	6.83%	5.05%
Arithmetic mean	11.81%	11.96%	9.80%	7.81%
Standard deviation	17.51%	20.85%	24.04%	23.27%
Average no. of stocks	234	218	197	195
Mid-Growth				
Geometric mean	10.29%	9.60%	8.88%	6.45%
Arithmetic mean	11.94%	11.96%	11.86%	8.92%
Standard deviation	18.40%	21.64%	24.37%	22.44%
Average no. of stocks	181	203	218	241
High-Growth				
Geometric mean	6.01%	7.33%	6.85%	4.97%
Arithmetic mean	8.11%	10.70%	10.47%	7.75%
Standard deviation	20.03%	25.79%	26.57%	23.17%
Average no. of stocks	154	186	236	267

Table 9 shows the liquidity and momentum double-sorted quartile portfolios. The liquidity spread is positive in all momentum quartiles and greater in higher momentum portfolios. The high-momentum portfolio has a liquidity spread of 8.08%, mid-high-momentum 5.22%, mid-low-momentum 2.37% and low-momentum 2.82%. The momentum spreads are significantly positive in all liquidity quartiles. The average number of shares is well diversified along different portfolios. This shows that liquidity and momentum are different styles. Ibbotson, et al. (2013) reach the same conclusion. However, there have been studies regarding a connection between liquidity and momentum. Sadka (2006) and Asness, et al. (2013) find that momentum returns are partially explained by market-wide aggregate liquidity. These finding do not affect the conclusions in this study since this study explicitly focuses on firm-level liquidity characteristic not the market-wide liquidity.

Table 9. *Liquidity and Momentum double-sorted quartile portfolios, 2001-2020*

Quartile	Illiquid	Mid-Illiquid	Mid-Liquid	Liquid
High-Momentum				
Geometric mean	15.71%	12.55%	12.32%	7.63%
Arithmetic mean	17.11%	15.22%	15.39%	9.91%
Standard deviation	17.16%	22.90%	25.08%	21.59%
Average no. of stocks	190	213	237	204
Mid-High-Momentum				
Geometric mean	11.64%	10.96%	8.44%	6.42%
Arithmetic mean	13.17%	12.91%	11.15%	8.54%
Standard deviation	17.46%	19.71%	23.06%	20.83%
Average no. of stocks	207	206	205	227
Mid-Low-Momentum				
Geometric mean	9.07%	8.41%	6.00%	6.70%
Arithmetic mean	10.75%	10.79%	8.48%	9.27%
Standard deviation	18.25%	22.08%	21.90%	23.16%
Average no. of stocks	230	210	191	213
Low-Momentum				
Geometric mean	3.34%	4.14%	2.12%	0.52%
Arithmetic mean	6.33%	8.14%	7.14%	5.27%
Standard deviation	25.76%	30.09%	32.73%	31.12%
Average no. of stocks	217	215	211	200

Overall, the fact that positive liquidity spreads exists within different size, value and momentum quartiles suggest that liquidity style is an alternative way for portfolio selection. Further evidence of this is the fact that liquidity style decreases portfolio risk. The standard deviations of the top style quartile portfolios and liquidity combined top style double-sorted portfolios are compared. The micro-cap portfolio has a standard deviation of 23.44% compared to the illiquid-micro-cap portfolio that has a standard deviation of 19.46%. Value and momentum produce similar results: high-value portfolio has a standard deviation of 24.35% compared to illiquid-high-value portfolio standard deviation of 19.50% and high-momentum portfolio has a standard deviation of 21.50% compared to illiquid-high-momentum portfolio standard deviation of 17.16%. In all cases the standard deviations decrease meaningfully. Even with the lower risk levels, **Figure 2** shows how the liquidity enhanced top size, value and momentum quartile portfolios overperform the comparable top and bottom quartile portfolios significantly. Combining liquidity style with other styles thus improves the Sharpe ratio.

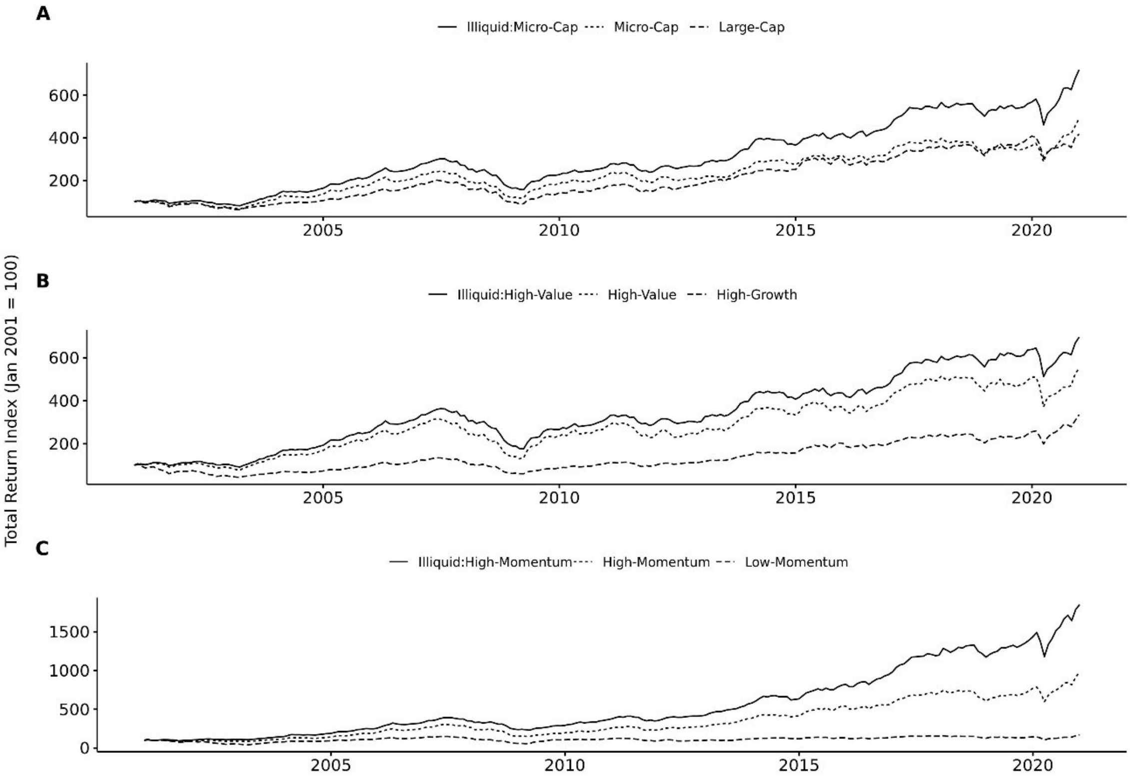

Figure 2. *Liquidity, Size, Value and Momentum top double-sorted portfolio, top quartile portfolio and bottom quartile portfolio total return comparison, 2001-2020*

To further analyze **the viability of the liquidity style**, I conduct a series of regression analysis on the foundations of arbitrage pricing theory, which states that the expected returns can be explained as a linear function of factors (Ross, 1976; Roll & Ross, 1995). Factors are portfolios where stocks in top style quartile are bought and stocks in the bottom style are sold short in equal value. The goal is to test how the well-established style factor returns explain the liquidity style factor returns. If the intersection term α is positive and statistically significant, an interpretation can be made that the existing model does not explain the liquidity returns. Three different models with long-short euro-neutral return timeseries and long-only return timeseries in accordance with the tests of Ibbotson, et al. (2013) are tested. The main difference compared to their analysis is that this study constructs the long-short size, value and momentum return timeseries from the generated quartile portfolios as the Ibbotson study uses the pre-calculated long-short style return timeseries from the website of French (2020). Using the pre-calculated timeseries would require the underlying investment universe to be approximately the same for the long-short liquidity portfolio and the long-short size, value and momentum portfolios. Since the universe in this study is custom built, the results could prove inaccurate. I did however test the liquidity style returns against pre-calculated European return timeseries to verify results. Using the French (2020) data yielded very similar results and these can be seen in **Appendix E**. The used models are the CAPM, the Fama & French (1993) three-factor model and the Carhart (1997) four-factor model.

In the CAPM, the monthly liquidity factor returns are explained with the market returns excess of risk-free rate

$$r_{L,t} = \alpha + \beta_M(r_{M,t} - r_{f,t}) + \varepsilon_t \tag{6}$$

where $r_{L,t}$ is the liquidity factor return for month t, α is the intercept term that tells us the monthly returns unexplained by the independent variables, β_M is the regression coefficient for the market beta factor, $r_{M,t}$ is the market capitalization weighted universe portfolio return for month t, $r_{f,t}$ is the annualized risk-free rate (Euribor 3m) for month t and ε_t is the error term. In the Fama-French three-factor model, the liquidity factor returns are explained with the market returns excess of risk-free rate and the size and value factors

$$r_{L,t} = \alpha + \beta_M(r_{M,t} - r_{f,t}) + \beta_S r_{S,t} + \beta_V r_{V,t} + \varepsilon_t \tag{7}$$

where β_S is the regression coefficient for the size factor, $r_{S,t}$ is the size factor return for month t, β_V is the regression coefficient for the value factor and $r_{V,t}$ is the value factor return for month t. In the Carhart four-factor model, the liquidity factor returns are explained with the market returns excess of risk-free rate and the size, value and momentum factors

$$r_{L,t} = \alpha + \beta_M(r_{M,t} - r_{f,t}) + \beta_S r_{S,t} + \beta_V r_{V,t} + \beta_{Mo} r_{Mo,t} + \varepsilon_t \tag{8}$$

where β_{Mo} is the regression coefficient for the momentum factor and $r_{Mo,t}$ is the momentum factor return for month t.

The long-short euro-neutral return timeseries are built by subtracting the monthly Q4 portfolio returns from the Q1 portfolio returns for each style. The market beta returns are calculated as monthly excess returns of the market value weighted universe portfolio over the risk-free rate. The risk-free rate is the annualized 3 months Euribor rate (Suomen Pankki, 2020). The long-short euro-neutral portfolios are called factors. The total return timeseries of these factors are presented in **Figure 3**. The momentum factor has done exceptionally well in the last 20 years as all other factors have had lackluster performance. Within the last 10 years the risk-free market portfolio has performed along with the momentum factor. The liquidity and value factor did well from 2001 to 2008, but after this the performance has been poor. The size factor has not seemingly produced returns in this timeframe.

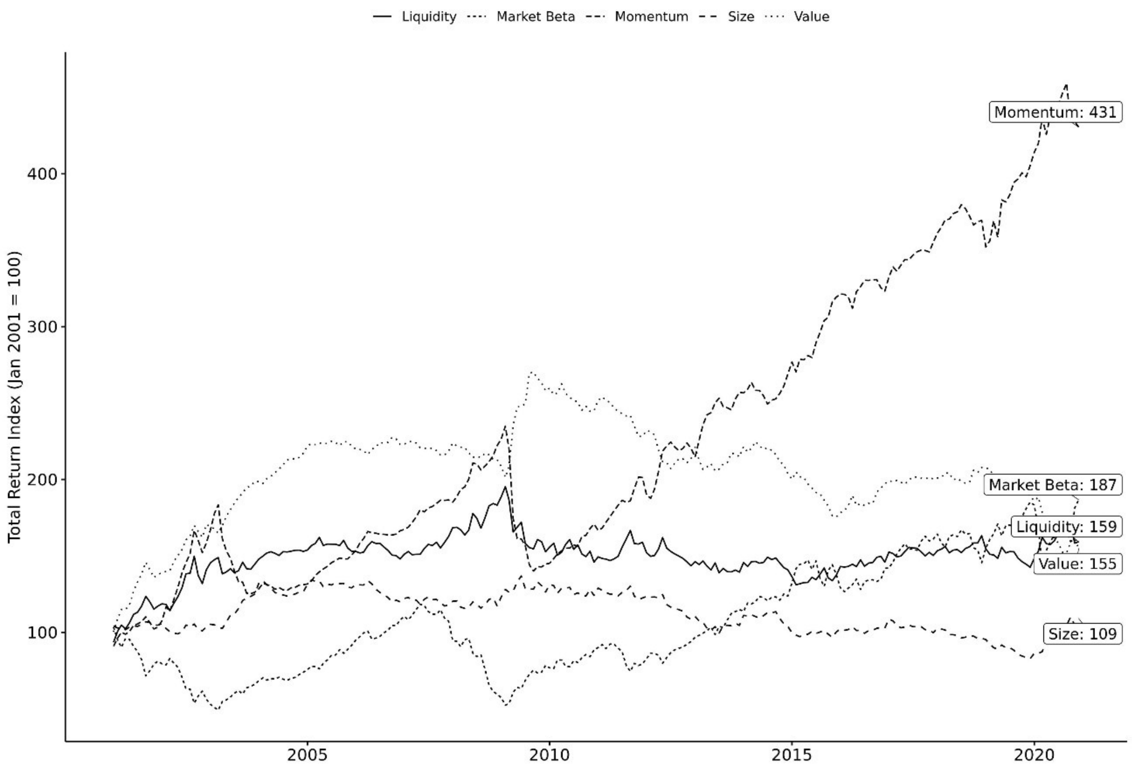

Figure 3. *Long-short factor indexed total returns, 2001-2020*

Tables 10 and 11 show the regression results which is divided into two columns. The right column "Liquidity factor" reports regression results when liquidity long-short factor returns are the dependent variable just as **equations (6)**, **(7)** and **(8)** show. In the left column "Illiquid long", the dependent variable is the illiquid quartile portfolio monthly returns excess of risk-free rate: one replaces $r_{L,t}$ with $r_{LQ1,t} - r_{f,t}$ where $r_{LQ1,t}$ is the illiquid quartile portfolio return for month t and $r_{f,t}$ is the risk-free rate for month t. This gives us the opportunity to analyze the long-only portfolio with the same regression analysis framework.

In **Table 10** the CAPM regression model shows that the illiquid quartile portfolio has a low beta of 0.64 when compared to the market portfolio. The liquidity factor is negatively related with the market portfolio with a beta of -0.52. The monthly alpha is positive and significant for the long-only (0.48%) and factor (0.42%) portfolio. In the three-factor model the illiquid long-only portfolio has a low beta of 0.67 with the size factor and a very low beta of 0.13 with value factor. Ibbotson, et al. (2013) report that the liquidity factor has a negative association with size and positive association with value. This analysis, on the contrary, shows that the liquidity factor is positively associated with size factor and has no meaningful association with value factor. The alpha is still positive and meaningful (0.37%) for both the long-only and factor portfolio. The long-only and factor portfolio both have a small positive beta with the momentum factor in the four-factor model, which is higher compared to the momentum factor results in the Ibbotson, et al. (2013) study. The greatest discrepancy between the studies is that in this study the addition of the momentum factor renders the liquidity monthly alpha insignificant in both the long-only and factor portfolio. Ibbotson, et al. (2013) state that the positive and significant monthly alphas for both the long-only and long-short factor portfolios, after accounting for the well-established factors, acts as evidence that illiquid portfolios are “not easily beaten”. This cannot be reasserted in the current setting.

In **Table 11** the size factor is omitted from the independent variables to see if the results improve, since the previous analysis of double-sorted liquidity and size portfolios led us to believe there might be a connection between the two. Excluding the size factor improves the monthly alpha closer to the levels seen in the original study. The long-only portfolio alpha is 0.37% (significant at 99% confidence level) in the “four-factor” model where size factor has been removed and the factor portfolio alpha is 0.23% (significant at 95% confidence level). This suggests that in the European stock market between years 2001 and 2020 liquidity and size styles act as proxies to each other at some level.

Table 10. *Liquidity long-short factor and illiquid long-only portfolio regression analysis with monthly returns, 2001-2020*

	Illiquid long				Liquidity factor			
	estimate	t-statistic	p-value[1]		estimate	t-statistic	p-value[1]	
Capital asset pricing model								
Monthly alpha	0.48% ± 0.12%	3.88	1.36×10^{-4}	***	0.42% ± 0.11%	4.01	8.23×10^{-5}	***
Market Beta	0.64 ± 0.03	23.29	2.62×10^{-63}	***	−0.52 ± 0.02	−22.11	1.23×10^{-59}	***
Adj. R Squared		0.694				0.671		
Fama-French three-factor model								
Monthly alpha	0.37% ± 0.08%	4.71	4.30×10^{-6}	***	0.37% ± 0.09%	4.22	3.47×10^{-5}	***
Market Beta	0.77 ± 0.02	41.48	2.23×10^{-110}	***	−0.44 ± 0.02	−21.49	1.72×10^{-57}	***
Size	0.67 ± 0.04	18.21	7.30×10^{-47}	***	0.44 ± 0.04	10.92	9.90×10^{-23}	***
Value	0.13 ± 0.03	3.63	3.42×10^{-4}	***	0.01 ± 0.04	0.15	8.78×10^{-1}	.
Adj. R Squared		0.879				0.781		
Carhart four-factor model								
Monthly alpha	0.13% ± 0.07%	1.74	8.29×10^{-2}	.	0.05% ± 0.07%	0.63	5.28×10^{-1}	.
Market Beta	0.87 ± 0.02	44.23	6.45×10^{-116}	***	−0.30 ± 0.02	−15.00	3.89×10^{-36}	***
Size	0.76 ± 0.03	22.80	1.81×10^{-61}	***	0.56 ± 0.03	16.45	5.79×10^{-41}	***
Value	0.26 ± 0.03	7.77	2.40×10^{-13}	***	0.18 ± 0.03	5.32	2.40×10^{-7}	***
Momentum	0.26 ± 0.03	9.04	6.15×10^{-17}	***	0.34 ± 0.03	11.64	5.04×10^{-25}	***
Adj. R Squared		0.910				0.861		

[1] Significancy codes: 0.001 (***), 0.01 (**), 0.05 (*), 0.1 (.)

Table 11. *Liquidity long-short factor and illiquid long-only portfolio regressions analysis on modified factor models (size factor omitted) with monthly returns, 2001-2020*

	Illiquid long				Liquidity factor			
	estimate	t-statistic	p-value[1]		estimate	t-statistic	p-value[1]	
Fama-French three-factor model (without size)								
Monthly alpha	0.43% ± 0.12%	3.59	4.04×10^{-4}	***	0.41% ± 0.11%	3.86	1.44×10^{-4}	***
Market Beta	0.65 ± 0.03	24.24	4.19×10^{-66}	***	−0.52 ± 0.02	−21.95	5.05×10^{-59}	***
Value	0.21 ± 0.05	3.94	1.09×10^{-4}	***	0.06 ± 0.05	1.32	1.90×10^{-1}	.
Adj. R Squared		0.711				0.672		
Carhart four-factor model (without size)								
Monthly alpha	0.37% ± 0.13%	2.88	4.36×10^{-3}	**	0.23% ± 0.11%	2.11	3.63×10^{-2}	*
Market Beta	0.68 ± 0.03	21.31	6.55×10^{-57}	***	−0.45 ± 0.03	−16.81	3.27×10^{-42}	***
Value	0.25 ± 0.06	4.17	4.24×10^{-5}	***	0.17 ± 0.05	3.48	5.91×10^{-4}	***
Momentum	0.07 ± 0.05	1.45	1.48×10^{-1}	.	0.20 ± 0.04	4.93	1.54×10^{-6}	***
Adj. R Squared		0.713				0.702		

[1] Significancy codes: 0.001 (***), 0.01 (**), 0.05 (*), 0.1 (.)

Further evidence about the relation of liquidity and size factors can be seen in **Table 12** where the long-short factor correlations calculated on monthly returns are showed. The positive correlation of 0.60 between liquidity and size factor is the highest among all the factors. Ibbotson, et al. (2013) report a negative correlation of -0.50. To verify that the large difference in the correlation with size is not caused by the composite variable for liquidity, long-short liquidity factors using only one of the composite variables in turn were built. The turnover ratio factor (the same methodology that the original study uses) has a small positive correlation of 0.22 with size. The other composite variables in the liquidity factor report the following correlations with size: 0.42 for the trading discontinuity ratio factor, 0.70 for the relative bid-ask spread factor and 0.77 for the liquidity ratio factor. Although the turnover ratio factor has the smallest correlation with size, it is still very far from the -0.50 correlation Ibbotson, et al. (2013) calculate. The liquidity factor also has a large positive correlation (0.50) with the momentum factor and a small positive correlation (0.12) with the value factor. Momentum and value correlation (-0.36) has remained low (Asness, et al., 2013). The strongest negative correlation amongst different factors is with the liquidity and market factors. This feature of the liquidity style is studied in the next chapter as it could offer good dispersion from the market portfolio.

Table 12. *Correlations of long-short factor portfolios calculated on monthly returns, 2001-2020*

	Liquidity	Market Beta	Momentum	Size	Value
Liquidity	1	−0.820	0.498	0.601	0.120
Market Beta	−0.820	1	−0.464	−0.351	−0.087
Momentum	0.498	−0.464	1	−0.097	−0.364
Size	0.601	−0.351	−0.097	1	0.154
Value	0.120	−0.087	−0.364	0.154	1

The liquidity enhanced top size, value and momentum portfolios (top left corner of tables 5-7) are used to conduct similar analysis than done with the illiquidity long-only portfolio. The illiquid high-momentum, high-value and micro-cap portfolio returns excess of the risk-free rate are regressed on the factors in **Table 13**. Each portfolio has a low beta, even lower than Ibbotson, et al. (2013) report. They also have a much higher association with size and momentum than in the original work. Value on the other is less related to the portfolios with the exception of the illiquid high-value portfolio. Monthly alpha for the liquidity enhanced portfolios is positive and significant in every case, expect high-value and micro-cap portfolios when the four-factor model is used.

Table 13. *Regression analysis of enhanced liquidity portfolios with monthly returns, 2001-2020*

	High-momentum, Illiquid				High-value, Illiquid				Micro-cap, Illiquid			
	estimate	t-statistic	p-value[1]		estimate	t-statistic	p-value[1]		estimate	t-statistic	p-value[1]	
Capital asset pricing model												
Monthly alpha	0.95% ± 0.15%	6.34	1.14×10^{-9}	***	0.52% ± 0.15%	3.43	7.10×10^{-4}	***	0.53% ± 0.15%	3.65	3.21×10^{-4}	***
Market Beta	0.60 ± 0.03	18.15	8.27×10^{-47}	***	0.67 ± 0.03	19.77	3.94×10^{-52}	***	0.67 ± 0.03	20.54	1.28×10^{-54}	***
Adj. R Squared		0.579				0.620				0.638		
Fama-French three-factor model												
Monthly alpha	0.88% ± 0.12%	7.43	1.98×10^{-12}	***	0.34% ± 0.09%	3.78	2.02×10^{-4}	***	0.39% ± 0.08%	4.75	3.49×10^{-6}	***
Market Beta	0.72 ± 0.03	25.69	2.55×10^{-70}	***	0.82 ± 0.02	38.51	9.92×10^{-104}	***	0.82 ± 0.02	42.42	2.09×10^{-112}	***
Size	0.68 ± 0.06	12.11	1.46×10^{-26}	***	0.73 ± 0.04	17.20	1.64×10^{-43}	***	0.84 ± 0.04	21.66	5.26×10^{-58}	***
Value	−0.08 ± 0.05	−1.58	1.15×10^{-1}	.	0.41 ± 0.04	10.32	7.74×10^{-21}	***	0.17 ± 0.04	4.59	7.15×10^{-6}	***
Adj. R Squared		0.738				0.869				0.887		
Carhart four-factor model												
Monthly alpha	0.38% ± 0.09%	4.14	4.89×10^{-5}	***	0.13% ± 0.09%	1.45	1.49×10^{-1}	.	0.15% ± 0.08%	1.91	5.69×10^{-2}	.
Market Beta	0.93 ± 0.02	37.41	5.86×10^{-101}	***	0.91 ± 0.02	37.44	4.99×10^{-101}	***	0.93 ± 0.02	44.20	7.59×10^{-116}	***
Size	0.85 ± 0.04	20.26	1.73×10^{-53}	***	0.80 ± 0.04	19.63	1.99×10^{-51}	***	0.92 ± 0.04	26.11	2.14×10^{-71}	***
Value	0.19 ± 0.04	4.55	8.70×10^{-6}	***	0.53 ± 0.04	12.81	7.46×10^{-29}	***	0.30 ± 0.04	8.46	2.96×10^{-15}	***
Momentum	0.54 ± 0.04	14.71	3.65×10^{-35}	***	0.22 ± 0.04	6.36	1.02×10^{-9}	***	0.26 ± 0.03	8.49	2.29×10^{-15}	***
Adj. R Squared		0.863				0.888				0.913		

[1] Significancy codes: 0.001 (***), 0.01 (**), 0.05 (*), 0.1 (.)

Finally, the **"low in cost"** criterion is analyzed. To meet this, the portfolio composition should not change significantly between successive portfolio updates. **Table 14** shows how stocks move between different style quartiles when updated. The value presented is the number observations a stock has moved to (or stayed in) a specific quartile divided by the total number of observations per quartile throughout the 2001 to 2020 period (18 update instances). One minus the migration value is the average turnover for a quartile portfolio, since the portfolio constituents are weighted equally.

On average 66.7% of stocks in liquidity quartile portfolios remain the same. This value is the average of the diagonal values for each style. The comparative figures are 75.9% for size, 59.5% for value and 27.0% for momentum. Ibbotson, et al. (2013) report similar values. This means that the characteristics on which the style portfolios are built on, change slower for size and liquidity compared to value and momentum. The high portfolio turnover (low migration) for momentum is well documented (Asness, et al., 2014). The Q1 portfolio migration values are approximately the same for liquidity (63.8%), size (66.2%) and value (66.1%), which suggest that liquidity style is indeed **low in cost**. Compared to the original study, the average migration in value was almost the same (65.2%) while liquidity and size were more stable at 77.3% and 83.5%, respectively. The NA - category is a group of stocks that are not in the universe in the start or the end of the examination period. On average 9.0% of the stocks in the universe go bankrupt, delist, stop complying with the universe rules or otherwise cease to exist per year.

Table 14. *Average migration between style quartiles one year after portfolio construction, 2001-2020*

		Year t + 1 Portfolio[1]				
Cross-Section	Year t Portfolio[1]	Q1	Q2	Q3	Q4	NA
Liquidity						
Q1 = Illiquid, Q4 = Liquid	Q1	63.8%	16.4%	2.3%	0.1%	17.4%
	Q2	14.8%	55.7%	19.3%	1.2%	9.0%
	Q3	1.1%	16.9%	62.4%	13.5%	6.2%
	Q4	0.0%	0.5%	11.3%	84.8%	3.3%
	NA	50.6%	28.7%	15.2%	5.5%	
Size						
Q1 = Micro-Cap, Q4 = Large-Cap	Q1	66.2%	13.1%	0.4%	0.0%	20.2%
	Q2	12.7%	69.2%	11.0%	0.1%	7.0%
	Q3	0.7%	9.2%	77.9%	7.0%	5.2%
	Q4	0.1%	0.2%	6.0%	90.3%	3.5%
	NA	51.2%	23.4%	15.1%	10.4%	
Value						
Q1 = High-Value, Q4 = High-Growth	Q1	66.1%	16.6%	3.2%	2.2%	11.8%
	Q2	19.6%	50.6%	18.0%	2.9%	8.8%
	Q3	4.2%	20.4%	53.2%	15.0%	7.3%
	Q4	2.6%	3.4%	18.0%	68.0%	8.0%
	NA	21.7%	24.9%	21.7%	31.7%	
Momentum						
Q1 = High-Momentum, Q4 = Low-Momentum	Q1	25.7%	21.4%	21.5%	22.4%	9.0%
	Q2	21.9%	26.8%	24.7%	19.7%	6.9%
	Q3	20.4%	25.9%	24.9%	21.5%	7.2%
	Q4	20.6%	17.6%	18.3%	30.7%	12.8%
	NA	30.5%	23.3%	28.5%	17.6%	

[1] NA = Missing from Universe

To analyze how returns are generated for the style quartiles, the return excess of the universe portfolio for each stock each rebalance period is calculated and the mean of these for each migration category is summarized. Values for migrations that have less than 100 observations are not shown, since they are likely less reliable to show the full picture. Unlike in the similar table in the original study, which uses annual returns, **Table 15** uses excess returns so that the values are comparable over time and are not affected by market events. The story is however the same. The excess returns of liquidity portfolio's increase as stocks move from a less liquid quartile to a more liquid quartile no matter which quartile the stock starts from, and vice versa. A similar pattern can be found in size and value, which is confirmed by Fama & French (2007). Momentum is the only style that behaves in an opposite fashion. If stocks move from Q1 to other quartiles the excess returns decrease and if stocks move to Q1 from other quartiles the excess returns increase.

Table 15. *Average returns excess of universe associated with migration of style quartiles, 2001-2020*

		Year t + 1 Portfolio[1]				
Cross-Section	Year t Portfolio[1]	Q1	Q2	Q3	Q4	NA
Liquidity						
Q1 = Illiquid, Q4 = Liquid	Q1	−0.9%	20.3%	49.6%		−18.9%
	Q2	−11.6%	0.4%	21.6%	51.2%	−23.1%
	Q3	−19.7%	−12.7%	2.1%	17.2%	−17.1%
	Q4			−9.1%	0.0%	−3.5%
	NA	28.6%	51.0%	39.4%	15.0%	
Size						
Q1 = Micro-Cap, Q4 = Large-Cap	Q1	−7.1%	69.7%			−32.5%
	Q2	−48.8%	−1.2%	65.2%		−3.0%
	Q3	−73.4%	−40.9%	2.6%	53.1%	2.5%
	Q4			−35.8%	2.4%	4.2%
	NA	50.6%	30.8%	16.3%	3.7%	
Value						
Q1 = High-Value, Q4 = High-Growth	Q1	−7.6%	33.2%	71.3%	62.6%	−24.0%
	Q2	−32.0%	−1.1%	32.4%	91.4%	−13.6%
	Q3	−48.1%	−26.1%	2.8%	48.8%	−12.5%
	Q4	−35.4%	−38.5%	−26.1%	10.3%	−19.9%
	NA	6.7%	21.1%	30.8%	71.1%	
Momentum						
Q1 = High-Momentum, Q4 = Low-Momentum	Q1	58.8%	7.5%	−12.9%	−41.7%	−9.5%
	Q2	48.1%	7.9%	−12.4%	−39.5%	−8.0%
	Q3	52.3%	7.6%	−12.3%	−40.0%	−13.4%
	Q4	72.7%	7.0%	−13.3%	−45.0%	−32.5%
	NA	131.9%	14.8%	−4.0%	−37.9%	

[1] NA = Missing from Universe. If less than 100 observations, no return is shown.

4.3 The effect of transaction costs

All calculations in this work so far have been without any consideration of transaction costs, yet they are crucial component of the performance especially in a low liquidity strategy. To tackle this, I run simple calculations on how transaction costs compare between the different portfolios. The liquid quartile portfolio and the universe portfolio are set in turn as the benchmark with fixed transaction costs and analyze the excess return after costs of the illiquid quartile portfolio while its transaction cost is varied. This way one can estimate whether the transactions cost could potentially erode the theoretical excess returns calculated without costs. The return after costs can be calculated as

$$R = r - t * c * 2 \tag{9}$$

for each portfolio, where R is the average annual return after costs, r is the average annual return without costs, t is the average annual turnover and c is the average annual transaction cost. A multiplier of two is applied since a stock is always bought and sold. Since there are no actual trades or a transaction cost model, variables R and c are un-knows. The average annual return without cost r (arithmetic mean from table 6) and the average annual turnover t (one minus migration value from table 14) are however known. **Figure 4** shows the return after transaction cost for the illiquid quartile portfolio excess of the liquid quartile and universe portfolios with different levels of transaction cost for the illiquid quartile portfolio.

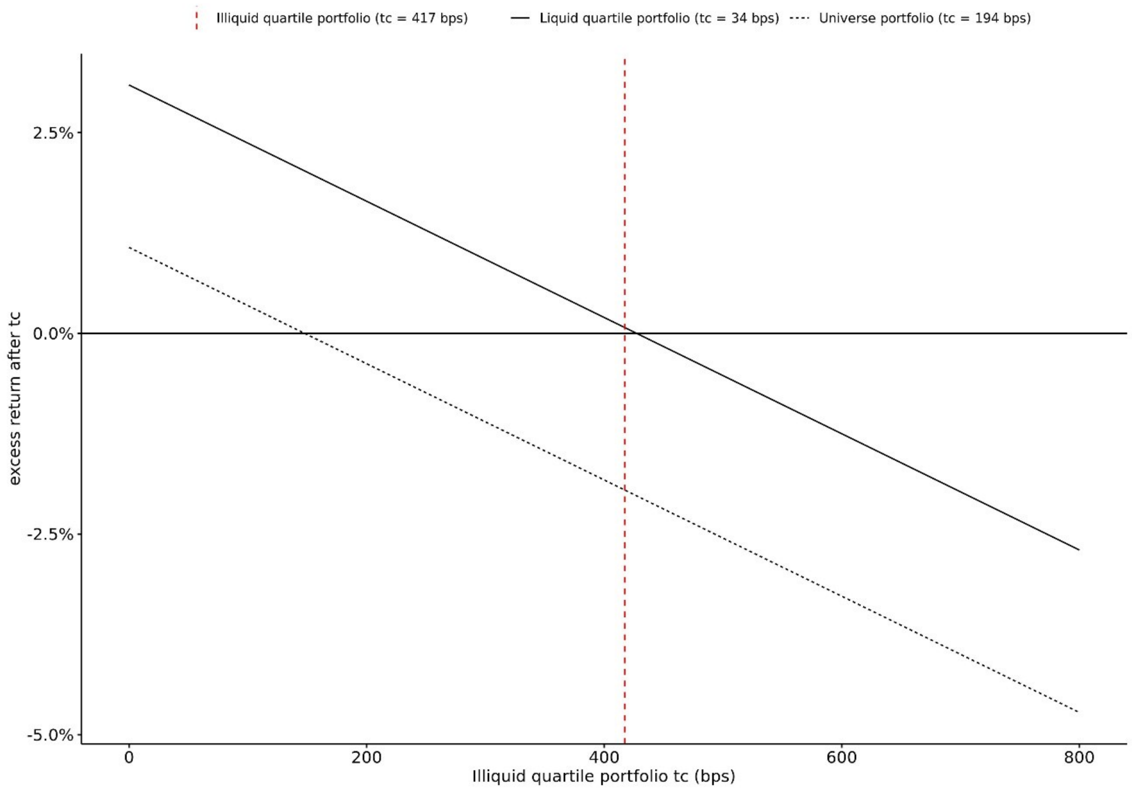

Figure 4. *Illiquid quartile portfolio return after transaction cost (tc) excess of liquid quartile and universe portfolios with varying transaction costs for the illiquid quartile portfolio. The liquid quartile and universe portfolio return after transaction costs are calculated with an average cost of 34 bps and 194 bps, respectively. The red vertical line is the mean bid-ask spread for the illiquid quartile portfolio, 2001-2020.*

The liquid quartile and universe portfolio return after transaction costs are calculated with fixed average transaction costs of 34 bps and 194 bps, respectively, using **equation (9)**.

These transaction costs are estimates based on the mean bid-ask spreads of the portfolios over the 2001-2020 period. Commissions, taxes, trade sizes compared to average volume and trading speed are neglected from the calculations. With this parametrization, an average transaction cost of 150 bps for the illiquid quartile portfolio would erode the excess return over the universe portfolio and an average transaction cost of 430 bps for the illiquid quartile portfolio would the excess return over the liquid quartile portfolio. The mean bid-ask spread for the illiquid quartile portfolio is 417 bps, which implies that a significant portion of the return could be lost when transaction costs are accounted for. If these values are used for calculating the return after cost for the illiquid quartile portfolio, the illiquid quartile portfolio underperforms the universe portfolio and the liquid quartile portfolio is approximately tied with the illiquid quartile portfolio in terms of annual returns after cost, -1.95% and 0.07%, respectively. I infer that the performance of the illiquid quartile portfolio is highly dependent on the efficient trading of the illiquid stocks and that the liquidity premium might be obsolete when factoring in transaction costs.

4.4 Defensive nature of the Liquidity style

This study previously reported that the liquidity factor has a strong negative association to the market portfolio and less liquid portfolios exhibit lower standard deviation of returns. This aspect of the liquidity style is taken under closer examination as the top style quartile portfolio returns excess of the market portfolio and factor portfolio returns are analyzed against market returns, volatility (the annualized standard deviation of returns) and maximum drawdown.

Figure 5 shows monthly market portfolio return on y-axis and style top quartile portfolio monthly returns excess of the market portfolio on x-axis. A regression line is fitted using the ordinary least squares (OLS) method with relevant statistics to help with the interpretation. The illiquid, micro-cap and high-momentum portfolios all have a significant and negative relation to market returns, but the illiquid portfolio has by far the strongest one (double the effect compared to high-momentum and 2.5 times the effect compared to micro-cap). When the market performs poorly, the illiquid portfolio is likely to overperform the market and vice versa. The high-value portfolio relation to market returns is insignificant at 95% confidence interval. Same conclusion can be drawn from **Figure 6** where the quartile portfolios are replaced by style long-short factors. The x-axis show the total return of the factor portfolios instead of return excess of market portfolio to preserve the analogy. The association to market returns are significant and slightly more negative than in the long-only examination. The order and magnitude of liquidity, size and momentum relative to each other stays the same. Value factor association to market returns remains insignificant.

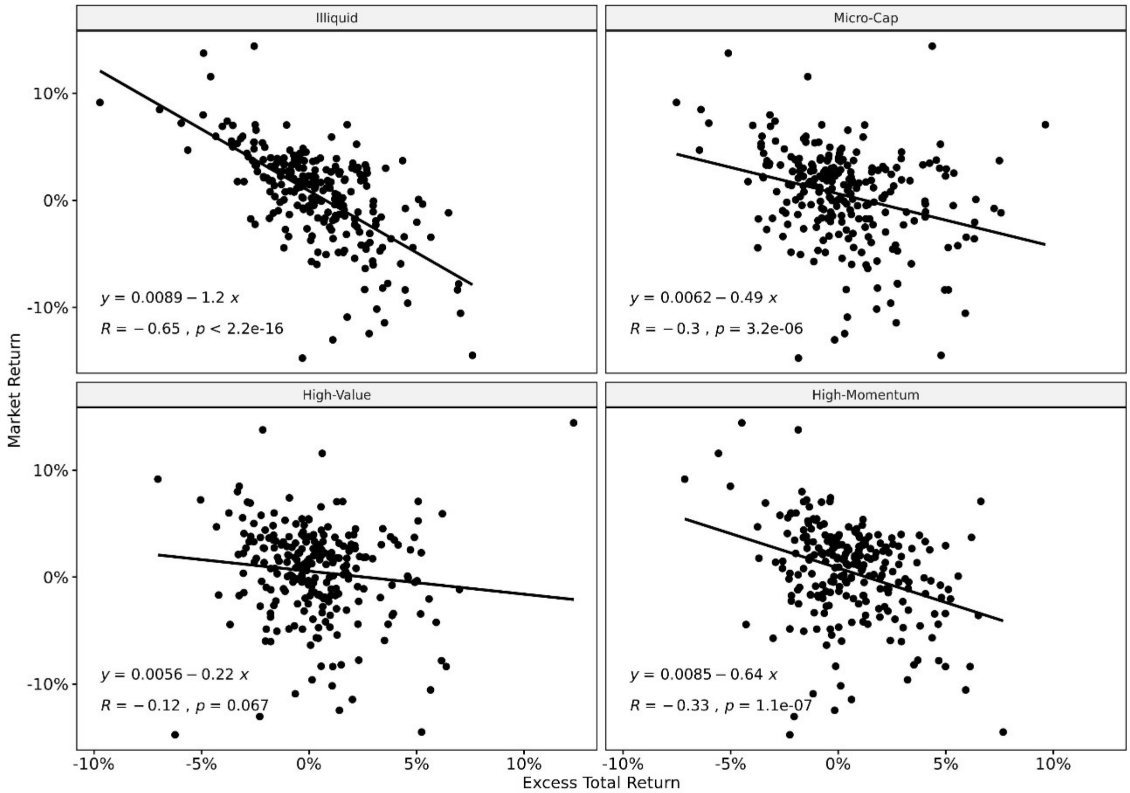

Figure 5. *Monthly style top quartile returns excess of the market portfolio viewed against monthly market returns, 2001-2020*

Figure 7 reports the annualized monthly market portfolio volatility on y-axis and style top quartile portfolio returns excess of the market portfolio on x-axis. Volatility is far less associated with the portfolio excess returns than the market return was. None of the top quartile portfolios had a significant association to market volatility. **Figure 8**, where the quartile portfolios are replaced with long-short factor portfolios, shows that the liquidity factor total return has a significant and positive relation to market volatility. Months were market volatility was higher, the liquidity factor was more likely to overperform the market portfolio. The fact that the liquid long-only portfolio had no significant relation to volatility suggests that the short leg of the factor (the liquid quartile portfolio) does poorly in high volatility regimes. The other factor portfolio total returns are not associated with market volatility.

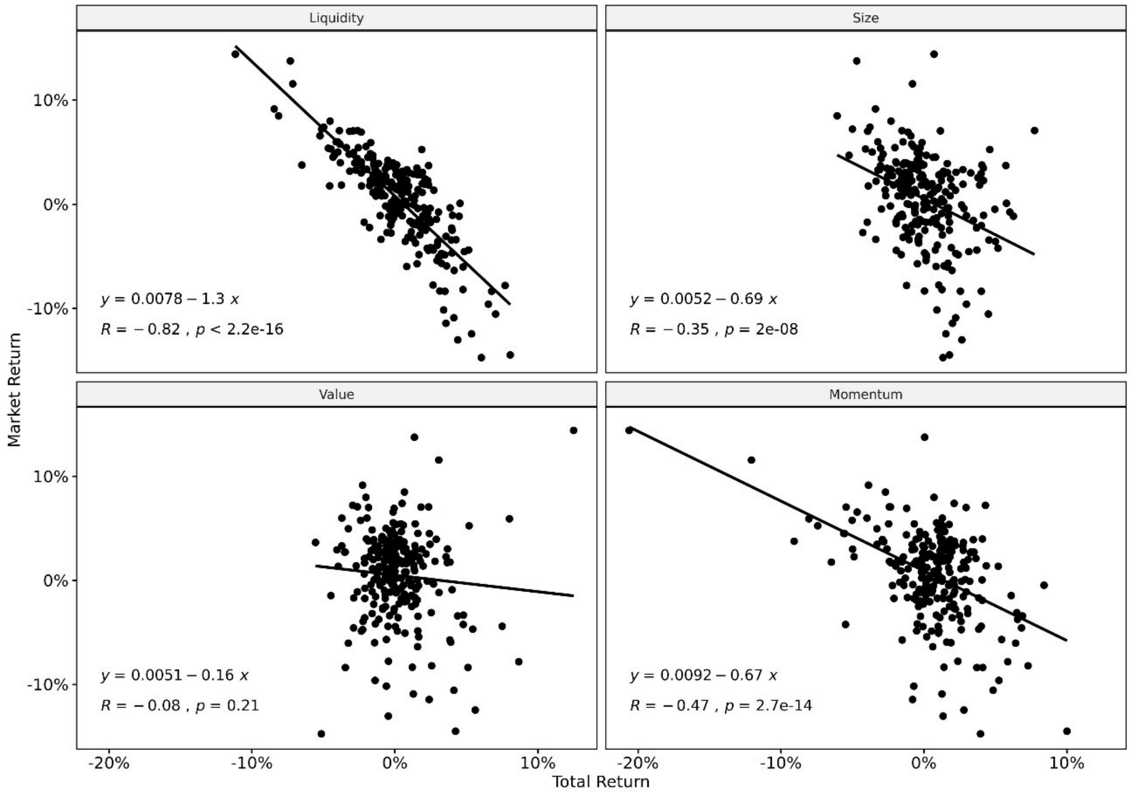

Figure 6. *Monthly style factor returns viewed against monthly market returns, 2001-2020*

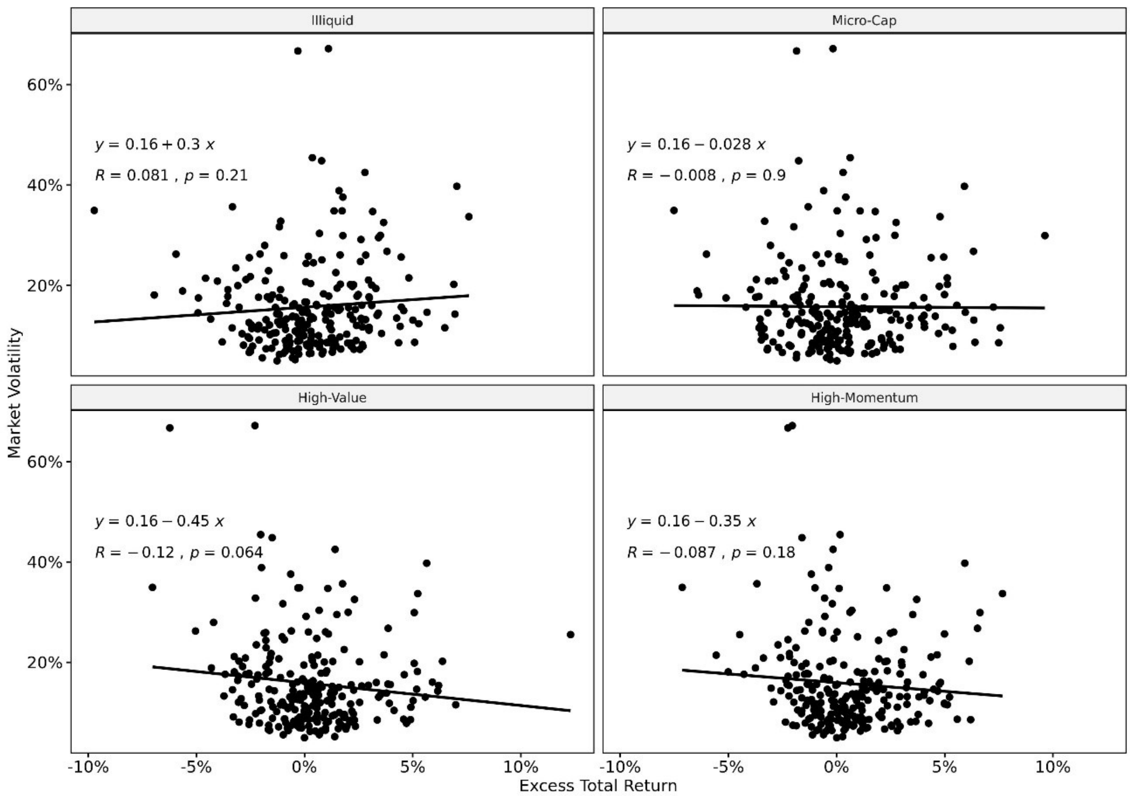

Figure 7. *Monthly style top quartile portfolio returns excess of the market portfolio viewed against annualized monthly market volatility, 2001-2020*

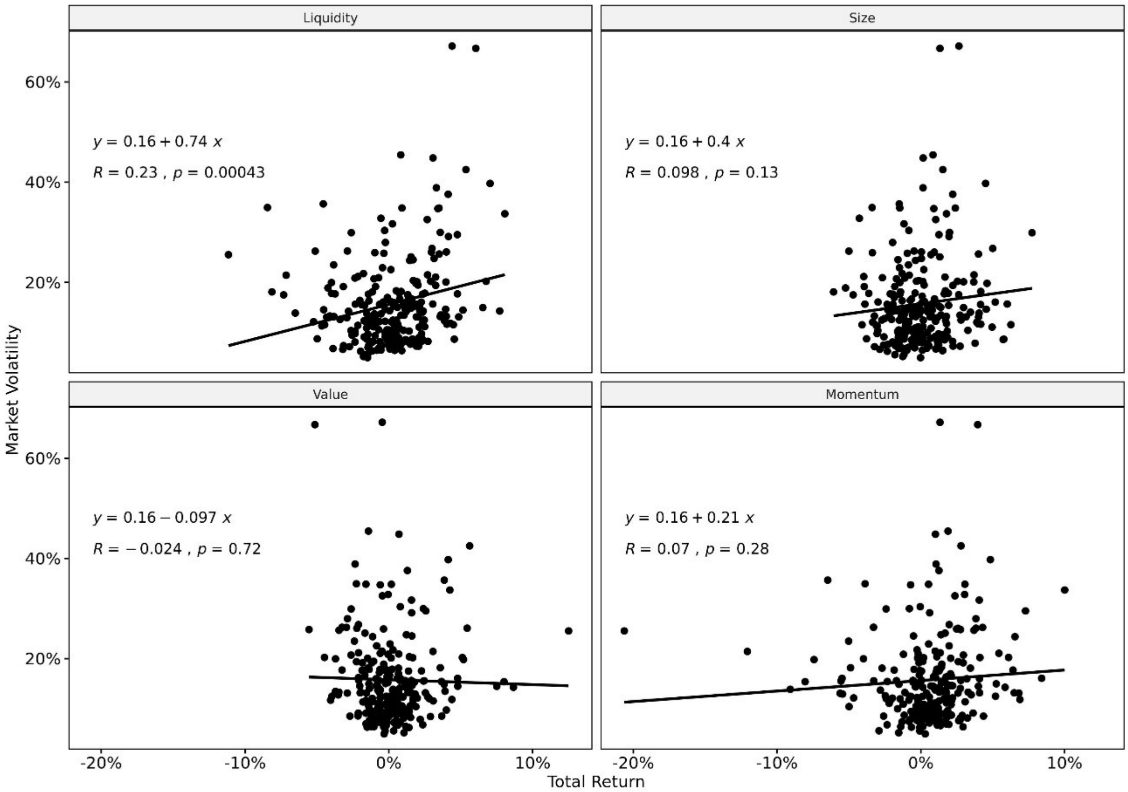

Figure 8. *Monthly factor portfolio returns viewed against annualized monthly market volatility, 2001-2020*

Maximum drawdown is a downside risk measure that describes the portfolio's loss from highest value to lowest value within a specified period. It is commonly used alongside volatility to assess the size potential losses. The formula for maximum dradown is

$$\frac{h - l}{h} \tag{10}$$

where h is the highest value before the largest drop in value and l is the lowest value before a new high value reached. The output is the loss in percentages from the highest value. In **Figure 9** I calculate monthly market portfolio drawdowns (y-axis) and compare them to style top quartile portfolio returns excess of the market portfolio (x-axis). Draw-downs smaller than 3% are not shown to better analyze effect in extreme regimes. The illiquid quartile portfolio is the only portfolio with a significant association. As the market portfolio has greater drawdowns, it will more likely overperform the market. The liquid factor exhibits the same behavior as is shown in **Figure 10**. The total return of the long-short factor is higher in periods when market drawdowns a greater. The size factor also has a similar but smaller relation with a confidence level of 95%. Value and momentum factor results are insignificant.

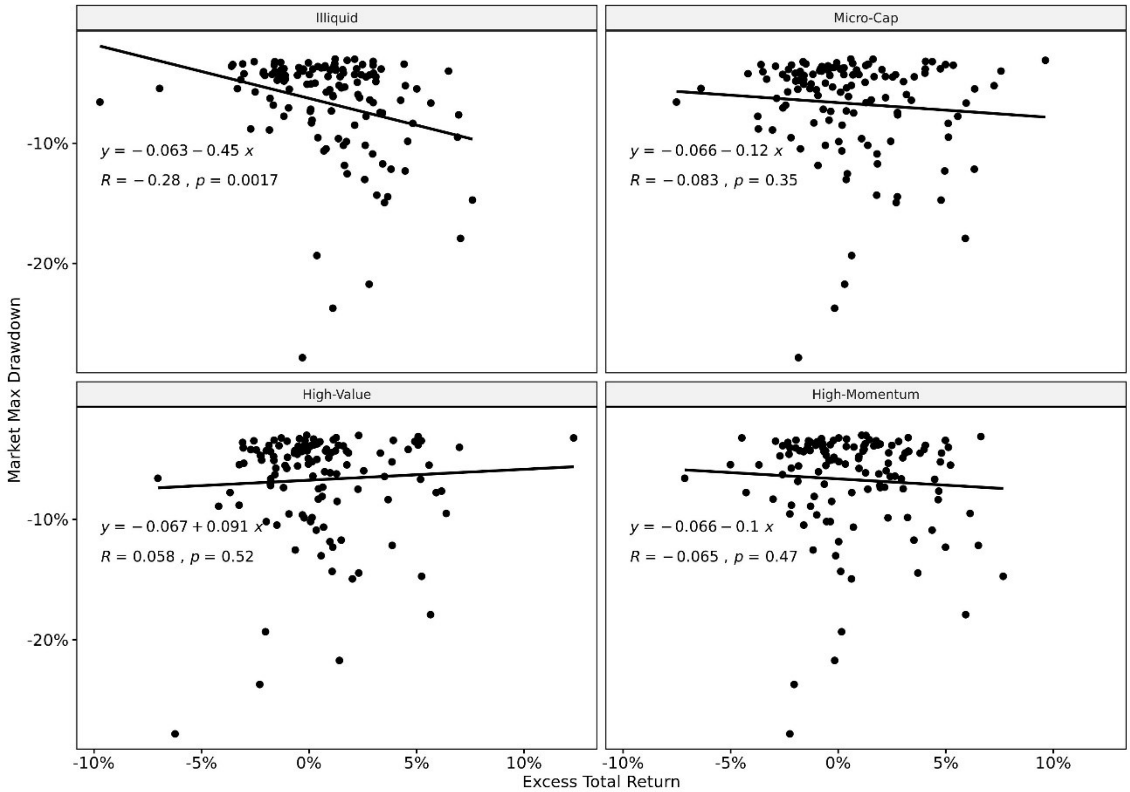

Figure 9. *Monthly style top quartile portfolio returns excess of market portfolio viewed against market maximum drawdown, 2001-2020. Months were the market maximum drawdown is greater than 3% are shown.*

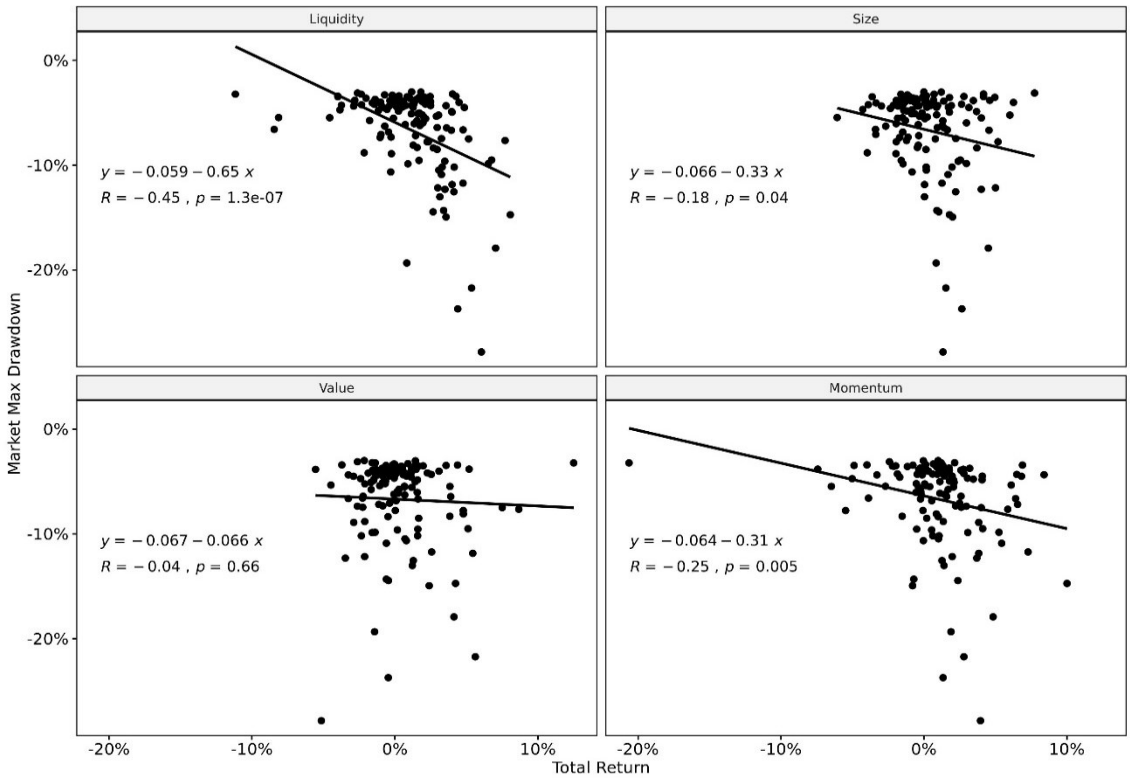

Figure 10. *Monthly factor portfolio returns viewed against monthly market maximum drawdown, 2001-2020. Months were the market maximum drawdown is greater than 3% are shown.*

These results show that liquidity style is defensive by nature: the liquidity factor and illiquid quartile portfolio both outperform when the market is in distress. Is the liquidity style another manifestation of a low beta or a low volatility strategy? Ibbotson & Idzorek (2014) conduct analysis identical to **Tables 7-9**, but on beta and volatility styles. They report that the liquidity spread exists within different beta and volatility quartiles, but the opposite (beta and volatility spreads in liquidity quartiles) was not always true. This suggest that the protection and diversification benefits liquidity style offers are unique.

4.5 Future research

Table 15 reported the average return excess of universe associated with migration of between quartiles. It showed that the liquidity excess returns were increasingly generated when a stock moved from a less quartile to more liquid quartile. Investigation into what drives the liquidity level of a stock should be analyzed further. Roulstone (2003) suggest that the number of analyst covering a firm is related to increasing stock liquidity and the disperion in analyst forecasts is related to decreasing stock liquidity.

Transactions costs were shown to potentially erode the liquidity spread in the analysis of chapter 4.3. This analysis was superficial and thus a more accurate transaction cost model should be built to analyze the transactions costs incurring in the illiquid quartile portfolio. Moreover, the bid-ask spread is not viewed as particularly good estimate for realized transaction costs (Datar, et al., 1998). Additionally, analysis on the feasible investment size (in euros) should be made. Transaction costs tend to increase as a function of investment size. An estimate of sustainable portfolio size could be generated by using the average daily volumes.

Chapter 4.4 reported that liquidity style behavior was similar to a low beta or low volatility style. The style comparison analysis of chapter 4.2 should be extended to volatility and beta styles.

5. CONCLUSIONS

This work set out to answer the questions: Is there a liquidity premium in the European stock market, how do estimated transaction costs affect the liquidity premium, and does liquidity overperform in certain market regimes?

The analysis framework of Ibbotson, et al. (2013) is replicated: Liquidity style is compared to the well-established size, value, momentum styles and tested against the four style investment criteria of Sharpe (1992). The new liquidity composite variable, which incorporates turnover ratio, relative bid-ask spread, liquidity ratio and trading discontinuity ratio, is "**identifiable before the fact**". The underlying liquidity measures had low rank correlation between each other thus new information was added when they were combined. The liquidity Q1 portfolio as well as the other style Q1 portfolios all beat the universe portfolio in terms of returns, thus all styles can be considered "**not easily beaten**". The returns of the liquidity Q1 portfolio were comparable to the other style Q1 portfolios. Liquidity beat size and value but got beaten by momentum. Each style had a positive premium (Q1 – Q4): Momentum 7.64%, liquidity 2.99%, value 2.54% and size 1.37%. The double-sorted portfolio analysis, where the liquidity was compared across the benchmark style quartile portfolios, reported a positive liquidity premium throughout different styles and quartiles. Momentum and value had positive premiums across liquidity quartiles, but size only a had positive premium in the illiquidity quartile suggesting that size could be a proxy for liquidity. The returns of the enhanced liquidity portfolios were greater than without liquidity, thus liquidity added new valuable information to other styles. Liquidity can therefore be determined as "**a viable alternative**". To further analyze the viability of liquidity, series of regressions were run where liquidity factor was explained by the CAPM, the three-factor model by Fama & French (1993) and the four-factor model by Carhart (1997). The liquidity factor added significant monthly alpha in the CAPM (long-only 0.48%***, long-short 0.42%***) and three-factor model (long-only 0.37%***, long-short 0.37%***). In the four-factor model, after the addition of momentum, the alpha was insignificant (long-only 0.13%, long-short 0.05%). Since the relation between size and liquidity was previously under question, the regression was run again without size resulting in a significant and positive alpha (long-only 0.37%**, long-short 0.23%*). Correlation between long-short liquidity and size factor monthly returns was 0.60. This serves as further evidence that size could be a proxy for liquidity as the economic intuition for liquidity is more convincing: Investors are willing to pay for liquidity. Two stocks with identical cash flows, the one with less liquidity will trade on a discount, since the trading costs are higher, and the trading horizon is longer. The liquidity premium can be captured by a passive investor (Ibbotson, et al., 2013). In terms of portfolio turnover liquidity (33.3%), size (24.1%) and value (40.5%) were comparative. Momentum had the highest turnover (73.0%). The liquid Q1 portfolio had an average annual turnover of 36.2%. Thus, liquidity style can be considered “**low in cost**”.

Results for liquidity style were encouraging. The liquidity style, using the new composite variable, is “identifiable before the fact”. Returns of liquidity Q1 portfolio overperformed the universe portfolio thus “not easily beaten”. The quartile migration analysis reports that liquidity style can be managed “low in cost”. Double-sorted portfolios analysis show that liquidity is “a viable alternative”, but further regression analysis challenged this by the similarities with size. Even if liquidity could not be accepted as a new style per Sharpe (1992) criteria along with the Carhart (1997) four-factor model, a significant **positive monthly premium for liquidity in the European stock market does exist**. Though, this is calculated before costs.

With a simple model, where average transactions costs are estimated based on the average bid-ask spreads of stocks in a portfolio, I show that the liquidity premium shrinks from an annual return of 2.99% without costs to an annual return of 0.07% when costs are applied. Thus, **after factoring in the estimated transactions costs, the liquidity premium ceases to exist**.

The monthly liquidity factor returns and liquidity Q1 excess returns were compared against monthly market portfolio returns, volatility and drawdown. Both returns had a strong association with negative market returns and market drawdown. In addition, the liquidity factor return had a weak association with higher market volatility. Thereby, **the liquidity style was more likely to generate excess returns in downturn market regimes**. The low beta nature of liquidity allows for it to be used as a diversification element.

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APPENDIX A: LIQUIDITY CHARACTERISTICS AND RETURNS

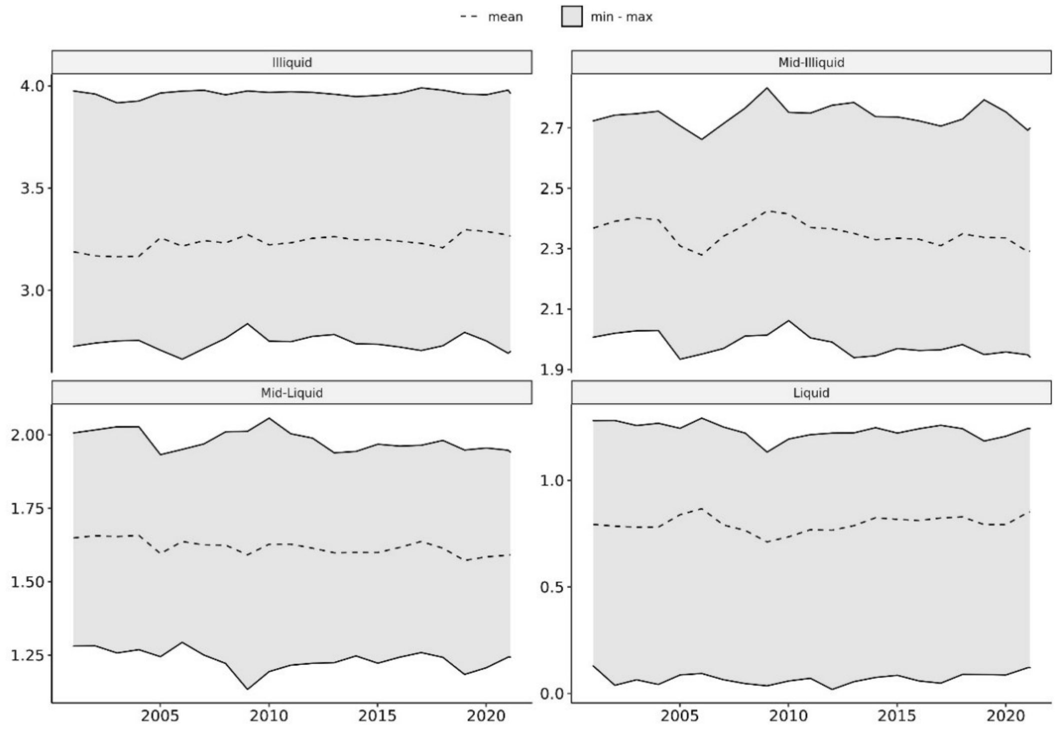

Figure 11. *Liquidity is split into four equal sized portfolios based on the ranked liquidity composite variable. The grey area shows the minimum and maximum values entering a specific portfolio and the dotted line is the mean of the values, 2000-2020.*

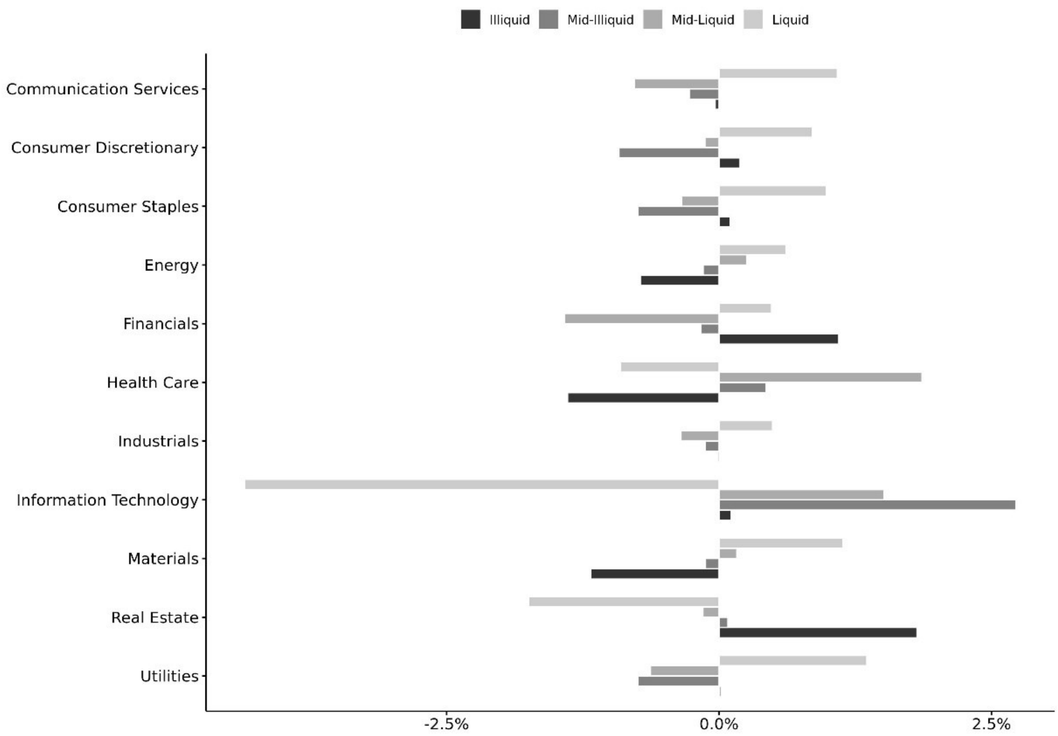

Figure 12. *The average GICS sector exposure excess of the universe portfolio for each liquidity quartile portfolio, 2000-2020.*

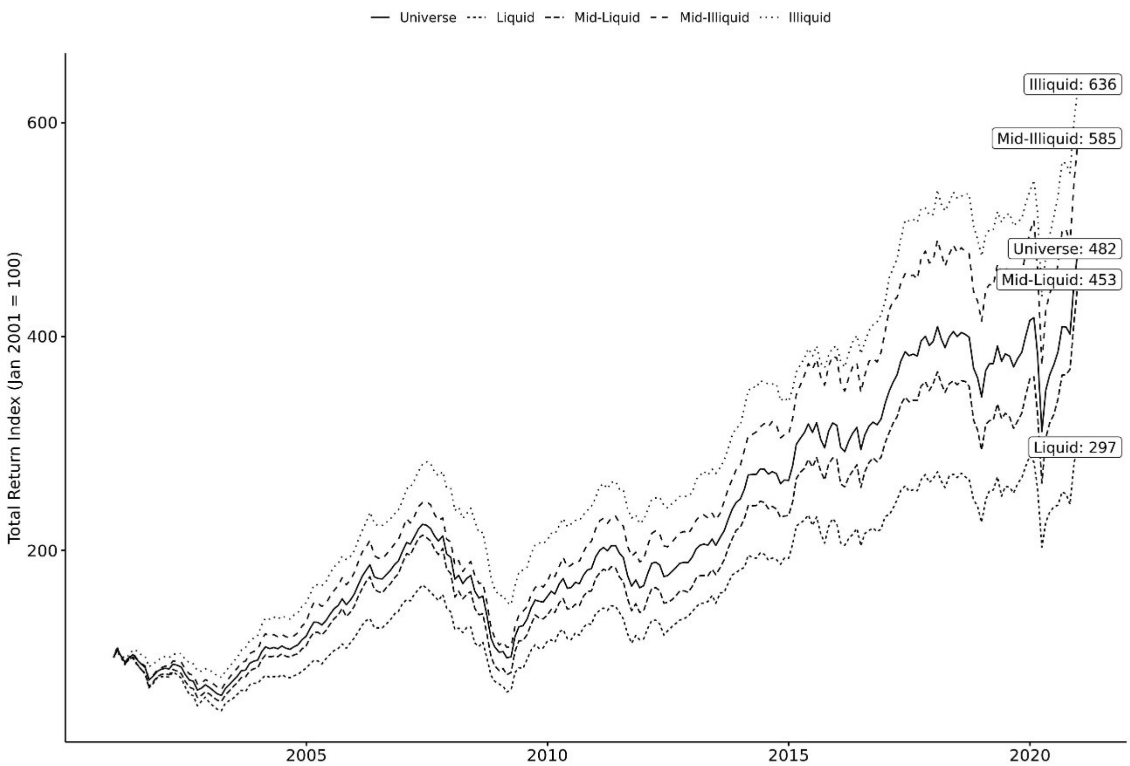

Figure 13. *Liquidity quartile and universe portfolio indexed total returns, 2001-2020.*

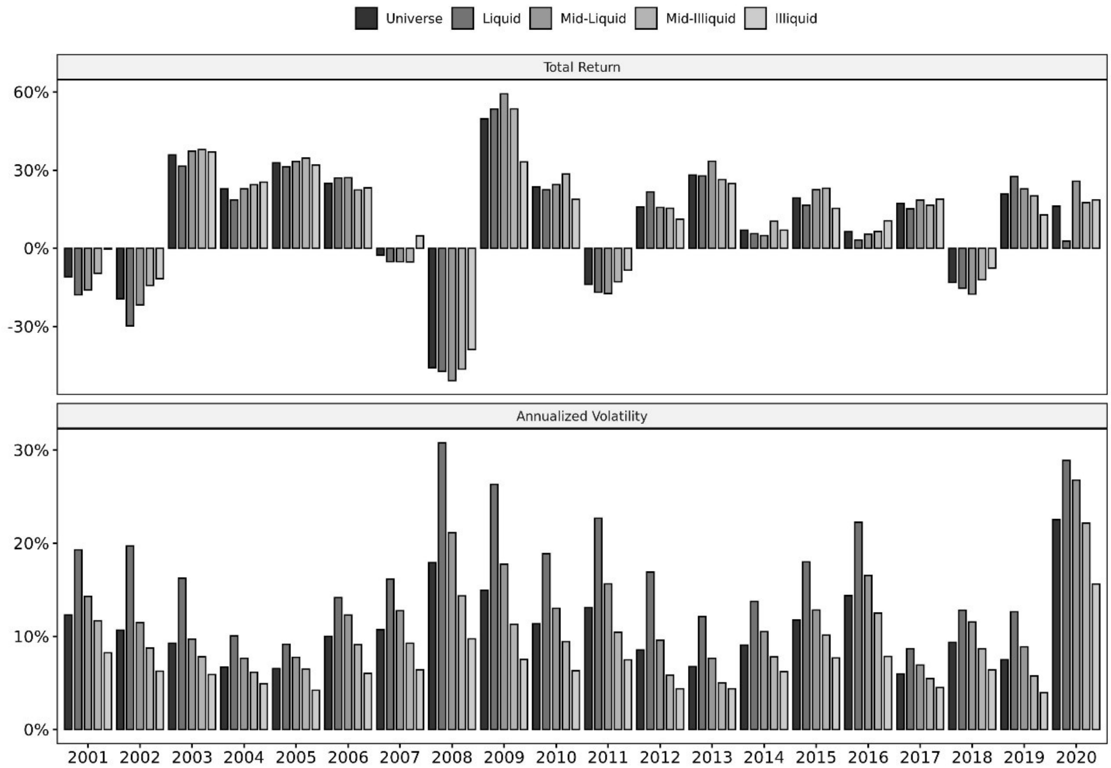

Figure 14. *Liquidity quartile and universe portfolio annualized returns and volatility, 2001-2020.*

APPENDIX B: SIZE CHARACTERISTICS AND RETURNS

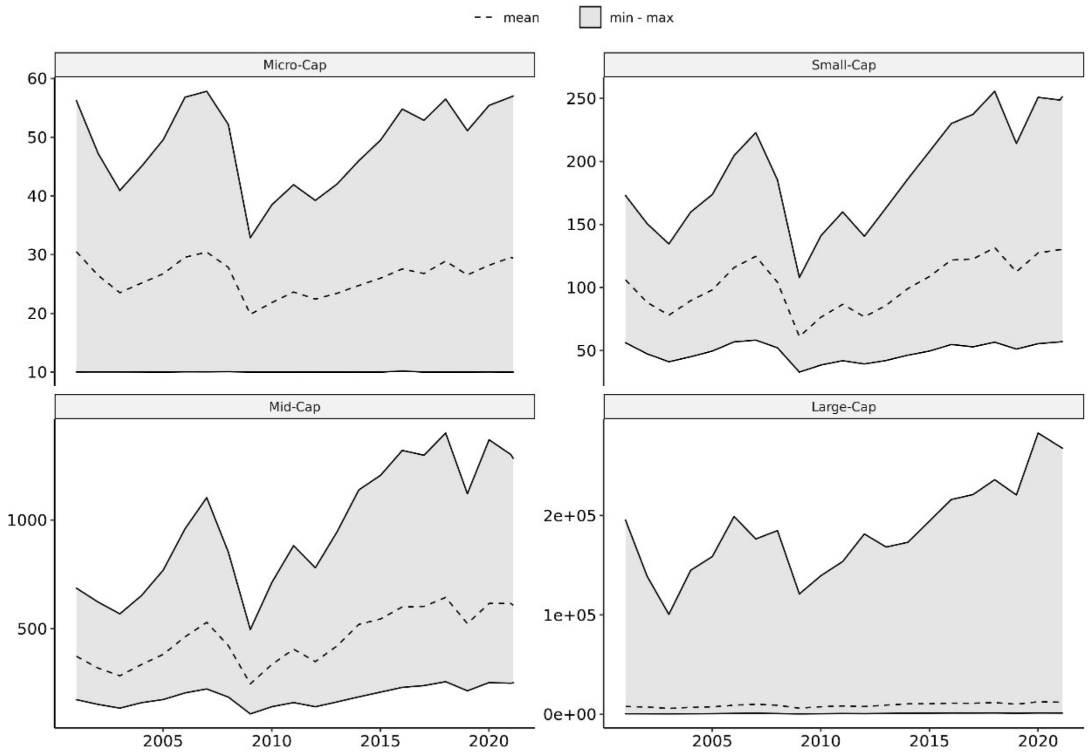

Figure 15. *Size is split into four equal sized portfolios based on the ranked market capitalization variable. The grey area shows the minimum and maximum values entering a specific portfolio and the dotted line is the mean of the values, 2000-2020.*

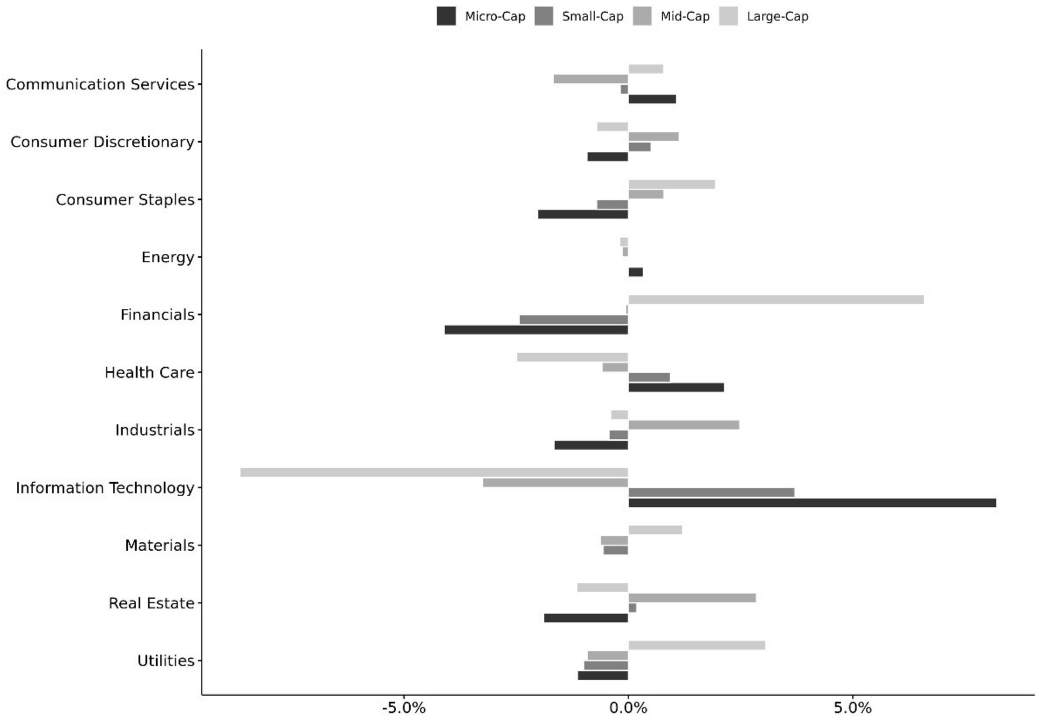

Figure 16. *The average GICS sector exposure excess of the universe portfolio for each size quartile portfolio, 2000-2020.*

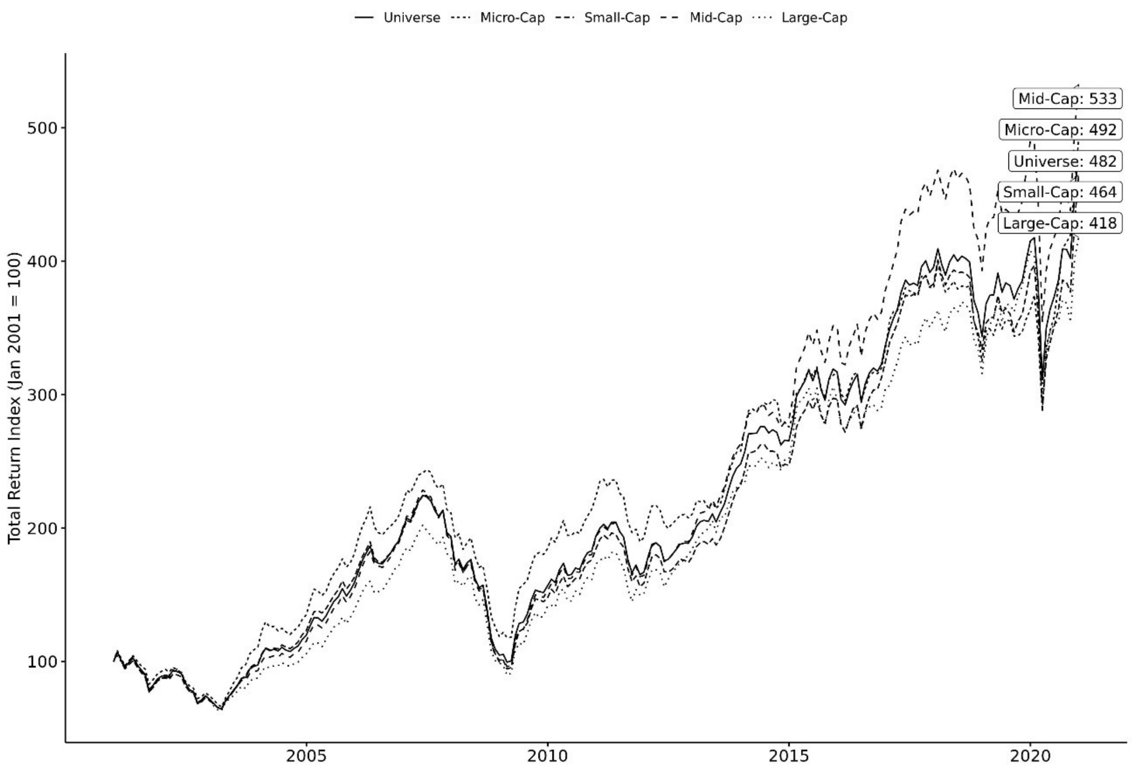

Figure 17. *Size quartile and universe portfolio indexed total returns, 2001-2020.*

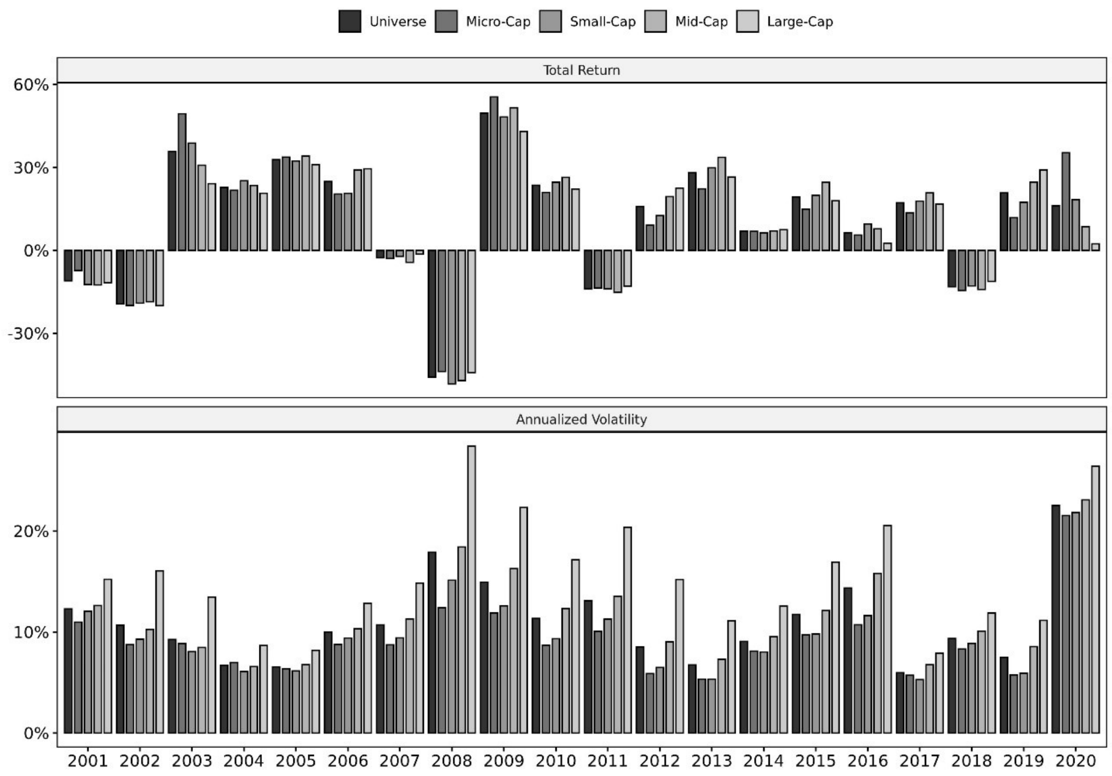

Figure 18. *Size quartile and universe portfolio annualized returns and volatility, 2001-2020.*

APPENDIX C: VALUE CHARACTERISTICS AND RETURNS

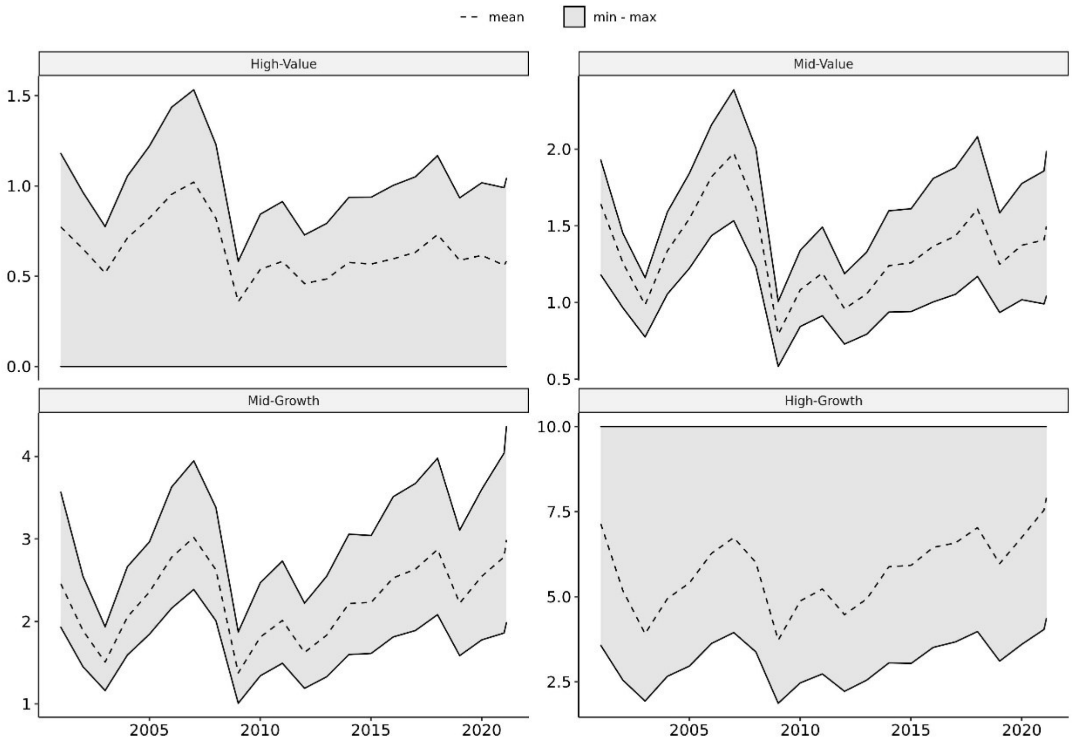

Figure 19. *Value is split into four equal sized portfolios based on the ranked book to price -ratio. The grey area shows the minimum and maximum values entering a specific portfolio and the dotted line is the mean of the values, 2000-2020.*

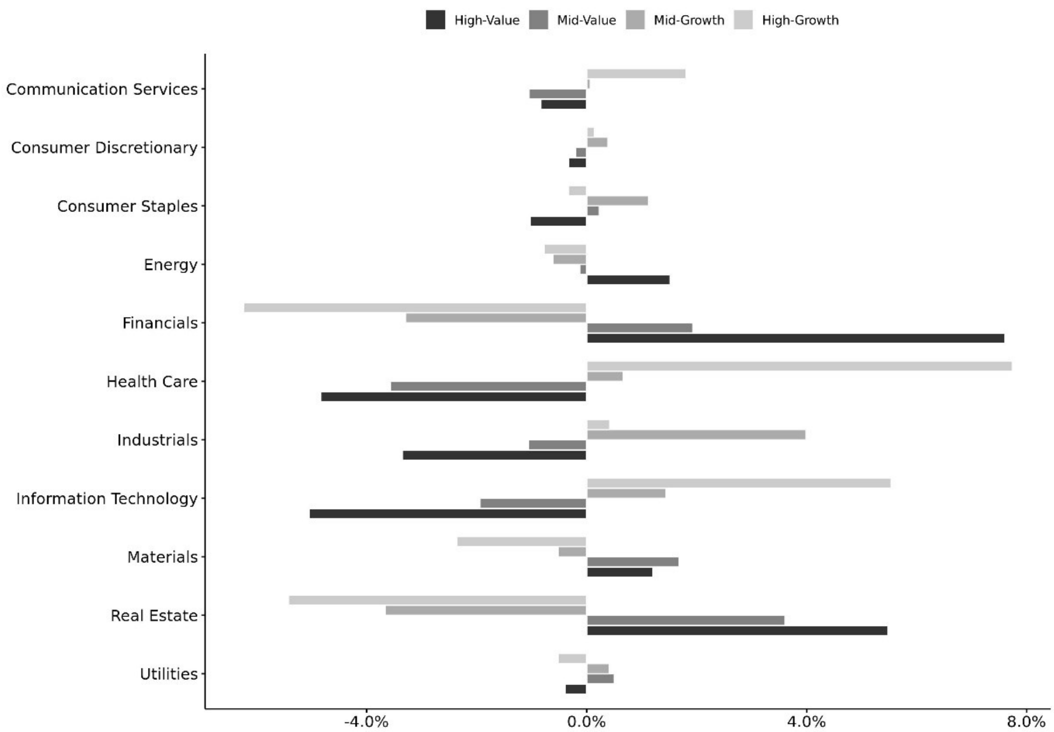

Figure 20. *The average GICS sector exposure excess of the universe portfolio for each value quartile portfolio, 2000-2020*

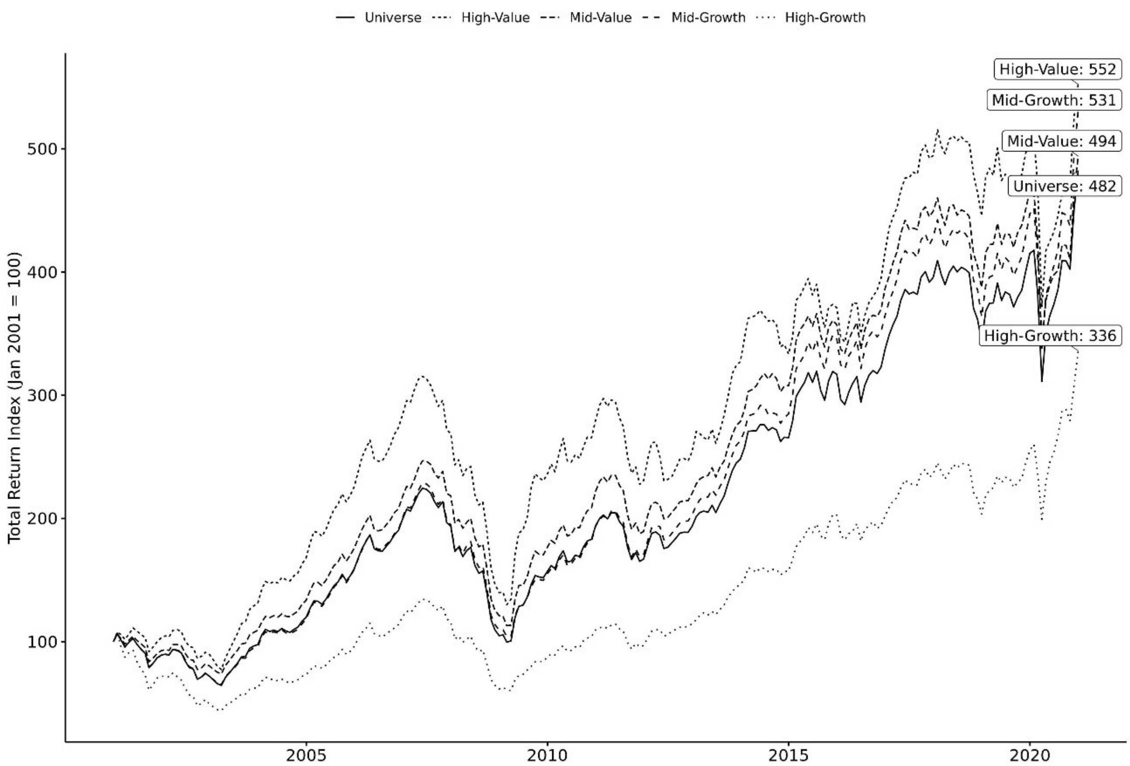

Figure 21. *Value quartile and universe portfolio indexed total returns, 2001-2020.*

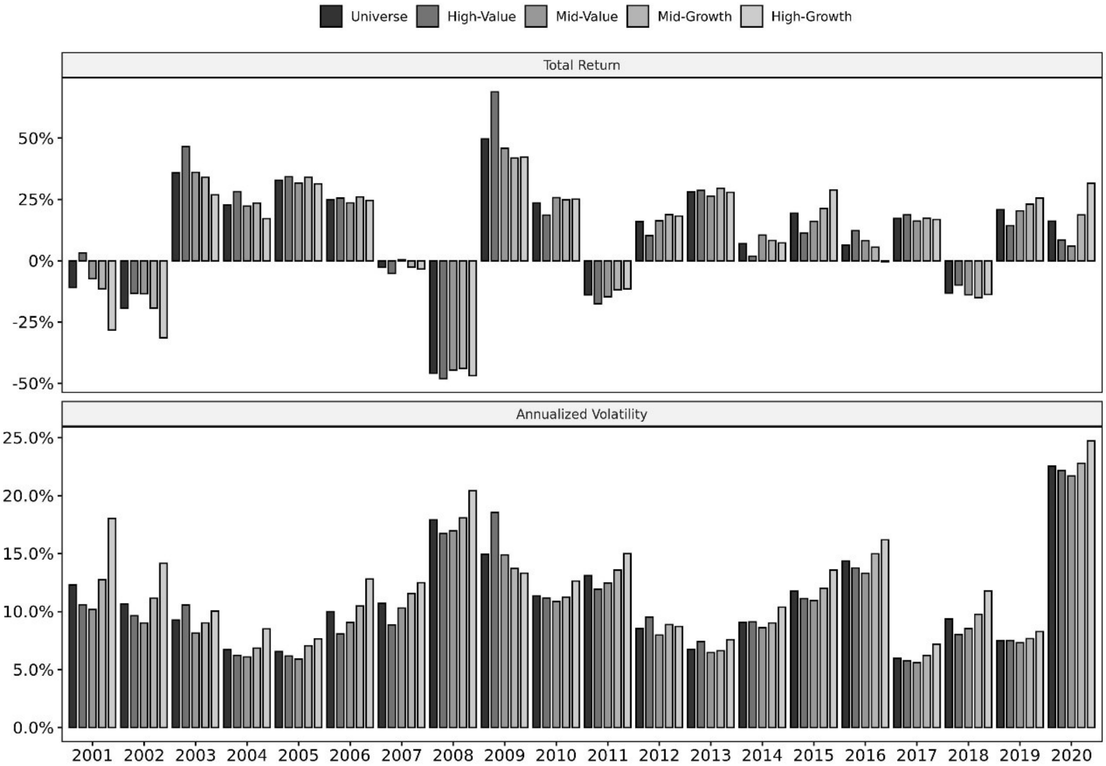

Figure 22. *Value quartile and universe portfolio annualized returns and volatility, 2001-2020.*

APPENDIX D: MOMENTUM CHARACTERISTICS AND RETURNS

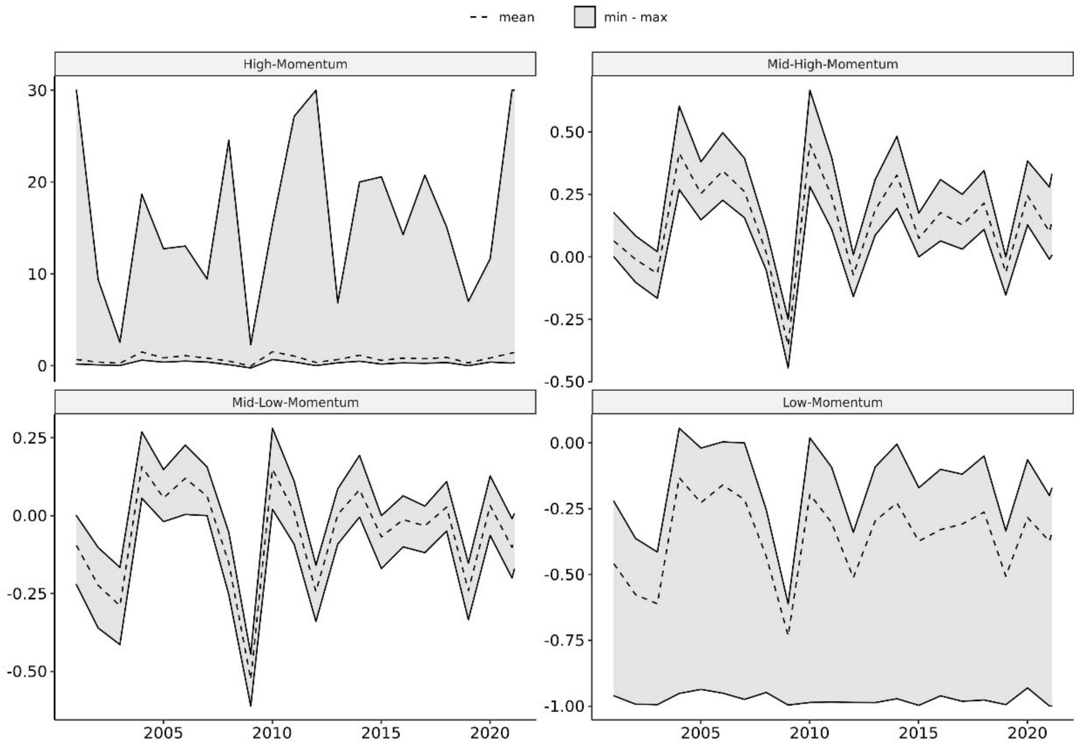

Figure 23. *Momentum is split into four equal sized portfolios based on the ranked total return in the previous year. The grey area shows the minimum and maximum values entering a specific portfolio and the dotted line is the of the values, 2000-2020.*

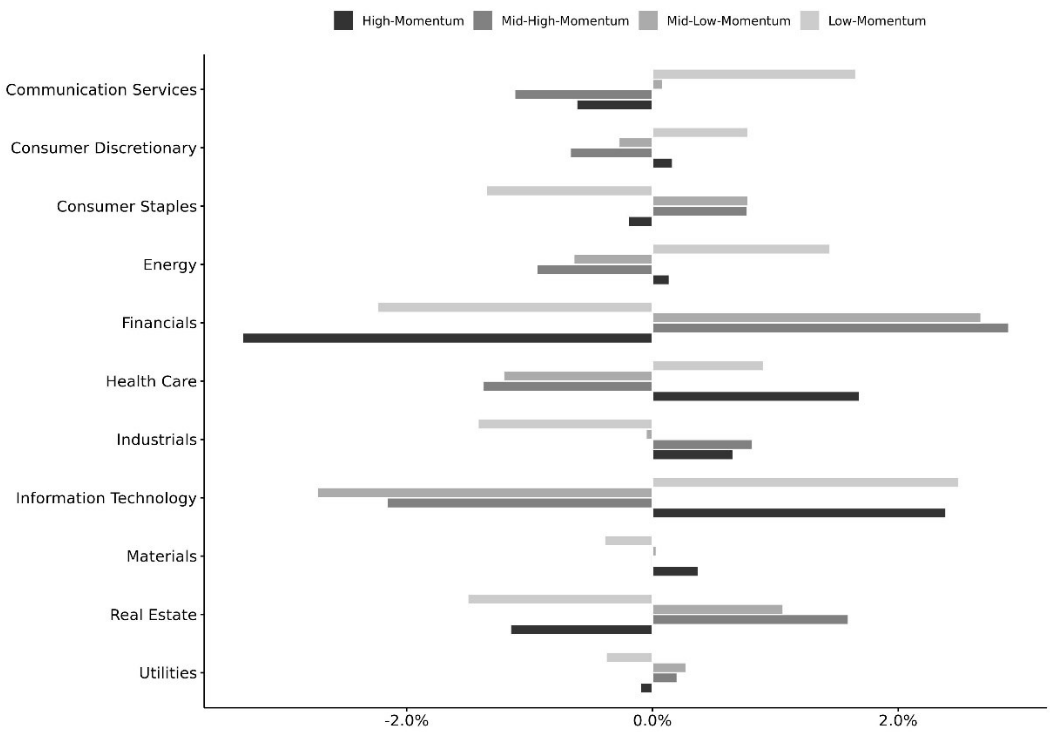

Figure 24. *The average GICS sector exposure excess of the universe portfolio for each momentum quartile portfolio, 2000-2020.*

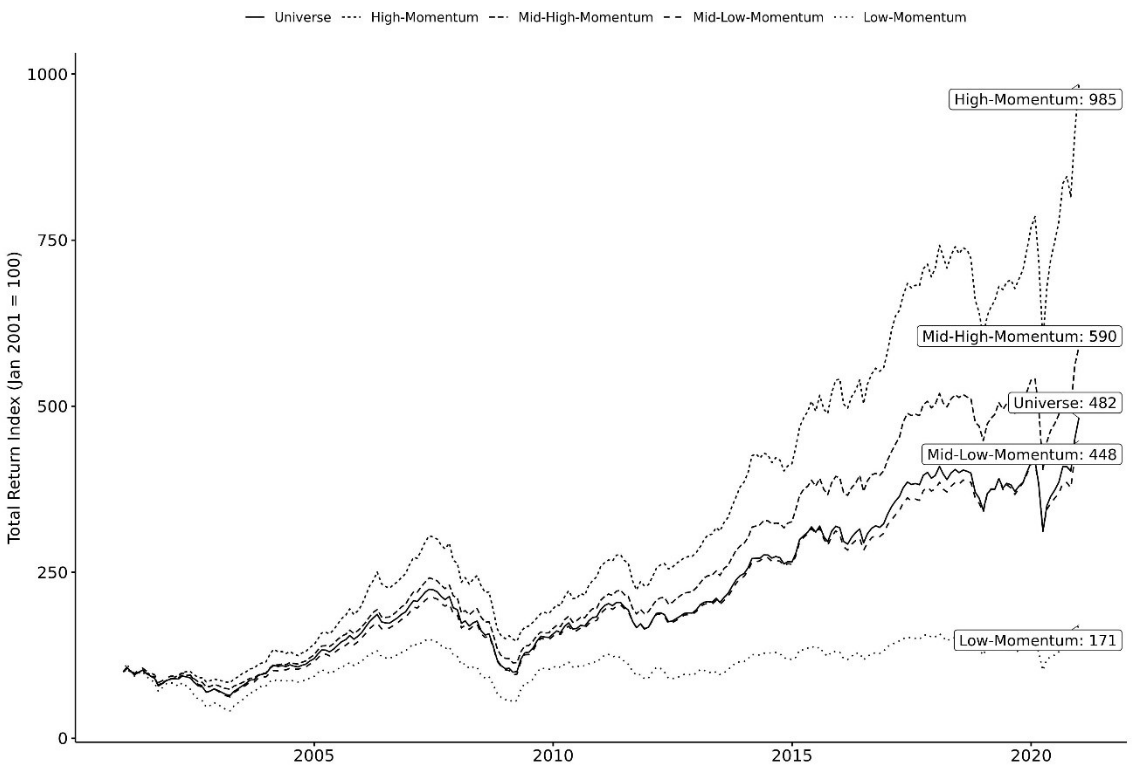

Figure 25. *Momentum quartile and universe portfolio indexed total returns, 2001-2020.*

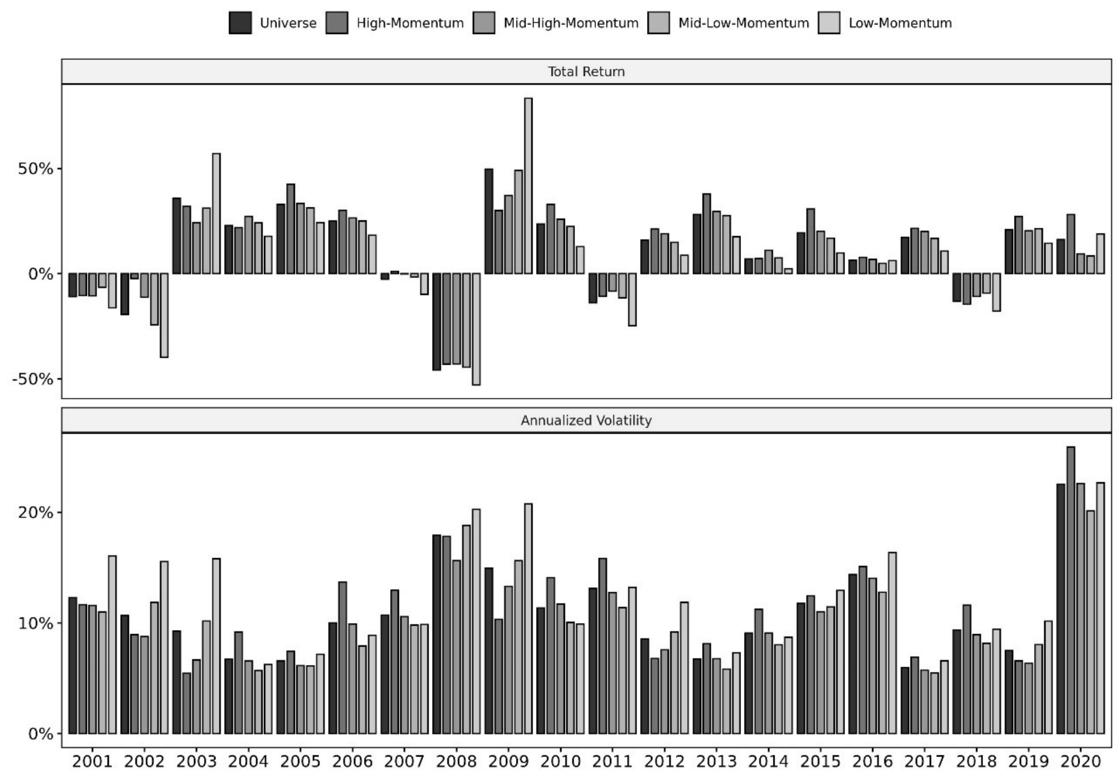

Figure 26. *Momentum quartile and universe portfolio annualized returns and volatility, 2001-2020.*

APPENDIX E: FAMA-FRENCH DATA

Datasets from website (French, 2020): Fama/French European 3 Factors and European Momentum Factor (Mom). Mkt-RF is market beta, SMB is size, HML is value and WML is momentum.

Table 16. *Liquidity regression analysis on pre-calculated Fama-French long-short monthly factor returns, 2001-2020 (French, 2020)*

	estimate	t-statistic	p-value[1]	
Capital asset pricing model				
Monthly alpha	0.42% ± 0.13%	3.16	1.78×10^{-3}	**
Market Beta	−0.36 ± 0.02	−14.83	1.10×10^{-35}	***
Adj. R Squared		0.478		
Fama-French three factor model				
Monthly alpha	0.33% ± 0.13%	2.60	1.00×10^{-2}	*
Market Beta	−0.37 ± 0.02	−15.42	1.45×10^{-37}	***
Size	0.36 ± 0.06	5.60	5.84×10^{-8}	***
Value	0.09 ± 0.05	1.69	9.20×10^{-2}	.
Adj. R Squared		0.542		
Extended four factor model				
Monthly alpha	0.07% ± 0.12%	0.56	5.73×10^{-1}	.
Market Beta	−0.29 ± 0.02	−11.55	9.61×10^{-25}	***
Size	0.32 ± 0.06	5.51	9.45×10^{-8}	***
Value	0.13 ± 0.05	2.82	5.26×10^{-3}	**
Momentum	0.24 ± 0.03	7.62	6.35×10^{-13}	***
Adj. R Squared		0.631		

[1] Significancy codes: 0.001 (***), 0.01 (**), 0.05 (*), 0.1 (.)

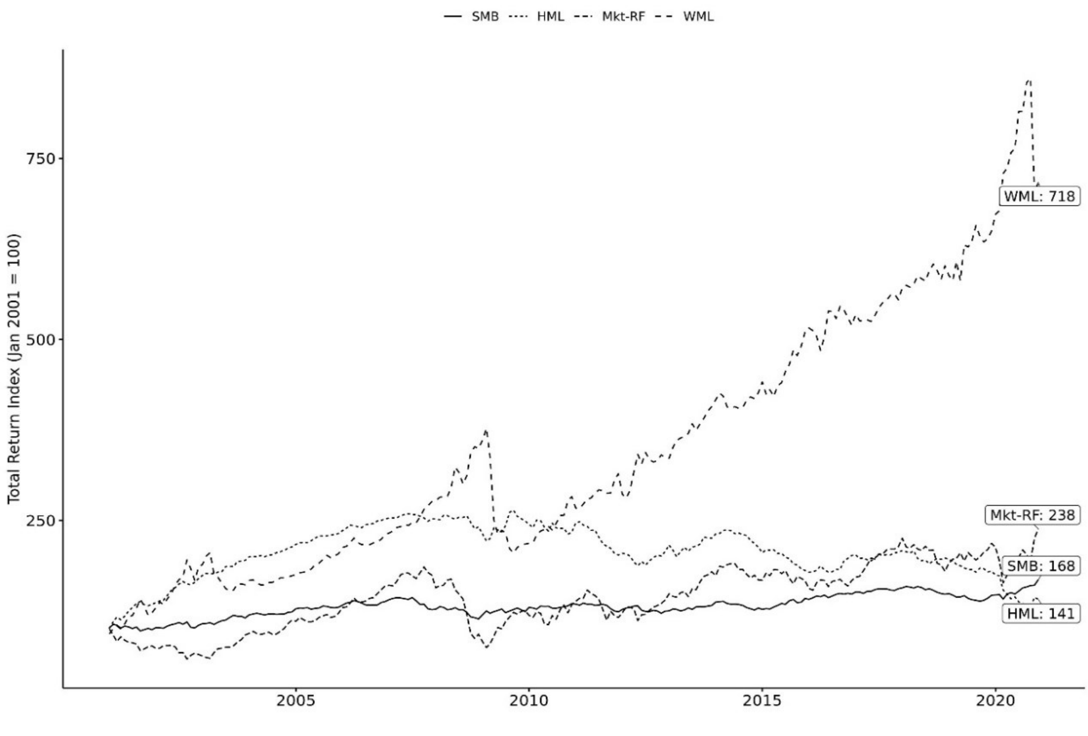

Figure 27. *Pre-calculated Fama-French long-short monthly factor indexed total returns, 2001-2020 (French, 2020)*