

Liquidity and anomalies: study on stock market liquidity and its affect on momentum and value investment returns.

Finance  
Master's thesis  
Taneli Saali  
2014

---

**Author** Taneli Saali

---

**Title of thesis** Liquidity and anomalies: study on stock market liquidity and its affect on momentum and value investment returns.

---

**Degree** Master's Degree

---

**Degree programme** Finance

---

**Thesis advisor(s)** Matti Suominen

---

**Year of approval** 2014**Number of pages** 77**Language** English

---

## Abstract

### Purpose of the study

This study focuses on the links between stock market liquidity and two of the most studied stock market anomalies: momentum effect and value effect. The aim is to increase knowledge from this area using daily stock market data and to confirm previous results often made using monthly stock market data.

### Data

There are two data sets used in this study. The first part is the daily NYSE stock market data obtained from the CRSP database. The second part is the daily Fama French three factors data downloaded from Kenneth French's webpage. The collected data is used to build nine different investment portfolios and six different liquidity factors.

### Results

First, the findings show no positive alphas for momentum or value investment strategies during the post 2008 financial crisis period. Second, there is a negative relationship between liquidity shocks and value investment returns, and positive relationship between liquidity shocks and momentum investment returns. Third, the unexpected liquidity shocks, rather than the expected changes in stock market liquidity, forecast momentum and value investment returns. And finally, the positive liquidity shocks have stronger effects than the negative shocks, both in statistical significance and in magnitude, when explaining future momentum and value investment returns.

---

**Keywords** Liquidity, momentum, value, market anomaly, arbitrage

---

---

**Tekijä** Taneli Saali

---

**Työn nimi** Likviditeetti ja anomaliat: tutkimus osakemarkkinoiden likviditeetistä ja sen vaikutuksesta momentum- ja value-sijoittamisen tuottoihin.

---

**Tutkinto** Kauppatieteiden maisteri

---

**Koulutusohjelma** Rahoitus

---

**Työn ohjaaja(t)** Matti Suominen

---

**Hyväksymisvuosi** 2014

**Sivumäärä** 77

**Kieli** Englanti

---

## Tiivistelmä

Likviditeetti ja anomaliat: tutkimus osakemarkkinoiden likviditeetistä ja sen vaikutuksesta momentum- ja value-sijoittamisen tuottoihin.

### Tutkielman tavoitteet

Tutkimus syventyy yhteyteen osakemarkkinoiden likviditeetin ja kahden eniten tutkitun osakemarkkinoiden poikkeavuuden, momentum-ilmiön sekä value-ilmiön, välillä. Tavoitteena on lisätä tietoa aiheesta käyttäen päivittäistä osakemarkkinainformaatiota, sekä vahvistamaan edellisiä usein kuukausittaisella osakemarkkinainformaatiolla tehtyjä tuloksia.

### Lähdeaineisto

Tutkimuksessa käytetään kahta data-kokonaisuutta. Ensimmäinen osa koostuu päivittäisestä NYSE osakemarkkinadatasta, joka on haettu CRSP-tietokannasta. Toisen osan muodostavat Kenneth Frenchin verkkosivuilta haetut Fama-French -tekijät. Aineiston pohjalta on muodostettu yhdeksän investointiportfoliota ja kuusi likviditeettitekijää.

### Tulokset

Ensimmäisenä löydöksenä ilmenee positiivisten alfojen puuttuminen sekä momentum- että value-investointistrategioilta vuoden 2008 finanssikriisin jälkeisenä aikana. Toiseksi, likviditeettishokkien ja value-sijoittamisen tuottojen välillä ilmenee negatiivinen suhde, kun taas likviditeettishokkien ja momentum-sijoittamisen tuottojen välillä vallitsee positiivinen suhde. Kolmanneksi, ennustamattomat likviditeettishokit, toisin kuin ennustetut muutokset osakemarkkinoiden likviditeetissä, ennustavat tulevia momentum- ja value-investointituottoja. Ja viimeiseksi, positiivisilla likviditeettishokeilla on vahvempi vaikutus kuin negatiivisilla shokeilla, sekä tilastolliselta merkitykseltään että vahvuudeltaan, selitettäessä tulevia momentum- ja value-sijoittamisen tuottoja.

---

**Avainsanat** Likviditeetti, momentum, value, markkina-anomalia, arbitraasi

---

## Table of Contents

1	Introduction.....	1
1.1	Theoretical background.....	2
1.2	The Thesis' contribution to Research.....	3
1.3	Overview of the results .....	4
1.4	Structure of the study .....	4
2	Literature review.....	5
2.1	Momentum .....	5
2.1.1	Early findings .....	5
2.1.2	Persistence over time .....	6
2.1.3	Theoretical discussion .....	8
2.1.4	Time series momentum .....	9
2.1.5	Momentum and value .....	11
2.2	Value .....	12
2.2.1	Brief history check.....	12
2.2.2	Anomaly or state variable? .....	13
2.3	Liquidity .....	14
2.3.1	Liquidity: the definitions .....	14
2.3.2	Liquidity and the expected returns .....	16
2.3.3	Liquidity and market efficiency.....	17
2.3.4	Different forms of liquidity .....	18
2.3.5	Autoregressive nature and commonality of liquidity .....	19

2.3.6	Liquidity and momentum .....	20
2.4	Other relative literature .....	21
2.4.1	Price reversals.....	21
2.4.2	Transaction costs .....	23
3	Hypothesis .....	26
4	Data and Methods.....	28
4.1	Data .....	28
4.2	Momentum and value measures .....	30
4.2.1	Cross sectional momentum .....	30
4.2.2	Value portfolio.....	31
4.2.3	Value and Momentum portfolio .....	31
4.2.4	Statistical characteristics of investment portfolios .....	32
4.3	Liquidity measures .....	33
4.3.1	Trading Volume .....	34
4.3.2	Turnover.....	34
4.3.3	Market liquidity .....	35
4.3.4	Proportional changes in market liquidity.....	36
4.3.5	Shocks in aggregate liquidity .....	36
4.3.6	Statistical characteristics of liquidity factors .....	37
4.4	Other data .....	38
4.5	Regressions.....	40
5	The results.....	42
5.1	First results: no positive alphas .....	43
5.2	Introducing liquidity.....	45
5.2.1	Uncontrolled liquidity: minor significance.....	45

5.2.2 Controlled liquidity: major significance .....	47
5.3 From present to the past: lagged connections.....	48
5.3.1 Uncontrolled correlations .....	49
5.3.2 Controlled correlations: strong evidence .....	50
5.4 Prolonged effect: evidence for lagged relation.....	52
5.5 The dummy approach: the positive shocks dominate .....	61
6 Conclusion.....	66
References.....	68

## 1 Introduction

“Why does momentum load positively and value load negatively on liquidity risk?” – Asness, Moskowitz and Pedersen (2013).

Ever since the development of the traditional views of expected stock returns around the capital asset pricing model (CAPM)<sup>1</sup> and the efficient market hypothesis (EMH)<sup>2</sup>, practitioners and academics have fiercely searched for market anomalies to either study them out of sheer academic interest or with profiteering purposes. At first, these hypotheses were found out to hold very well (Fama, 1970) but many current financial theories set limits to arbitrage (Shleifer and Vishny, 1997), present long lasting anomalies (Jegadeesh and Titman, 1993) and find evidence against the random walk in stock prices in general (e.g. Lo and MacKinlay, 1988).

This study is motivated by recent findings by Asness, Moskowitz and Pedersen (2013) who present persistent value and momentum return premium across a vast variety of asset classes and different markets. They find a significant link between liquidity risk and both momentum and value returns. This link forms the foundation for this study and focus is on the role that market liquidity plays in explaining the behavior of these two strong market anomalies: value effect<sup>3</sup> and momentum effect<sup>4</sup>.

The results are in line with the findings by Asness, Moskowitz and Pedersen (2013) and find a negative relationship between stock market liquidity shocks and value investment returns, and a positive relationship between stock market liquidity shocks and momentum investment returns. These results are reached when studying the lagged daily effects from liquidity shocks. The positive liquidity shocks drive this effect more strongly than the negative shocks.

---

<sup>1</sup> Developed by Sharpe, W., 1964, Capital asset prices: A theory of market equilibrium under conditions of risk, *Journal of Finance* 19, 425-442, Lintner, J., 1965, The valuation of risk assets and the selection of risky investments in stock portfolios and capital budgets, *Review of Economics and Statistics* 47, 13-37 and Treynor, J. (unpublished), (Brealey, R., Myers, S., Allen F., 2008, Principles of corporate finance, McGraw-Hill/Irwin, Singapore.)

<sup>2</sup> Developed and tested in the early 1960's (by e.g. Fama, E., 1965, The behavior of stock-market prices, *Journal of Business* 38, 35-105) after the random walk findings in the stock markets by Kendal, M., 1953, The analysis of economic time series, part I. Prices, *Journal of Royal Statistical Society* 96, 11-25.

<sup>3</sup> Value effect stands for the long lasting anomaly where assets returns are affected by its book-to-market ratio.

<sup>4</sup> Momentum effect, founded by Jegadeesh and Titman (1993), is the strongest and most persistent anomaly in financial markets. It stands for the effect that past performances have on expected returns of an asset.

## 1.1 Theoretical background

The very foundations of the academic research in finance have been heavily influenced by the capital asset pricing model (CAPM)<sup>5</sup>. The CAPM states that every asset's cross sectional differences in expected returns should be explained purely by their betas ( $\beta$ ).<sup>6</sup> The CAPM offered a theoretical framework on how the assets should be priced based on their correlation with market returns.

However, the empirical evidence showing different market anomalies started to build up. For example Banz (1981) presents that size also affects the stock market return in a way that can't be explained by the CAPM; and the findings from Stattman (1980) and Rosenberg, Reid and Lanstein (1985) present the book-to-market ratio to explain the cross section differences in stock markets.

These results lead to the development of the Fama-French three-factor model (Fama and French, 1993), where size and book-to-market ratio are added to the original CAPM. Later, the discovery of momentum investing returns (Jegadeesh and Titman, 1993) and its ability to explain the cross sectional return differences for mutual fund returns (Carhart, 1997) lead to the inclusion of momentum returns as the fourth explanatory variable for asset returns.

So why are the markets not perfect and different anomalies persist long after their discovery? One sound and robust explanation offered is the limits of arbitrage by Shleifer and Vishny (1997), which builds the theoretical framework where arbitrageurs are limited by the outside investor monitoring their performance. This framework clearly highlights the conclusion that some amount of arbitrage profits are needed for the arbitrage process to function properly and markets can never fully reach the theoretical perfect ideal levels.

When we look at market anomalies, such as excess momentum and value investing profits, through these limits of arbitrage framework the possibility of time varying levels of anomaly profits can be

---

<sup>5</sup> See Introduction Chapter.

<sup>6</sup> Beta ( $\beta$ ) stands for the correlation coefficient from the CAPM regression  $R_a = R_f + \beta(R_m - R_f)$ , where  $R_a$  stands for the expected return for the asset a,  $R_f$  stands for the risk-free rate of return and the  $R_m$  stands for the expected market returns.



seen. In this setting, when the arbitrageurs make their investment decisions, they should be concerned by the net profits after the trading costs. This would clearly build a theoretical link between the arbitrage returns and the ease of trading i.e. market liquidity. The changes in market liquidity should change the net profitability of arbitrage activity and thus limit the amount of the mispricing possible to arbitrage away as presented in Shleifer and Vishny (1997).

## **1.2 The Thesis' contribution to Research**

The research broadens the results from Asness, Moskowitz and Pedersen (2013) by demonstrating a similar negative relationship between liquidity shocks and value investment returns, and a positive relationship between liquidity shocks and momentum investment returns. The results from this research confirm these previous results using the post 2008 financial crisis data.

Second, the study relates to Lee and Swaminathan (2000), who present that past trading volume predicts the magnitude and persistence of momentum returns. This study focuses on daily returns and therefore fills a clear gap for this area of research (ibid.) also, since the focus has usually been on the much longer run relations between momentum returns and trading volume (months and years).

And third, the research focus on the post 2008 financial crisis period contributes to the findings by Daniel and Moskowitz (2012), who present a clear connection between market crashes and returns from momentum investment strategy, and Chordia, Subrahmanyam and Tong (2013), who show the decline in anomaly-based trading strategies such as momentum and value. For these reasons it seems important to study the connections between momentum and value investment returns and liquidity in post 2008 financial crisis environment in order to grasp a better understanding of these phenomena.

### **1.3 Overview of the results**

At first when studying the general profitability of momentum and value investment strategies, no abnormal returns are found during the studied, post 2008 financial crisis, period, i.e. neither of these strategies are able to obtain a positive alpha during this period.

Next the research focuses on the role that overall market liquidity levels have on momentum and value returns. The positive relationship between momentum returns and market liquidity is obtained even throughout the preliminary testing and this relationship is found to strengthen as the testing advances. On the other hand, the relationship between value and market liquidity initially looks insignificant, but when further studied, is negative.

The methodology moves from studying market liquidity levels, to the study of expected and unexpected changes in liquidity. This part demonstrates how unexpected changes in liquidity, but not the expected ones, affect momentum and value investment returns. The liquidity shocks correlate positively with momentum returns and negatively with value returns.

These unexpected liquidity shocks are studied even further by using the dummy variable approach, where different liquidity shocks are divided into different dummy variable categories, to study the difference between positive and negative liquidity shocks. The positive liquidity shocks contribute much stronger to these results than the negative ones.

The most important finding in general is the fact that liquidity and unexpected liquidity have a time varying effect on momentum and value returns. The initial reaction is rather low and the full effect is reached only after a small time lag. In momentum returns the strongest effect occurs one trading day later from the liquidity shock and with value returns three trading days after the liquidity shock. This slow moving effect highlights the importance of using daily data to study market anomalies and opens very interesting new doors for further studies.

### **1.4 Structure of the study**

The rest of the thesis is structured as follows. Chapter 2 reviews the previous literature on momentum and value anomalies, market liquidity, price reversals and transaction costs. Chapter 3

links previous findings together and introduces the two main hypotheses studied. Chapter 4 presents data and methodology. Chapter 5 presents the main findings and further robustness studies and finally Chapter 6 sums up the thesis.

## **2 Literature review**

This chapter reviews the academic research on momentum and value investing strategies, liquidity and two other closely related subjects for this study (transaction costs and stock price reversals). The aim is to build a solid foundation for the hypothesis building by presenting widely the previous academic research and linking them tightly into the thesis in order to reflect the results thoroughly.

### **2.1 Momentum**

*“...strategies which buy stocks that have performed well in the past and sell stocks that have performed poorly in the past generate significant positive returns over 3- to 12-month holding periods.”* –Jegadeesh and Titman (1993).

The first investment strategy presented is momentum investing. It is a widely used investing strategy where the investor takes a long position in assets that have performed well in the past and short position in the badly performing ones. There are many different ways of using this investing strategy and the academic literature on this subject is long and wide. This chapter aims to present the fundamental findings from this field, build an overall picture on the relevant academic literature and link the previous findings into this study.

#### **2.1.1 Early findings**

Earliest academic signs of abnormal momentum investment returns in stock markets are by Levy (1967) who discovers significant excess returns from buying stocks that are clearly higher than their past 27 week price average. These results are however later criticized by Jensen and Bennington

(1970) who claim these findings merely as results from extensive data mining<sup>7</sup> and that the results cannot be generalized outside Levy's sample period.

Another earlier result from long horizon momentum returns is presented by De Bondt and Thaler (1985, 1987) who present stock market overreactions and find that during 3 to 5 year holding periods the shares that performed poorly in the past 3 to 5 years, out-performed in the next 3 to 5 years. The overreaction is presented as an over-response to new information where the extreme reaction is followed by correction to the opposite direction. However, these results have been criticized to be due to the systemic risk and size effect rather than actual overreaction (Chan 1988, Ball & Kothari 1989 etc.).

The first really ground breaking and robust findings on abnormal momentum investing returns in stock markets come from Jegadeesh and Titman (1993). It presents significant positive returns from buying past winners and selling past losers with 3 to 12 month holding periods and no link between these returns and systemic risk or delayed returns of these stocks are found. Data in this study includes monthly stock returns from 1965 to 1989. There are 32 trading strategies used: look back periods of 1, 2, 3 or 4 quarters and hold periods of 1, 2, 3 or 4 quarters, and also the very same 16 strategies using a one week waiting period before portfolio formation. This is done to avoid the bid-ask spread, price pressure and lagged reaction.

### **2.1.2 Persistence over time**

Later, Fama and French (1996) document, that momentum returns are indeed the only CAPM-related anomaly which is unexplained by the Fama and French (1993) three-factor model. This is a major change in the way the momentum investing returns are seen. Their position is in a way promoted from a market anomaly, to an important pricing factor and later the four-factor model including the momentum effect has been widely used in the academic literature.

These results emphasize one of the most fascinating elements of momentum returns, that unlike most of the anomalies in financial sector which vanish shortly after their discovery (e.g. Schwert,

---

<sup>7</sup> A falsely positive result resulting from massive amount of trials without any really robust causality behind the findings.

2003), momentum strategy has been found profitable long after its discovery (e.g. Jegadeesh and Titman, 2001 & 2002). Plenty of explanations have been offered to explain this anomaly (see e.g. Barberis, Shleifer, and Vishny, 1998; Daniel, Hirshleifer, and Subrahmanyam, 1998; Hong, Lim, and Stein, 2000; Chordia and Shivakumar, 2002; Grinblatt and Han, 2005; and Avramov and Chordia, 2006) but no real consensus between scholars exists and this clearly stresses the importance of further studies on this subject.

Industry momentum, buying (selling) stocks from the best (worst) performed industry, is studied by Moskowitz and Grinblatt (1999). This study shows that an industry momentum component seems to explain large part of the momentum phenomenon seen in the stock markets. After adjusting the momentum to the industry momentum, the statistically significant momentum returns seem to vanish. These results are partly verified by Grundy and Martin (2001) where the industry momentum was found to contribute, but not to dominate, the stock market momentum returns.

Return consistency, the frequency of positive or negative stock returns in the past, is looked into by Grinblatt and Moskowitz (2004) and Watkins (2003) who present this return consistency to contribute to the momentum investing returns. They document that stocks with high frequency of positive returns over the prior 6 or 12 months have higher future returns and stocks with high frequency of negative returns have lower future returns.

The role of analyst coverage is studied by Hong, Lim and Stein (2000) who find that momentum is weaker for the larger firms with stronger analyst cover. They argue that this can be caused by slower information diffusion. Both of these results are also confirmed by, for example, Gutierrez and Kelley (2008) using weekly data. These results are relevant to this study, since the stocks from the larger firms tend to also be the most liquid ones and this can actually be seen as a possible supporting evidence also for the role of stock liquidity.

Gutierrez and Kelley (2008) study the weekly returns and find that despite the brief reversal in the first weeks, the returns for the 52 weeks following the extreme weekly returns are actually in the same direction as the extreme event, i.e. they found momentum effect from the weekly returns. These results are relevant to this thesis in two ways. First, the verification of momentum return findings from the weekly data raise a clear interest for studying even shorter periods (daily data within this thesis) and second, the first weeks' reversal returns are taken into account in this study by adding a waiting period before portfolio formation to avoid the price reversal effect.

The need to include the waiting period is also emphasized by the findings from Chan (2003) who claims that market under-reacts to explicit news (publicly released firm specific news) and overreacts to implicit news (news only implied by the price change) and the study by Gutierrez and Kelley (2008) documenting the short reversal and longer momentum in both of these cases.

Also the macro environment has been documented to affect the momentum as Chordia and Shivakumar (2002) find no significant returns from momentum strategy during recessions but document large payoffs during the expansions. Similar results are reached by Avramov and Chordia (2006) who show how an optimizing investor can load on momentum on different phases of the economic cycle. These results highlight the need for studying the relations between momentum and value investing returns, and market liquidity during different economic conditions.

Avramov, Chordia, Jostova and Philipov (2007) document a connection between momentum and credit ratings. They find large and significant momentum in low-grade firms, but none among the high-graded firms. Their data consists of the years 1985 to 2003 and could be affected by the dot-com bubble. Also, the momentum is stronger in firms with higher information uncertainty (Jiang, Lee and Zhang, 2005; and Zhang, 2006). All of these findings point out to the direction that the largest, most scrutinized and stable firms will suffer less from the momentum phenomenon, which clearly underlines the possibility of some third variable influencing to these profits. One of such factors could be market liquidity.

### **2.1.3 Theoretical discussion**

Interesting theoretical models that build to explain momentum returns include Berk, Green and Naik (2002) who build a model that mimics firms' investment decision processes with growth options and show by simulation that the dynamics of investment decisions can explain the documented success of contrarian and momentum investing. Also the model build by Kogan (2001), to explain the dynamics of irreversible investments, provides positive return persistence. Grinblatt and Han (2005) argue that the well known disposition effect should contribute to momentum, as investors hold losing shares too long and sell winners too early, it will lead to under-reaction in both of the cases. Zhang (2006) on the other hand offers the psychological biases causing a misreaction to news as a potential explanation to momentum reactions. Many researches

build theoretical models that imply that rational learning can induce momentum and reversal in returns (Veronesi, 1999; Lewellen and Shanken, 2002; Brav and Heaton, 2002).

The pure existence of cross sectional differences in the expected returns<sup>8</sup> is one of the explanations offered for the existence of momentum phenomenon by Conrad and Kaul (1998). This study presents results that show momentum returns as mere results of buying stocks with higher expected returns according to efficient market hypothesis and selling the lowest ones. This explanation fits nicely in the perfect market hypothesis as all the profits will be results of excess risk taking. Unfortunately for those academics yearning for a perfect world, Jegadeesh and Titman (2002) break this bubble by showing that the results by Conrad and Kaul (1998) are inaccurate and in fact the momentum returns cannot be explained by just the cross sectional differences in the expected returns.

Ahn, Boudoukh, Richardson and Whitelaw (2002) raise an interesting question about the weight that should be put on small trades made at possibly overvalued or undervalued prices. They argue that it could be possible to find the momentum effect purely due to the few uninformed investors trading on very low liquidity shares. This problem can be avoided by focusing the study on the more liquid stocks and rule out the most illiquid ones and this approach is followed in this thesis (see Chapter 4.1 Data).

#### **2.1.4 Time series momentum**

*“Time series momentum represents one of the most direct tests of the random walk hypothesis”* – Moskowitz, Ooi and Pedersen (2012).

Time series momentum is quite similar in nature and can be (and should be) coexisting with its cross sectional counterpart. Unlike in cross sectional momentum where stocks are selected based on their past relative performance to other stocks, in the time series momentum strategy environment stocks performance is benchmarked to its own past performance. Intuitively these strategies can yield very similar possible portfolios because if a stock performs very well (poorly) related to its

---

<sup>8</sup> The fundamental factor in the field of finance is that assets differ in their riskiness to investors (i.e. correlate differently with market returns as presented in the CAPM introduced earlier) and thus differ in their expected returns.

own past performance, it will quite often do so also when compared to other stocks as well. Yet there are differences and the findings from this field greatly contribute to the overall picture for liquidity's role explaining momentum and value investing profits.

Fama and French (1988), motivated by Summers (1986), reach fascinating findings in stock markets. They find a negative autocorrelation in industry and decile portfolios. The autocorrelations become negative in a 2 year horizon and reach minimum values in 3-5 year horizons. On a longer period the correlation vanishes. The most astonishing part of these findings is the time period of their study, from 1926 to 1985, and the correlation persists for the whole 60 year period. Similar results from an even larger set of data is obtained by Poterba and Summers (1988) who show positive serial correlation in short horizons and negative on longer ones. Both of these results shed some light for the longer horizon stock returns and their possible autoregressional nature.

Recent and quite astonishing findings by Moskowitz, Ooi and Pedersen (2012) show significant time series momentum in equity index, currency, commodity and bond futures. Each of the studied 58 instruments provide significant results and the portfolio of these instruments provides significant abnormal returns with little exposure to standard asset pricing factors and actually performs best during times of extreme market reactions. They document that for each instrument, the past 12 month excess return is a positive predictor of future profits. They also find evidence that these profits are closely related to the trading activities of speculators and hedgers and speculators seem to profit at the expense of the hedgers. They decompose the momentum in these future instruments into the component coming from the spot markets and one from the roll yield coming from the shape of the futures curve. They find that both of these elements contribute to the time series momentum but only the spot price changes are linked by the long-term reversal effect. They find no evidence that the returns compensate the tail events, but rather the returns are largest when stock market reactions are the most extreme.

Moskowitz, Ooi and Pedersen (2012) have three slight differences compared to most studies on momentum. First, they find no evidence that illiquidity causes momentum, rather that it might have a small positive affect. Second, they find no significant relation between time series momentum and funding liquidity (between TED and TS-Momentum) or market volatility. Third, they find a significant relation between time series and cross sectional momentum but state that they are still



not the same thing. Very interestingly, they find that the correlation of time series momentum across different assets is stronger than the passive long positions on the same assets, which they claim implies a common component behind time series momentum which is not present in the underlying assets themselves.

All in all, this study differs from the traditional momentum studies as it focuses on time-series momentum rather than the cross sectional one and also since the focus is on the future markets, it makes the comparison harder and the difference between spot and future markets statistical properties (Ahn, Boudoukh, Richardson, Whitelaw, 2002) can offer one explanation for the different results.

### **2.1.5 Momentum and value**

A fundamentally different kind of study by Asness, Moskowitz and Pedersen (2013) studies the global market portfolio of stocks, bonds, currencies and commodities jointly and finds significant cross correlation between value strategy (and momentum strategy) between these global asset classes. They also document a negative correlation between momentum strategy and value strategy within and across these asset classes. They document a positive relation between liquidity risk and value and negative with liquidity risk and momentum, and claim that this may indicate that liquidity risk could be "*an important common component of value and momentum*" (ibid.). They argue for the limits of arbitrage as an important factor behind this phenomenon as momentum returns seem to be highest during times of low liquidity when trading costs are to be the largest and thus the net profits remain the same for arbitrageurs.

The differences and similarities of liquidity proxies are nicely demonstrated by the Asness, Moskowitz and Pedersen (2013). First, they find only little correlation between different liquidity proxies. This offers the explanation why their results from the relationship between liquidity and momentum differ from some of the earlier results (Pastor and Stambaugh, 2003; Sadka, 2006)<sup>9</sup>. Second, and much more interesting, result is that all of the liquidity proxies load negatively on the

---

<sup>9</sup> Asness, Moskowitz and Pedersen (2013) also confirms the earlier results by using the same liquidity proxies and in those studies but reach to different results when using the wider range of liquidity estimators.

value returns and somewhat negatively on the momentum returns (Asness, Moskowitz and Pedersen, 2013). When these two results are combined it seems that even with the differences these liquidity proxies have they are all connected to the value and momentum effects by some larger underlining effect. One explanation offered by Asness, Moskowitz and Pedersen (2013) is the restrictions that arbitrageurs may face during illiquid times and this explanation would also be in line with the limited arbitrage by Shleifer and Vishny (1997) and slow moving capital by Mitchell, Pedersen and Pulvino (2007).

## 2.2 Value

*"[The results] suggest that there is an economic story behind the size and book-to-market effects in average stock returns."* -Fama and French (1993).

The second market anomaly studied is value investing strategy, more specifically the book-to-market effect<sup>10</sup>. This chapter briefly introduces the historical field from value investing and then discusses more deeply the previous findings related to momentum investing strategy and market liquidity.

### 2.2.1 Brief history check

*"The book value of a common stock was originally the most important element in its financial exhibit."* - Graham and Dodd (1934).

Earlier academic literature presents several unique market anomalies based on different value investment strategies. Basu (1977), for example, presents the findings that the stock portfolios with low P/E -ratios<sup>11</sup> manage to provide higher absolute and risk adjusted earnings than the portfolios

---

<sup>10</sup> Book-to-market effect stands for the effect that those stocks with high market values of equity compared to their book value of equity (growth stocks) are outperformed by those stocks with low market values of equity compared to the book value of equity (value stocks).

<sup>11</sup> P/E -ratio stands for the price-earnings ratio calculated by dividing the market price of the share with its earnings per share.

with high P/E -ratios. This relation is confirmed by Jaffe, Keim and Westerfield (1989) and also, that also the size effect<sup>12</sup> contributes to these results which also confirm the earlier results presenting a similar size effect (e.g. Banz, 1981; Reinganum, 1981).

Value strategy, based on buying stocks with high book-to-market ratios (value stocks) and selling stocks with low book-to-market ratios (growth stocks), provides consistent abnormal returns according to Rosenberg, Reid and Lanstein (1985), confirming the earlier results from Stattman (1980). Similar results are reached by Chan, Hamao and Lakonishok (1991) and in addition, explanatory power is discovered from the earnings yield, cash flow yield and size factors.

### **2.2.2 Anomaly or state variable?**

These results, of excess risk adjusted returns by different value based strategies, lead to adding two explanatory variables to the basic CAPM: the size factor (SMB) and the value factor (HML) (Fama and French, 1993)<sup>13</sup>. Since the size effect and the value effect cannot be explained by the CAPM they ought to include some information from an unknown risk factor relevant to asset pricing.

The methodological switch to add the unexplained anomalies as explanatory variables (state variables) rather as explained variables makes it possible to focus on studying the new anomalies discovered and at the same time, switching the focus somewhat away from these variables themselves. This thesis focuses on the behavior of the two of the core pillars in finance literature, since both value and momentum have been widely used when studying other market anomalies.

There are countless amounts of empirical studies focusing on value effect and many of them offer new theoretical explanations for this effect. The role of the growth options is examined by Zhang (2005), who presents the quite controversial explanation that growth options might be less risky than the real investments and thus the value effect could be a result of rational expectations. This is strongly against the "general wisdom" that growth options should be the source of high betas

---

<sup>12</sup> The size effect stands for the stock market anomaly where small stocks (by market value of equity) outperform the large stocks (by the market value of equity) in risk adjusted returns.

<sup>13</sup> Later, based on the findings from Carhart (1997), also the momentum factor (MOM) was added to the CAPM as explanatory variable.

because they are most valuable in good economic conditions (Grinblatt and Titman, 2001). This framework also eliminates the explanatory role of the irrational overreaction hypothesis offered by De Bondt and Thaler (1985) and Lakonishok, Shleifer and Vishny (1994), where market anomalies, such as value or momentum, could be due to just a mere overreaction by the investors and the inability of arbitrage mechanisms to correct them.

This framework, of value returns role as a result of unobserved rational risk from the different risks between fixed investments and growth options (Zhang, 2005), actually remove the anomaly state from the value effect and verifies its rationality as solid pricing (or state) factor. This explanation is rather important for this thesis, especially when analyzing the results, since it actually makes a remarkable difference between momentum effect and value effect. The reasoning is quite straightforward, if value returns are not an anomaly and should be present at the markets but the momentum returns are viewed as an anomaly, the increase of market efficiency (and liquidity) should diminish the momentum returns but actually strengthen the value returns.

## **2.3 Liquidity**

Liquidity is one of the corner stone's in the classical perfect market assumption (Fama, 1970) and it has been intensely studied for decades. Yet there seems to be quite little consensus on what is the best way to measure it (Goyenko, Holden and Trzcinka, 2009) or even how does it exactly affect the markets. This section presents the previous studies on liquidity and builds the theoretical links between academic findings.

### **2.3.1 Liquidity: the definitions**

*"Liquidity is a quality of assets which... is not a very clear or easily measurable concept."* - Boulding (1955).

There are many different dimensions to liquidity and multiple ways to define it. Demsetz (1968) describes liquidity, in his study of transaction costs in NYSE, as a cost of immediacy for investors wanting an immediate execution of their trade and therefore have to "pay" the bid-ask spread, or at

least half of it. On a more general level, Lippman and McCall (1986) present a way to define liquidity through the time needed to exchange an asset to money. The methods and details of these definitions can change but the main idea still always remains the same; liquidity enhances the ability to trade stocks quickly, with minimum price impact. Perfect liquidity would allow any amount of stocks to be traded immediately without any affect on the market price. Perfect illiquidity would on the other hand be the situation where you cannot trade any amount for any price. In modern financial theory, the real world trading is found somewhere between these two extremes.

A review on market frictions by Stoll (2000) presents market frictions as a compensation for the supplier for immediacy, such as market makers. He divides this friction into two parts, real and informational friction, and finds both of these friction classes contributing to the total costs for demanders of immediacy.

The real friction is the straightforward part of the total friction and it has been studied for decades (e.g. Garman, 1976; Amihud and Mendelson, 1980; and Stoll, 2000). It can be seen as a compensation for the real resource usage by the market makers, such as capital and labor, and a compensation for risk bearing and other inventory costs. The informational friction is the more complex part and is studied by behavioral finance (e.g. Copeland and Galai, 1983; Glosten and Milgrom, 1985; and Kyle, 1985). It arises from the information asymmetry between traders. Stoll (2000) presents informational friction as “*the value of the information lost to more timely or better informed traders.*”

This division of market friction into two parts by Stoll (2000) can lead to the following market dynamics. Since it takes time to load off capital and labor costs (real friction) but the asymmetry of information (informational friction) is always present, there can be difference in the marginal affect that these two parts of friction have. These differences can lead to lagged adaptation by market makers to changing market conditions and then cause some lag to changes in market efficiencies when arbitrageurs are reacting to these changes. This dynamic is rather important for this thesis when reflecting the lagged connections in the Chapter 5.4.

### 2.3.2 Liquidity and the expected returns

This section presents the strong evidence supporting the connection between liquidity and asset returns. Amihud and Mendelson (1986, 1989) show that stocks with lower liquidity yield significantly higher returns when studying the connections between bid-ask spreads and market returns. These results are confirmed by Brennan and Subrahmanyam (1996) using the methods from Glosten and Harris (1988) and Hasbrouck (1991).

The yield difference between U.S. treasury notes and bills is studied by Amihud and Mendelson (1991). They present that notes which are less liquid offer better yields than other notes with the same maturities. This clearly shows that investors are willing to pay premium for liquidity and is in line with the argument by Jacoby, Fowler and Gottesman (2000) that expected illiquidity (bid-ask spread) should affect investment decisions.

The results by Amihud (2002) confirm earlier results that stock liquidity and expected liquidity explains the differences in expected returns. He shows that expected illiquidity has a positive effect on expected returns but unexpected changes in liquidity have a negative effect on the returns for corresponding period. These results are very intuitive, investors demand higher returns for less liquid investments and when liquidity changes unexpectedly, the value of these investments adjust to this new situation.

A specific model to clarify this relation is offered by Acharya and Pedersen (2005). They present that, the correlation between aggregate market illiquidity to both stock specific returns and stock specific illiquidity should increase the stock specific required return and also that the relationship between stock specific illiquidity and market returns should decrease it.

Incredibly interesting results are presented by Pastor and Stambaugh (2003) who find that stock returns are cross-sectionally related to their sensitivity to changes in aggregate liquidity. They document an astonishing 7.5% annual excess return for stocks with high sensitivity to liquidity compared to the stocks with low sensitivity.<sup>14</sup> They model the aggregate liquidity level with price reversals, following Campbell, Grossman and Wang (1993) who build a model where risk-averse

---

<sup>14</sup> However, their time period (from 1966 to 1999) ends at the height of the dot-com bubble and one should use some caution when generalizing these results to different time periods.

market makers, defined in Grossman and Miller (1988), provide liquidity to the demanders of immediacy and are compensated with higher expected returns.

### **2.3.3 Liquidity and market efficiency**

Interesting, robust and very relevant results come from Roll, Schwartz and Subrahmanyam (2007). They study the relationship between stock market liquidity and the index future basis. They find evidence that suggests that liquidity enhances the future cash pricing systems efficiency. In other words, the improvement in liquidity decreases profitable arbitrage situations. A very similar conclusion is made by Chordia, Roll and Subrahmanyam (2008) in their study of return predictability from the daily order flow data. They find the predictability to diminish as liquidity improves. They conclude that these results are in line with the hypothesis of increasing arbitrage activity during liquid times and the enhancement of market efficiency. These results build the foundation for my hypothesis section by demonstrating the connection between market liquidity and arbitrage profits.

A similar kind of connection between market efficiency and liquidity is found by Sadka and Scherbina (2007); they present a link between mispricing and liquidity by studying stocks with high analyst disagreement. Earlier research by Diether et al. (2002) shows that stocks with higher analyst disagreement on future earnings tend to underperform other stocks. This effect was documented to continue for 6 months. One possible explanation offered in the literature by Sadka and Scherbina (2007) is that, even as analysts tend to disagree more about bad news (Ciccone 2003), the full extent of these news are withheld from the markets (McNichols and O'Brien, 1997; and Hong, Lim and Stein, 2000).

The results by Sadka and Scherbina (2007), showing that less liquid stocks tend to be more severely overpriced before the announcement dates, are in line with the theoretical models by Kyle (1985) and Glosten and Milgrom (1985) which predict that trading costs increase with information asymmetry. These trading costs can prevent trading by informed investors if they trade only when the profits exceed the trading costs. Then the price of the stock should lie in the no-arbitrage bounds around the fair value (Shleifer, 2000) and this would lead to the theoretical result that lower liquidity increases the mispricing.

These results are important guidelines when studying the connections between momentum and value investment returns, and market liquidity as they clearly imply that the increase (decrease) in market liquidity should increase (decrease) the arbitrage activity and therefore affect the returns from these investment strategies.

### **2.3.4 Different forms of liquidity**

This section presents four different ways of looking at the stock market liquidity: stock specific liquidity, aggregate liquidity, liquidity changes and liquidity shocks.

#### ***2.3.4.1 Stock specific liquidity***

Many earlier studies on stock market liquidity focus on stock specific liquidity (e.g. Amihud and Mendelson (1986), Brennan and Subrahmanyam (1996), Datar, Naik and Radcliffe (1998)) and are all able to find that less liquid shares have higher average returns.

#### ***2.3.4.2 Aggregate liquidity***

Later on, focus started to move towards aggregate market liquidity. Amihud (2002) shows expected illiquidity to be priced variable and illiquidity in this sense provides premium in the stock returns. Methodology following Amihud (2002) has been widely used to proxy the aggregate market liquidity and found to provide robust results (Goyenko, Holden and Trzcinka, 2009).

#### ***2.3.4.3 Liquidity changes***

Most of the earlier studies on liquidity e.g. Amihud and Mendelson (1986), Brennan and Subrahmanyam (1996), Amihud (2002) focus on the levels of market liquidity and its changes, either aggregate or stock specific, and define it as a relevant factor for asset pricing.



The level of liquidity can be seen as the static component of trading costs that affect asset prices but the findings of commonality in liquidity by Chordia et al. (2000) raise the need for another dynamic way of defining liquidity, via liquidity shocks (i.e. innovations in liquidity).

#### **2.3.4.4 Liquidity shocks**

Pastor and Stambaugh (2003) present the fascinating results that sensitivity to innovations in aggregate liquidity seems to affect the stock returns. They build a model that proxies the aggregate liquidity through temporary price changes due the order flow and show that the correlation to innovations in market liquidity seems to significantly increase the stock returns.

#### **2.3.5 Autoregressive nature and commonality of liquidity**

Chordia, Roll and Subrahmanyam (2001) study aggregate market spreads, depths and trading activity for U.S. equities. They document that the average daily liquidity is highly volatile and negatively serially dependent. They find strong day-of-the-week effect where Tuesdays presented risen liquidity and Fridays significantly decreased liquidity. They also report a large increase in effective spreads in down markets and the, only marginal, recovery in up markets. This, down market variable, is the most significant variable in their analysis. This autoregressive nature of liquidity is also relevant to this study within the hypothesis building and as the results from expected and unexpected liquidity changes are found to differ.

Hasbrouck and Seppi (2001), Huberman and Halka (2001), and Chordia, Roll, and Subrahmanyam (2000) find a commonality in the time-series movement of liquidity using relatively short samples ranging from two months to a year. Chordia, Roll and Subrahmanyam (2001) find support to the Chordia, Roll and Subrahmanyam (2000) result of commonality in liquidity. However, they highlight that these results are from 1988 to 1998, at a time of a strong bull markets, and the results can differ in other environments. Similar results of predictable patterns in liquidity is documented by Admati and Pfleiderer (1989) and Foster and Viswanathan (1990).

A fascinating aspect of "liquidity anomaly", i.e. the autoregressive cyclical nature of liquidity, is pointed out by, among others, Chowdhry and Nanda (1991) and Admati and Pfleiderer (1988). They argue that the liquidity anomaly is in matter of fact self-perpetuating, as if investors realize the lower liquidity, they should rationally avoid trading during those times, which would even further reduce liquidity. This framework is also used within the hypothesis building to separate liquidity changes from liquidity shocks, and to argue why their affect on momentum and value returns should differ.

### **2.3.6 Liquidity and momentum**

One of the papers closely related to this thesis is Lee and Swaminathan (2000) who study the link between price momentum and trading volume. They find that past trading volumes predict both the magnitude and the persistence of momentum returns, and even more interestingly that most of the excess returns in volume-based investment strategies rise due to the changes in trading volumes, rather than its static levels. They report that "Firms whose recent volume is higher (lower) than volume four years ago experience significantly lower (higher) future returns." (ibid.) These results highlight the relevance of studying both market liquidity and its changes, when connecting it to the returns from momentum and value investing.

More light is shed to the link between the changes in liquidity and momentum returns also by Pastor and Stambaugh (2003). They show that the stock returns' sensitivity to the innovations in the aggregate liquidity affect the stocks' expected returns in a way that stocks that are more sensitive to these changes have higher expected returns. They also report that liquidity risk factor accounts for half of the momentum excess profits as adding the liquidity innovation factor to their regression reduces the momentum portfolios alpha by nearly fifty percent. These results raise the clear need for adding the unexpected liquidity shocks to this study.

A parallel research for my study Avramov et al. (2013) focuses on the connections between market illiquidity and momentum payoffs. The illiquid market periods are followed by negative shocks in momentum returns and the disappearance of positive momentum returns in the recent times becomes significant again following the low market illiquidity (ibid.). These findings clarify the

role that market liquidity plays when explaining changes in the momentum investing returns and are in line with the results presented in this study.

## **2.4 Other relative literature**

This section briefly summarizes two relative fields to this study: price reversals and the transaction costs. The first one is strongly linked to the daily stock market movements and thus relative to this study and the latter is very strongly connected to the market frictions and hence, liquidity.

### **2.4.1 Price reversals**

*“The results documented here reliably reject the hypothesis that the stock prices follow random walks.”* – Jegadeesh (1990).

This chapter presents a major ingredient when studying daily stock returns: the price reversal effect. Even though the price reversal effect is not the core focus of this study it is mandatory to take them into account when studying the reliability of the results.

Early academic findings by Dann, Mayers and Raab (1977) give an indication towards the later findings of price reversals as they show that stock prices tend to decrease after a trade with a large block of stocks. This block trade illiquidity effect is however balanced in a matter of minutes i.e. they actually find an intra-day price reversal.

Later, really groundbreaking findings by Lehmann (1990) and Jegadeesh (1990) show that a contrarian strategy based on last week's or month's performance generated significant abnormal returns of approximately 1.7% per week and 2.5% per month, respectively. This is a clear violation of even a weak form of the efficient market hypothesis (Fama, 1970) and the magnitude of these abnormal returns is astonishing. These results are amplified by Bremer and Sweeney (1991) who show that large negative results are followed by abnormally positive earnings in the next two days. They used -10% negative daily return as a trigger value and documented a 2.2% average cumulative rebound. This is also a confirmation for the earlier results from Brown, Harlow and Tinic (1988)

who show that negative price shocks were followed by abnormally positive returns for up to 60 days using -2,5% returns as the trigger.

Bremer and Sweeney (1991) mention in a side comment that one of the possible reasons for this effect is illiquidity. Support for this argument is established by Jegadeesh and Titman (1995) who find a relation between short-term price reversal profits and bid-ask spreads. These results imply that the returns from this strategy could be due to the illiquidity on the markets. This strong correlation between short term price reversals and liquidity (bid-ask spread in this case) have allowed the price reversal to be also used as an effective proxy for liquidity.

Interesting detail is shown by Cox and Peterson (1994) who study the price reversal effect and confirm the earlier findings of mean reversal, but it reduces over time and vanishes after October 1987. Smaller firms also reverse more than the large ones. They present that the short-term price reversal can be explained by the bid-ask bounce and the degree of market liquidity. They find no evidence to support the market overreaction hypotheses. They also report statistically significant "anti" mean reversal for the longer maturity (4-20 days). The diminishing of the reversal profits in October 1987 is the most interesting detail, since it happens at the same time as the Black Monday crash. This is an important detail related to this study since the thesis focuses on the post 2008 financial crisis time period.

A vast amount of other theoretical explanations has been offered for price reversals. Lo and MacKinlay (1990) show that a large part of these returns could be due to the delayed stock price reactions. The pioneering studies in this field by Rosenberg, Reid and Lanstein (1985), Jegadeesh (1990) and Lehmann (1990) argue that short-term reversal profits are caused by the trading costs which hurt the arbitrage mechanism. This kind of reasoning is also supported by the studies on price reversals and bid-ask spread where the price reversals are found mostly to fall within the bid-ask bounds (Kaul and Nimalendran, 1990; Ball, Kothari and Wasley, 1995; and Conrad, Gultekin and Kaul, 1997).

Avramov, Chordia and Goyal (2006) find a strong relationship between short-run reversals and stock liquidity. However, they state that the profits from contrarian trading seem to be smaller than the expected trading costs. They show a link between liquidity and reversal profits using the Amihud (2002) measure of liquidity. The results support the rational equilibrium framework (Campbell, Grossman and Wang, 1993) and show that there are much stronger reversals with less

liquid stocks. Avramov, Chordia and Goyal (2006) use the transaction cost estimates by Keim and Madhavan (1997) and market impact cost analysis by Korajczyk and Sadka (2004) and conclude that there doesn't seem to be profits for outside investors, i.e. non-market-maker investors, due to the high transaction costs. These are also quite relevant results as this study focuses on investing strategies that require a lot less trading and are since less affected by the role of the transaction costs.

Another important finding from the price reversal field comes from Groot, Huij and Zhou (2012). Their findings are relevant in two different ways: first to highlight the tenacious nature of these returns even during the most liquid times and second the clear imperfections in transaction cost estimation traditions. The researchers show that the trading costs in short-term trading are mainly due to trading with small cap stocks. They find that reversal strategies generated 30 (when focusing on largest U.S stocks) to 50 (when using an algorithm to improve results) basis points per week net profit after trading costs. They also find a weekly return of 20 basis points in European stock markets when focusing on the largest stocks and using a smarter trading algorithm. The study uses both Keim and Madhavan (1997) model and estimates provided by Nomura to estimate the transaction costs. The first model seems to be unfit to estimate the most recent transaction costs as it predicted even positive costs. (Groot, Huij and Zhou, 2012)

Groot, Huij and Zhou (2012) argue that as the reversal profits are significant among the large cap stocks during the most recent decades when the market liquidity has been greatly increased, they explain that these profits are due to the imbalances by market makers and a compensation for inventory risks (e.g. Jegadeesh and Titman, 1995). This argumentation is also relevant to this study, since similar perspective to the arbitrage strategy return development is hypothesized in the hypothesis section.

#### **2.4.2 Transaction costs**

This section looks into an important factor in the profitability of momentum and value investing, the transaction costs. The importance of transaction cost rises from the active portfolio re-allocation needed for these investing strategies and the findings which many researchers have reached, that

momentum returns diminish after taking into account the transaction costs (e.g. Lesmond, Schill and Zhou, 2004; Korajczyk and Sadka, 2004).

The relation between transaction costs and excess market returns is studied by Stoll and Whaley (1983) and Schultz (1983). Both of these studies study the robustness of the excess returns from holding small companies. Stoll and Whaley (1983), motivated by the findings of excess returns before transaction costs earned from investing in small firms presented by Banz (1981) and Reinganum (1981), find no statistically significant excess post-transaction cost returns from buying small companies. These tests were duplicated by Schultz (1983) who studied even smaller stocks with higher transaction costs presenting the groundbreaking and robust results, that the excess returns by small firms can't be explained merely by transaction cost differences.

The following three papers presented build the theoretical foundation on transaction costs in the form of price impacts: Kyle (1985), Glosten and Harris (1988) and Breen, Hodrick and Korajczyk (2002), to mention just a few.

First Kyle (1985) builds a theoretical model where three kinds of traders are present: insider investor with inside information, noise traders and market makers, and they make their investment decisions in a dynamic trading environment. This paper shows that in this setting the discrete trading with asymmetry of information, the frequent trading can lead to constant volatility and efficient price setting in the semi-strong sense. (Kyle, 1985)

The bid-ask spread is studied by Glosten and Harris (1988). In this theoretical paper they present a theoretical view using elasticity of supply and demand to illustrate the possibility of economic rents in bid-ask spreads. They find evidence to support this view in the empirical analysis of the FTSE100. (Glosten and Harris, 1988)

And finally the relation between transaction costs and trading volumes is studied by Breen, Hodrick and Korajczyk (2002). They build a theoretical model of price impact that study the ease of trading shares without price impact. They first rank all of the trades as either buyer or seller initiated and then calculate the net turnover in the observed time period by calculating the buyer initiated trading volume minus seller initiated trading volume and then scaling this to the shares outstanding. This net turnover is used to proxy the price impact linking it to the price changes during that period. (Breen, Hodrick and Korajczyk, 2002)

Another, quite popular, method for estimating transaction costs is presented by Keim and Madhavan (1997). This method is used for example by Avramov, Chordia and Goyal (2006) to demonstrate that there are no significant net profits from short term reversals in investment strategies. However, Groot, Huij and Zhou (2012), a paper presented in the previous chapter, show that the Keim and Madhavan (1997) method should be used with caution. They found it to provide downward biased estimates and even to become negative in some cases, a clear misvaluation from the model (Groot, Huij and Zhou, 2012).

Another interesting, and a very robust, way to evaluate transaction costs and momentum comes from Korajczyk and Sadka (2004). They study the maximum size of a fund that perform momentum strategy and still remains profitable. They show that the excess returns of some momentum strategies disappear only after \$4.5 billion to over \$5.0 billion is allocated to these strategies. This investment is the marginal investment and doesn't include the currently active traders (*ibid.*) and also reports of a weakening of the profitability of momentum strategies after transaction costs. These profits do not completely vanish but diminish severely.

Finally, the recent findings by Frazzini, Israel and Moskowitz (2012) raise a serious doubt on the magnitude of the transaction costs obtained from the previous studies. They use live trading data from large institutional money managers amounting to nearly one trillion dollars in trading volume and conclude that the real transaction costs are "less than a tenth" compared to previous results in literature.

As a concluding remark about transaction costs, there seem to be no robust reasons for using estimates by Keim and Madhavan (1997) which have been shown to provide speculative results in recent times (Groot, Huij and Zhou, 2012) or any other method that would overestimate the real transaction costs by large institutional investors with a huge margin (Frazzini, Israel and Moskowitz, 2012) since after all, momentum and value investments are very much usable by many of these large institutions.

### 3 Hypothesis

*“a liquidity risk factor accounts for half of the profits to a momentum strategy...”* – Pastor and Stambaugh (2003).

This section presents the two main hypotheses of this thesis. Both of these hypotheses aim to study momentum and value investment returns and their connections to fluctuations in market liquidity from different perspectives. The first one focuses on market liquidity and the second one to the shocks in market liquidity.

*H1: Market liquidity affects momentum and value investment returns.*

The first hypothesis is built around the argumentation that liquidity increases market efficiency and should therefore lower arbitrage profits and other opportunities for obtaining positive alpha investments. Thus it can be implied that in times of low liquidity (high liquidity), momentum and value investment returns should be the largest (lowest), due to more inefficient (efficient) market conditions. The following academic results support this view and clearly indicate that liquidity affect the market returns, ex-post and ex-ante.

First studying the vast amount of evidence showing that liquidity affect asset prices (e.g. Amihud and Mendelson, 1986; Amihud, 2002) and add these findings to the persistence in liquidity, found by e. g. Amihud (2002) presenting that higher liquidity in time  $t$  predicts higher liquidity in time  $t+1$ . This implies that liquidity predicts future returns (Acharya and Pedersen, 2005). When adding these factors to the theoretical framework offered by Shleifer and Vishny (1997), where market efficiency is provided by special arbitrageurs investing capital of outside investor monitoring the arbitrageur' performance, these effects can be studied from the perspective where market liquidity diminishes the excess profits from strategies such as momentum and value investments. This view is also supported by Chordia, Roll and Subrahmanyam (2008) who find the predictability in stock markets diminishing as liquidity improves and conclude that this increasing arbitrage activity during liquid times enchases market efficiency.



This first hypothesis is tested by studying the relationship between the average daily market liquidity and momentum and value investment returns, as the null hypothesis tested here is that there are no correlations between momentum and value returns, and market liquidity.

*H2: Unexpected shocks in market liquidity, rather than simple proportional changes, affect momentum and value returns.*

The second hypothesis is also based on the findings by Amihud (2002) confirming that expected illiquidity has a positive effect on expected returns but unexpected changes in liquidity have a negative effect on a corresponding period's returns and the framework by Shleifer and Vishny (1997) where when an unexpected shock occurs in market liquidity, not only does it affect the profits by these investment strategies per se, but also to affect the restrictions for the special arbitrageurs in the markets.

When market liquidity suddenly dries up, there are two simultaneous effects. First, investments suffer losses and the arbitrageurs are forced to lower their holdings in their positions due to the outside investor pressure (margin calls, to mention one, can be seen as such pressure) and this causes some price pressure for the very same investments that they are holding; and second, as market liquidity lowers, they are not able to enter profitably to the same positions (net after the trading costs) as before. Both of these factors can be seen to hurt the returns for these arbitrageurs and affect the prices of the assets they are investing in.

This special role of unexpected shocks can also be studied from the theoretical, self fulfilling prophecy type of a perspective offered by e.g. Chowdhry and Nanda (1991) and Admati and Pfleiderer (1988). They argue that the "liquidity anomaly" (the cyclical nature of liquidity) is in matter of fact a self-perpetuating, as if investors find out about the lower liquidity, they should rationally avoid trading during those times, which would even further reduce the liquidity. In this setting, the unexpected liquidity shocks should have a unique position when comparing to the simple level of market liquidity or its basic changes as they present the unexpected change.

This hypothesis is tested using the same AR(2) model to proxy liquidity shocks (LS) following Asness, Moskowitz and Pedersen (2013) and comparing these results to the purely proportional market liquidity change factor (LC).

## 4 Data and Methods

This chapter presents the data and methodology used in this thesis. First, the data used in this study is presented and analyzed. Second, different momentum and value measures are established and the choices made are discussed and linked to the previous literature. Third, the different ways to proxy liquidity are presented and the motivational selection of the main methods is reflected based on the previous literature.

### 4.1 Data

There are two different data sets used for this study. First, stock market data gathered from the CRSP database and second, the Fama-French three-factors from the Kenneth French webpage<sup>15</sup>. All data used in this study is daily stock market data. First I introduce the stock market data from the CRSP database and all the factors calculated from this dataset and the details of Fama-French three-factors are then later introduced in the Section 4.4.

The stock market data from CRSP database consists of all of the NYSE listed ordinary shares<sup>16</sup> from 2009 to 2012<sup>17</sup>. The filtering of the dataset follows Amihud (2002) with minor changes<sup>18</sup>. All the shares must fulfill the following criteria in order to be qualified to this dataset:

1. The share must be listed in the NYSE at the end of the previous year.

---

<sup>15</sup> <http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/index.html>.

<sup>16</sup> Selected by using NYSE code (1) as a conditional statement for exchange code.

<sup>17</sup> Stocks must have been listed in the NYSE at the end of the previous year in order to qualify for the data set. i.e. 31.12.2008, 31.12.2009, 31.12.2010 and 30.12.2011 for the year's 2009, 2010, 2011 and 2012, respectively, are used as threshold listing days.

<sup>18</sup> First, a 1\$ threshold for the stock price is used as my dataset doesn't consist pre-decimalization unlike Amihud (2002) and since the higher 5\$ threshold seems unnecessarily limiting for the time period studied here. Second, no market capitalization filtering is necessary since they are eliminated already during the data selection phase. Third, I used only the trading data availability as an eliminatory factor as a day of no price change (included with Amihud (2002) as eliminatory factor also) but still trading volume would stand as a day of perfect liquidity in my view and such shares should definitely be involved when studying liquidity.

2. The share must have at least 200 days of trading volume data available during the previous year.
3. Shares with share prices lower than \$ 1 at the end of the previous year are eliminated.
4. 1% outliers are eliminated from the liquidity measure data.

Four different data measures from CRSP database are used in this study: share price (P), trading volume (V), daily return (R) and number of shares outstanding (S).

The following table (Table 1) provides the basic statistical information from the data set used for momentum and liquidity factor calculations:

**Table 1**

**Number of shares in the data set**

This table presents the number of shares qualified for the data set. *No. of shares, original sample*, presents the number of individual shares in the raw data set before the filtering. The *No. of shares, beginning of the year* presents the number of shares qualified for the final data set at the beginning of that particular year and the *No. of shares, end of the year* presents the number of shares in the final data set at the end of that particular year.

Portfolio	2009	2010	2011	2012
No. of shares, original sample	2433	2404	2443	2466
No. of shares, beginning of the year	1770	1770	1751	1841
No. of shares, end of the year	1770	1700	1670	1776

This is the raw data for the four factors, share price (P), trading volume (V), daily return (R) and number of shares outstanding (S) introduced earlier. The following two sections (Section 4.2 and Section 4.2) present the methodology on how these factors are transferred to the momentum and liquidity factors used in this study.

## 4.2 Momentum and value measures

This section presents the three portfolio classes studied: First, the cross sectional momentum factor (M), second the value factor (V) and the combined 50/50 value-momentum portfolio (MV). These portfolios proxy the arbitrage profits from momentum and value investing strategies in this study.

### 4.2.1 Cross sectional momentum

This section presents the four momentum portfolios, the details on how they are built.

Momentum portfolios are formed using the past 12 months (252 trading dates) returns to build up equally weighted portfolios following the traditional methodology in momentum literature (Jegadeesh and Titman, 1993;<sup>19</sup> Sadka, 2006; Asness, Moskowitz and Pedersen, 2013). The portfolios are formed for three months (63 trading dates) and rebalanced after each three months (63 trading dates) period in order to avoid possible problems with overlapping data. Following the previous literature, a lag of one month (21 trading dates) is used for main momentum portfolios to mitigate the problems with price reversals, bid-ask bounces and other short term imperfections, and also to give conservative results that mimic the time needed for arbitragers to enter their positions in stock markets. The one month lag is important for the robustness of the results and improves the momentum returns<sup>20</sup> (Bhootra, 2011). In addition, two portfolios of no lag periods are studied to reveal the affect that immediate portfolio allocation would have on the momentum returns.

There are two different momentum portfolio strategies applied in this study. First, a one-third portfolio where top (bottom) third performing stocks are bought (sold) and second a 10% portfolio where top (bottom) 10% of these NYSE listed shares are bought (sold) for the portfolio in similar way. The first portfolio formation method is motivated by Asness, Moskowitz and Pedersen (2013) to add simplicity and robustness to the results. The second method is used to obtain the results from

---

<sup>19</sup> Jegadeesh and Titman (1993) used look back periods of 1, 2, 3 and 4 quarters and also holding periods of 1, 2, 3 and 4 quarters.

<sup>20</sup> This result is also confirmed here as the one-month-lack portfolios outperform the portfolios without such lag period.

the shares most heavily affected by the momentum phenomenon i.e. the most radically performed stocks in the past 12 months (252 trading dates).

There are, in total, four momentum portfolios used:  $M_{10\%,0}$  portfolio with 10% investments with no lag between look back and investment period,  $M_{10\%,21}$  portfolio with similar 10% investment but with 21 day lag period before investing,  $M_{1/3,0}$  portfolio with one-third investments with no lag between look back and investment period and finally  $M_{1/3,21}$  portfolio with one-third investments with 21 day lag period before investing.

#### 4.2.2 Value portfolio

The value portfolio is formed with the HML values obtained from the Kenneth French database<sup>21</sup> and it defines the daily returns from value investing as:

$$V_t = HML_t$$

Where  $V_t$  is the return from value investing in a day  $t$  and  $HML_t$  is the daily HML value obtained from the Kenneth French database.

#### 4.2.3 Value and Momentum portfolio

A combination portfolio is built using daily value and momentum returns following Asness, Moskowitz and Pedersen (2013) as the average return from these individual strategies.

$$MV_t = 0,5V_t + 0,5M_t$$

Where  $M_t$  is the daily momentum return as defined in the Section 4.3.1 and  $MV_t$  presents the return from the combined value and momentum portfolio.

---

<sup>21</sup> See Section "4.5 Other data" for detailed information.

#### 4.2.4 Statistical characteristics of investment portfolios

This section presents the basic statistical details for the momentum (M), value (V) and combination portfolios (MV).

The following table (Table 2) presents the correlations between the nine investment portfolios studied.

**Table 2**

**Cross sectional correlations between investment portfolios.**

This table presents the cross sectional correlation between the momentum (M), value (V) and combination portfolios (MV). These measures are calculated from the 733 day period used as active study period and not including the look back period (year 2009 and first 21 days of 2010).

	V	M <sub>10%, 0</sub>	M <sub>10%, 21</sub>	M <sub>1/3, 0</sub>	M <sub>1/3, 21</sub>	MV <sub>10%, 0</sub>	MV <sub>10%, 21</sub>	MV <sub>1/3, 0</sub>	MV <sub>1/3, 21</sub>
V	1								
M10%, 0	0.089	1							
M10%, 21	0.124	0.921	1						
M1/3, 0	0.111	0.966	0.873	1					
M1/3, 21	0.140	0.908	0.972	0.911	1				
MV10%, 0	0.352	0.964	0.898	0.938	0.891	1			
MV10%, 21	0.379	0.882	0.965	0.843	0.943	0.931	1		
MV1/3, 0	0.416	0.912	0.837	0.950	0.878	0.969	0.891	1	
MV1/3, 21	0.439	0.852	0.920	0.862	0.951	0.918	0.974	0.926	1

Table 2 clearly demonstrates two important factors. First, the correlations between momentum portfolios (and combination portfolios) are very strong ranging from 0.87 to 0.97 (from 0.89 to 0.97). And second, that the correlation between value returns and momentum returns are very low 0.09. This statistical detail is an important starting point since it clearly highlights the difference between these two investment strategies.

The following table, Table 3, presents basic statistical characteristics of the nine portfolios studied.

Table 3

**Statistical characteristics of momentum (M), value (V) and combination portfolios (MV).**

This table presents the basic statistical measures for returns of the nine investment portfolios studied. These measures are calculated from the 733 day period used as active study period and not including the look back period (year 2009 and 21 days of 2010).

	$M_{10\%,0}$	$M_{10\%,21}$	$M_{1/3,0}$	$M_{1/3,21}$	$MV_{10\%,0}$	$MV_{10\%,21}$	$MV_{1/3,0}$	$MV_{1/3,21}$	V
Average	0.045	0.070	0.004	0.016	0.022	0.033	0.001	0.006	-0.004
Variance	2.413	2.512	1.656	1.702	0.694	0.722	0.505	0.517	0.200
Kurtosis	15.024	15.782	18.565	18.753	12.594	12.885	14.082	13.977	0.764
Skewness	1.428	1.624	1.522	1.726	1.082	1.250	1.039	1.230	-0.102
Min	-7.636	-7.304	-7.092	-6.813	-4.238	-4.072	-3.966	-3.826	-1.640
Max	15.237	15.001	13.175	12.956	7.718	7.600	6.687	6.578	1.690
Cumulative returns	27.94 %	52.06 %	-3.11 %	5.40 %	14.59 %	23.68 %	-1.43 %	2.24 %	-3.87 %
Nr of obs.	733	733	733	733	733	733	733	733	733

The Table 3 provides one rather important detail. Even as the correlations between all of the momentum portfolios is very strong (between 0.87 and 0.97), the average returns and cumulative returns differ greatly. The difference between the cumulative returns from the best performing portfolio ( $M_{10\%,21}$ ) and the worst performing portfolio ( $M_{1/3,0}$ ) was an astonishing 55.17% points.

The four combination portfolios ( $MV_{10\%,0}$ ,  $MV_{10\%,21}$ ,  $MV_{1/3,0}$  and  $MV_{1/3,21}$ ) share the similar common features as the four momentum portfolios ( $M_{10\%,0}$ ,  $M_{10\%,21}$ ,  $M_{1/3,0}$  and  $M_{1/3,21}$ ). They all have positive average daily returns from the studied time period and strong correlation between each other (ranging from 0.89 to 0.97), yet there are quite remarkable differences in the cumulative returns (lowest return -1.43% and highest 23.68%). Also all the skewness factors are positive and kurtosis factors positive and relatively large. This would imply peaked return distributions with longer tails, especially to the right side of the distribution.

The differences between momentum and value investment returns are also clearly visible from the Table 3. The average (and cumulative) returns from value factor is negative, kurtosis is much lower, skewness is negative and it has much lower variance. All and all, the value factor seems to be much less volatile and evenly distributed than the momentum factors.

### 4.3 Liquidity measures

This section introduces the six different liquidity measures used in this thesis. Instead of using the same liquidity measures as in Asness, Moskowitz and Pedersen (2013), two widely used market

liquidity proxies are used (trading volume and turnover) and aim to compliment the results by Asness, Moskowitz and Pedersen (2013).

#### 4.3.1 Trading Volume

*"...our results show that the effect of trading volume on price momentum is more complex than prior research suggests." - Lee and Swaminathan (2000).*

The first market liquidity measure used is the trading volume. It has been widely used in the academic literature and for example, Chordia, Subrahmanyam and Anshuman (2001) present a strong negative correlation between innovations in trading volume and equity returns.

The trading volume measure used is the natural logarithm of the dollar volume of trading following Chordia, Subrahmanyam and Anshuman (2001):

$$VOL_{s,t} = P_{s,t} V_{s,t} \quad (1)$$

Where  $VOL_{s,t}$  is the daily trading volume of share  $s$  in day  $t$ ,  $P_{s,t}$  is the price of the share  $s$  in a day  $t$  and  $V_{s,t}$  is the trading volume of the share  $s$  in a day  $t$ .

The average market trading volume is formed by the following calculation:

$$L_{TV} = \ln \left[ \frac{1}{N} \sum_{s=1}^N P_{s,t} V_{s,t} \right] \quad (2)$$

Where  $L_{TV}$  is the liquidity proxy obtained from the trading volume and  $N$  is the number of shares in the portfolio as defined in the Data section 4.1.

#### 4.3.2 Turnover

The second liquidity measure used is the turnover (e.g. Chordia, Subrahmanyam and Anshuman, 2001; Banerjee, Gatchev and Spindt, 2007). It is based on the same underlying assumption as the trading volume; the most actively traded stocks are also the most liquid ones, but in this method the size effect is controlled by using the following formula:



$$TO_{s,t} = \frac{V_{s,t}}{S_{s,t}} \quad (3)$$

Where  $TO_{s,t}$  is the turnover of share  $s$  in a time  $t$  and  $S_{s,t}$  is the shares outstanding for the share  $s$  in a time  $t$  and the  $V_{s,t}$  is the trading volume of the share  $s$  in a day  $t$ .

The average turnover ratio is:

$$L_{TO} = \frac{1}{N} \sum_{i=1}^N \left( \frac{V_{s,t}}{S_{s,t}} \right) \quad (4)$$

Where  $L_{TO}$  is the liquidity proxy obtained from the turnover and the  $N$  is the number of shares in the portfolio as defined in the Data section 4.1.

### 4.3.3 Market liquidity

Now that the liquidity measures have been defined, the three different methods on how to use them are presented next. The first method is used to explain the connection between stock market momentum and value returns and the level of market liquidity uses the pure market liquidity as the explanatory variable:

$$L = \bar{L}_t \quad (5)$$

Where  $\bar{L}_t$  is the market liquidity in a time  $t$ .

All of the market liquidity measures are calculated as equal-weighted averages of the daily liquidity estimates for stocks in NYSE. Using equal-weighted liquidity portfolios instead of the value-weighted follows the studies by Amihud (2002), Pastor and Stambaugh (2003) and Acharya and Pedersen (2005). These market liquidity measures are the two measures,  $L_{TV}$  and  $L_{TO}$  presented earlier in this chapter, in the last two sections.

#### 4.3.4 Proportional changes in market liquidity

The method for changes in market liquidity follows the proportional liquidity change factor used in Chordia et al. (2000) and the factor for this liquidity change LC is defined as follows:

$$LC = \frac{\bar{L}_t - \bar{L}_{t-1}}{\bar{L}_{t-1}} \quad (6)$$

Where  $\bar{L}_t$  is the market liquidity factor at time t (ex post) and  $\bar{L}_{t-1}$  is the market liquidity at time t-1 (ex ante).

#### 4.3.5 Shocks in aggregate liquidity

The third liquidity estimator category differs significantly from the previous two and presents the theoretically soundest estimator. As the changes in liquidity is studied by using the AR(2) model, the focus is on the unexpected shock rather than just the anticipated changes in liquidity.

Liquidity shocks are defined as the residuals from the AR(2) model following Asness, Moskowitz and Pedersen (2013). These estimates are obtained from the following regression model:

$$L_t = \alpha + \beta_1 L_{t-1} + \beta_2 L_{t-2} + \varepsilon \quad (7)$$

Where  $L_t$ ,  $L_{t-1}$  and  $L_{t-2}$  are the liquidity measures in the time t, t-1 and t-2 respectively and the residual  $\varepsilon$  represents the liquidity shocks. The liquidity shock measure  $\varepsilon$  is used as the liquidity shock proxy to connect the changes in aggregate liquidity changes to the momentum returns and the following measure for innovations in liquidity is defined:

$$LS_t = \varepsilon \quad (8)$$

Where  $LS_t$  is the measure for shocks in aggregate liquidity and  $\varepsilon$  stands for the residuals from the AR(2) regression (Regression 7) and stands as the estimator for market liquidity shocks in this study.

### 4.3.6 Statistical characteristics of liquidity factors

This section presents and analysis the basic statistical characteristics for the liquidity factors and the correlations between them.

The Table 4 presents correlations between the six liquidity factors.

**Table 4**

#### **Cross correlations between the liquidity factors**

This table presents the cross correlations between all of the six liquidity factors presented earlier in this chapter.

	$L_{TV}$	$L_{TO}$	$LC_{TV}$	$LC_{TO}$	$LS_{TV}$	$LS_{TO}$
$L_{TV}$	1					
$L_{TO}$	0.887	1				
$LC_{TV}$	0.435	0.364	1			
$LC_{TO}$	0.361	0.366	0.934	1		
$LS_{TV}$	0.775	0.669	0.878	0.788	1	
$LS_{TO}$	0.689	0.740	0.786	0.790	0.900	1

Table 4 presents two major factors. First, the correlation between daily liquidity measures  $L_{TV}$  and  $L_{TO}$  are much stronger with the liquidity shock measures  $LS_{TV}$  and  $LS_{TO}$  (ranging from 0.67 to 0.78) than with the measures of the simple proportional liquidity changes  $LC_{TV}$  and  $LC_{TO}$  (ranging from 0.36 to 0.46) and second, that the correlation between the liquidity shock measures  $LS_{TV}$  and  $LS_{TO}$  and the measures of the proportional liquidity changes  $LC_{TV}$  and  $LC_{TO}$  are very strong (ranging from 0.79 to 0.88). The latter correlation is rather significant, as the strong correlation between the unexpected liquidity changes (LS) and the proportional liquidity changes (LC) reach such a high level, yet their relationships with the momentum and value returns differs significantly, as we will see later.

The following Table 5 presents basic statistical characteristics for the six liquidity factors.

**Table 5****Summary of statistical characteristics of the liquidity factors.**

This table presents the basic statistical measures for the six liquidity factors used in this study:  $L_{TV}$ ,  $L_{TO}$ ,  $LC_{TV}$ ,  $LC_{TO}$ ,  $LS_{TV}$  and  $LS_{TO}$ . These measures are calculated from the 733 day period used as active study period and not including the look back period (year 2009 and first 21 days of 2010).

	$L_{TV}$	$L_{TO}$	$LC_{TV}$	$LC_{TO}$	$LS_{TV}$	$LS_{TO}$
Average	17.637	0.008	0.000	0.018	0.000	0.000
Standard Deviation	0.211	0.002	0.011	0.201	0.163	0.001
Min	16.500	0.003	-0.086	-0.790	-1.334	-0.008
Max	18.501	0.021	0.056	1.645	0.473	0.009
Skewness	-0.552	1.952	-0.426	2.155	-1.227	0.863
Kurtosis	5.144	8.643	9.910	14.177	9.546	6.159
Nr of obs.	733	733	733	733	733	733

Table 5 presents two interesting details. First, the trading volume ( $L_{TV}$ ) seems to be much more stable than the turnover ( $L_{TO}$ ) as its proportional changes are much lower. Second, the high kurtosis and negative skewness indicate the presence of negative shocks for the three trading volume measure ( $L_{TV}$ ,  $LC_{TV}$  and  $LS_{TV}$ ) and the high kurtosis and positive skewness indicate positive shocks for the three turnover measure ( $L_{TO}$ ,  $LC_{TO}$  and  $LS_{TO}$ ). These differences are interesting since the overall correlations between these liquidity proxies are very high in all of the three categories (L, LC and LS) as we saw from the Table 4.

#### 4.4 Other data

This section presents the details on the two Fama-French factors used as control variables and the risk-free return used in calculating the excess returns. This is daily data downloaded from the Kenneth French web pages<sup>22</sup> and includes three factors:  $R_{m-f}$ ,  $SMB$  and  $R_f$ , standing for market excess returns, small minus big factor and risk-free returns, respectively.

<sup>22</sup> <http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/index.html>

The daily values are used for three years 2010-2012 and there are 733 observations for each of these three factors. The following Table 6 presents the main statistical measures from the two main factors<sup>23</sup>  $R_{m-f}$  and  $SMB$ .

**Table 6**

**Summary of Fama-French Factor Characteristics**

This table presents the statistical details from the two Fama-French factors used as control variables. These measures are calculated from the 733 day period used as active study period and not including the look back

	$R_{m-f}$	$SMB$
Average	0.051	0.012
Standard deviation	1.211	0.554
Min	-6.960	-2.010
Max	4.980	3.560
Skewness	-0.347	0.233
Kurtosis	3.611	2.480
Nr of obs.	733	733

The Table 6 highlights two important details from the studied time period. First, the average market return  $R_{m-f}$  is positive for this period<sup>24</sup> and second the negative skewness and positive (and very high) level of kurtosis indicating a "fat tail" for the negative market returns.

The correlation between Fama-French three-factors (including the value factor introduced earlier) also provides some interesting details. Especially the strong correlation between the  $R_{m-f}$  and  $SMB$  (0.53) and between  $R_{m-f}$  and  $HML$  (0.34). The correlation between  $SMB$  and  $HML$  are on the other hand found out be very low (0.06).

<sup>23</sup> The role of the third one,  $R_f$  (the risk free return) is more or less irrelevant during the studied time period as the historically low interest rates caused it to take only two values: 0.001% (209 times) and 0% (545 times).

<sup>24</sup> And more importantly the cumulative returns amounting to 37.25% from 2010 to 2012.

## 4.5 Regressions

This chapter presents the regressions used and links these methods in the previous literature and theory. First regressions (Regressions: 9, 10 and 11) are used to see whether there are any abnormal returns for momentum and value investment strategies. Second part of the regressions (Regressions 12, 13, 14, 15, 16 and 17) adds the liquidity to these regressions and evaluates the role that market liquidity plays with momentum and value phenomena. The third part of the regressions (Regressions 18, 19 and 20) focuses on the slow moving affect of liquidity and the last regressions (Regressions 21, 22 and 23) present the dummy variable approach used for segmenting the liquidity shocks.

First regression model is used to evaluate the performance of the momentum portfolio and its ability to provide abnormal returns. The following modification from the Fama-French three model is used for this purpose<sup>25</sup>.

$$M_t = a_M + \beta_R R_{m-f,t} + \beta_{SMB} SMB_t + \varepsilon_M \quad (9)$$

Where  $M_t$  is the excess return (over the risk-free return  $R_{f,t}$ ) of momentum portfolio at day t,  $a_M$  is the alpha of the momentum portfolio  $M_t$ .  $\beta_R$  and  $\beta_{SMB}$  present the relation between the momentum portfolio  $M_t$  to the two control measures  $R_{m-f,t}$  and  $SMB_t$ .

Then the similar regressions are performed for the value portfolio  $V_t$  and the 50/50 combination portfolio  $MV_t$  using the same two Fama-French factors  $R_{m-f,t}$  and  $SMB_t$  as control variables. This methodology is motivated by Asness, Moskowitz and Pedersen (2013) where they found clear connections between liquidity risk and returns from both momentum and value investment strategies.

$$V_t = a_V + \beta_R R_{m-f,t} + \beta_{SMB} SMB_t + \varepsilon_V \quad (10)$$

$$MV_t = a_{MV} + \beta_R R_{m-f,t} + \beta_{SMB} SMB_t + \varepsilon_{MV} \quad (11)$$

---

<sup>25</sup> The HML is not used as a control variable in this thesis since it is used as an explained variable.

Where  $V_t$  stands for the daily return from the value investment strategy and  $MV_t$  as the daily return from the combined momentum and value strategy.

Then, additional liquidity factors are introduced to study liquidity's affect on momentum, value and combination portfolio returns. The following six regressions focus on this particular issue.

$$M_t = a_M + \beta_L \bar{L}_t + \varepsilon_M \quad (12)$$

$$V_t = a_V + \beta_L \bar{L}_t + \varepsilon_V \quad (13)$$

$$MV_t = a_{MV} + \beta_L \bar{L}_t + \varepsilon_{MV} \quad (14)$$

$$M_t = a_M + \beta_R R_{m-f,t} + \beta_{SMB} SMB_t + \beta_L \bar{L}_t + \varepsilon_M \quad (15)$$

$$V_t = a_V + \beta_R R_{m-f,t} + \beta_{SMB} SMB_t + \beta_L \bar{L}_t + \varepsilon_V \quad (16)$$

$$MV_t = a_{MV} + \beta_R R_{m-f,t} + \beta_{SMB} SMB_t + \beta_L \bar{L}_t + \varepsilon_{MV} \quad (17)$$

Where  $\bar{L}_t$  is the liquidity factor (L, LC and LS) of the market at a time period t, as introduced earlier in this chapter and the  $\beta_L$ , presents the relation between the used liquidity factor  $\bar{L}_t$  and the returns in the momentum, value and combination investment strategies studied. The first three regressions (Regressions 12, 13 and 14) focus on the uncontrolled explanatory power of the liquidity (L), liquidity changes (LC) and liquidity shocks (LS) have and the second part of the regressions (Regression 15, 16 and 17) focus on the controlled explanatory power.

The following six regressions are similar to the Regressions 12, 13, 14, 15, 16 and 17 in all other aspects except the liquidity factor used. For the following regressions the liquidity factor is the past liquidity  $\bar{L}_{t-x}$ .

$$M_t = a_M + \beta_L \bar{L}_{t-x} + \varepsilon_M \quad (18)$$

$$V_t = a_V + \beta_L \bar{L}_{t-x} + \varepsilon_V \quad (19)$$

$$MV_t = a_{MV} + \beta_L \bar{L}_{t-x} + \varepsilon_{MV} \quad (20)$$

$$M_t = a_M + \beta_R R_{m-f,t} + \beta_{SMB} SMB_t + \beta_L \bar{L}_{t-x} + \varepsilon_M \quad (21)$$

$$V_t = a_V + \beta_R R_{m-f,t} + \beta_{SMB} SMB_t + \beta_L \bar{L}_{t-x} + \varepsilon_V \quad (22)$$

$$MV_t = a_{MV} + \beta_R R_{m-f,t} + \beta_{SMB} SMB_t + \beta_L \bar{L}_{t-x} + \varepsilon_{MV} \quad (23)$$

Where  $\bar{L}_{t-x}$  presents the lagged liquidity factor where  $x$  presents the number of trading date lags used (range from 1 to 5).

The last part uses dummy variable approach to divide the liquidity shock measures (LS) into six parts based on the sign and magnitude of the liquidity shock and runs the following regressions:

$$M_t = a_M + \beta_R R_{m-f,t} + \beta_{SMB} SMB_t + \beta_L D_t + \varepsilon_M \quad (24)$$

$$V_t = a_V + \beta_R R_{m-f,t} + \beta_{SMB} SMB_t + \beta_L D_t + \varepsilon_V \quad (25)$$

$$MV_t = a_{MV} + \beta_R R_{m-f,t} + \beta_{SMB} SMB_t + \beta_L D_t + \varepsilon_{MV} \quad (26)$$

The  $D_t$  factor presents the liquidity shock dummies used. There are six different dummies which are introduced in more detail in the dummy variable section (Section 5.5).

## 5 The results

This chapter presents the results and analyses them using the theoretical framework and methodology build in the previous chapters.

First, the Section 5.1 presents the findings of no positive alphas for both momentum and value investment strategies. Second, the Section 5.2 adds the liquidity measures and demonstrates minor explanatory power it poses over momentum and value returns. Third, the Section 5.3 introduces a one day lagged liquidity measures and finds significant correlations between liquidity measure and momentum returns. Fourth, the Section 5.4 studies the time structure of these correlations and presents the clearly slowly moving affect that market liquidity and unexpected liquidity shocks have on both momentum and value investment returns. And finally, the Section 5.5 divides the different unexpected liquidity shocks into six categories and reveals that the affect is mainly driven by the positive liquidity shocks, rather than the negative ones.



## 5.1 First results: no positive alphas

This section studies the overall performance of momentum and value investment strategies. Regressions 9, 10 and 11 study whether there seems to be positive alphas for these investment strategies.

The following Table 7 presents these results and shows the regression coefficients between the investment strategies and the two Fama-French factors ( $R_{m-f}$  and SMB) used as control variables:

**Table 7****Regression coefficients between investment returns and two Fama-French factors, and the alphas for these investment strategies.**

This table presents the results from the Regressions 10, 11 and 12. First column (Portfolio) presents the nine different momentum, value and combination portfolios used in this study. The second column presents the excess returns (alpha), third one the regression coefficients with the market returns (beta of the fund) and the final column with the SMB factor.

Portfolio	Alpha	$R_{m-f}$	SMB
$M_{10\%, 0}$	0.035 (-0.61)	0.232** (4.19)	0.121 (1.33)
$M_{10\%, 21}$	0.050 (0.90)	0.290** (5.33)	0.389** (3.27)
$M_{1/3, 0}$	-0.003 (-0.07)	0.151** (3.24)	0.075 (0.74)
$M_{1/3, 21}$	0.002 (0.04)	0.210** (4.60)	0.238** (2.38)
$MV_{10\%, 0}$	0.012 (0.40)	0.193** (6.69)	0.016 (0.25)
$MV_{10\%, 21}$	0.020 (0.67)	0.222** (7.78)	0.130* (2.08)
$MV_{1/3, 0}$	-0.007 (-0.27)	0.153** (6.12)	-0.027 (-0.50)
$MV_{1/3, 21}$	-0.004 (-0.17)	0.182** (7.42)	0.054 (1.01)
V	-0.011 (-0.70)	0.155** (10.22)	-0.128** (-3.91)

None of the four momentum portfolios studied here are able to provide statistically significant positive alphas i.e. the excess momentum profits seem to have disappeared during the studied post financial crisis period. These results are in line with the results by Daniel and Moskowitz (2012) showing the crash in momentum profits after market declines. The very same results are obtained when studying the returns from value and the combination investment strategies. The absence of positive alphas in all of these portfolios confirms the results by Chordia, Subrahmanyam and Tong (2013) as the excess profits for arbitrage strategies such as momentum and value diminished as market liquidity improved in recent times.

Interestingly, all of the investment strategies correlate positively and statistically significantly with the market returns  $R_{m-f}$ . This detail highlight the strong connections between market conditions and both momentum and value returns even when these investment strategies perform badly.

## **5.2 Introducing liquidity**

The main focus of this thesis is reached by studying the role that liquidity plays with momentum and value returns. First, the connection between liquidity and both momentum and value returns are studied without any control variables and then the two control variables ( $R_{m-f}$  and SMB) are added.

### **5.2.1 Uncontrolled liquidity: minor significance**

This section presents the results from the regressions 12, 13 and 14 where the momentum, value and combination portfolios returns are explained by the three different liquidity factors: liquidity level (L), the changes in liquidity (LC) and the liquidity shocks (LS).

Table 8

**Regression coefficients between momentum, value and combination portfolios with market liquidity factor (L), proportional liquidity change factor (LC) and liquidity shock factor (LS).**

This table presents the results from the Regressions 12, 13 and 14 where portfolio returns (M, MV and V) are explained by the daily liquidity factors (L, LC and LS). The regression uses today's portfolio returns as explained variable and the today's liquidity factor as an explanatory factor without any control variables used.

Portfolio	$L_{TV}$	$L_{TO}$	$LC_{TV}$	$LC_{TO}$	$LS_{TV}$	$LS_{TO}$
$M_{10\%, 0}$	0.457 (1.67)	62.452* (2.08)	-7.110 (-1.30)	-0.468 (-1.63)	-0.066 (-0.19)	-8.014 (-0.20)
$M_{10\%, 21}$	0.566* (2.04)	83.651** (2.76)	-2.292 (-0.41)	-0.229 (-0.79)	0.217 (0.60)	32.600 (0.79)
$M_{1/3, 0}$	0.230 (1.01)	38.003 (1.52)	-8.127 (-1.79)	-0.517* (-2.17)	-0.241 (-0.82)	-23.681 (-0.70)
$M_{1/3, 21}$	0.350 (1.53)	59.620* (2.38)	-4.150 (-0.91)	-0.312 (-1.30)	0.013 (0.04)	14.277 (0.42)
$MV_{10\%, 0}$	0.193 (1.32)	24.641 (1.54)	-2.659 (-0.91)	-0.217 (-1.42)	-0.006 (-0.03)	-5.718 (-0.26)
$MV_{10\%, 21}$	0.247 (1.66)	35.240* (2.16)	-0.250 (-0.08)	-0.097 (-0.62)	0.136 (0.70)	14.589 (0.66)
$MV_{1/3, 0}$	0.079 (0.64)	12.417 (0.91)	-3.168 (-1.27)	-0.241 (-1.85)	-0.093 (-0.58)	-13.551 (-0.73)
$MV_{1/3, 21}$	0.139 (1.10)	23.225 (1.68)	-1.179 (-0.47)	-0.139 (-1.05)	0.034 (0.21)	5.428 (0.29)
V	-0.071 (-0.91)	-13.170 (-1.53)	1.792 (1.14)	0.034 (0.42)	0.054 (0.53)	-3.421 (-0.29)

The Table 8 presents a solid starting point for the study on the role that market liquidity play with momentum and value returns. Even as the results are somewhat ambiguous, they provide two major insights for this study.

First, the initial results seem quite insignificant. This is quite an important starting point as the explanatory power of market liquidity seems rather weak without any control variables. This is very much expected, since previous studies have found only weak links between these factors and one shouldn't expect the market liquidity to be the only explanatory factor behind momentum and value investing returns. Second, the  $L_{TO}$  is able to provide solidly significant returns with momentum portfolios where two results are statistically significant with a 5% level and one with a 1% level. As an interesting detail the most significant results are obtained from the  $M_{10\%,21}$  portfolio, where 21 days waiting period is used before investing, minimizing the possible price reversal effect introduced earlier in this thesis and the 10% momentum portfolio is used where the stocks with

most extreme past returns are used when building the portfolio. This  $M_{10\%,21}$  portfolio should therefore be theoretically the portfolio with the strongest and clearest proxy for the momentum returns in general. This is clearly something to look more deeply into and the next section introduce the control variables and start to build a more whole picture for these phenomena.

### 5.2.2 Controlled liquidity: major significance

This section introduces the control variables  $R_{m-f}$  and SMB are introduced and presents the findings from the Regressions 15, 16 and 17.

**Table 9**

**Regression coefficient between momentum, value and combination portfolios with market liquidity factor (L), proportional liquidity change factor (LC) and liquidity shock factor (LS) with Fama French two factors ( $R_{m-f}$  and SMB) as controlling variables.**

This table presents the results from the Regressions 15, 16 and 17 where portfolio returns (M, MV and V) are explained by the daily liquidity factors (L, LC and LS). The regression uses today's portfolio returns as explained variable and the today's liquidity factor as an explanatory factor with the two Fama French factors ( $R_{m-f}$  and SMB) as controlling variables.

Portfolio	$L_{TV}$	$L_{TO}$	$LC_{TV}$	$LC_{TO}$	$LS_{TV}$	$LS_{TO}$
$M_{10\%, 0}$	0.593* (2.21)	85.265** (2.88)	-6.351 (-1.18)	-0.376 (-1.33)	0.078 (0.22)	29.397 (0.72)
$M_{10\%, 21}$	0.742** (2.81)	113.449** (3.91)	-1.593 (-0.30)	-0.126 (-0.45)	0.397 (1.16)	82.726* (2.07)
$M_{1/3, 0}$	0.317 (1.4)	52.582* (2.11)	-7.607 (-1.69)	-0.458 (-1.93)	-0.148 (-0.51)	-0.380 (-0.01)
$M_{1/3, 21}$	0.475* (2.14)	80.869** (3.32)	-3.592 (-0.81)	-0.236 (-1.01)	0.143 (0.5)	49.748 (1.49)
$MV_{10\%, 0}$	0.301* (2.14)	42.29** (2.73)	-1.834 (-0.65)	-0.128 (-0.87)	0.118 (0.65)	24.444 (1.15)
$MV_{10\%, 21}$	0.375** (2.7)	56.382** (3.7)	0.545 (0.20)	-0.003 (-0.02)	0.277 (1.54)	51.109* (2.44)
$MV_{1/3, 0}$	0.162 (1.34)	25.949 (1.94)	-2.462 (-1.02)	-0.169 (-1.32)	0.004 (0.03)	9.556 (0.52)
$MV_{1/3, 21}$	0.241* (2.02)	40.092** (3.05)	-0.454 (-0.19)	-0.058 (-0.46)	0.150 (0.97)	34.620 (1.92)
V	0.008 (0.1)	-0.685 (-0.08)	2.683 (1.83)	0.121 (1.56)	0.157 (1.65)	19.492 (1.76)

Table 9 confirms the preliminary findings from the previous section (Section 5.2.1) showing the positive connection between daily momentum returns and market liquidity. Here the results are much stronger as seven out of eight momentum portfolios provide statistically significant results, four of them with even at a 1% confidence level. The only portfolio without significant results is the noisiest portfolio<sup>26</sup>  $M_{1/3,0}$  and even its results hint strongly towards a positive regression coefficient. Value, on the other hand, doesn't seem to load at all to the market liquidity. This also leads to much lower results with the combination portfolios MV's, but nevertheless, six out of eight of them also load positively on the market liquidity factor L.

The real significance of this table is realized when comparing these controlled results more closely to the uncontrolled ones. Where the uncontrolled results are pretty much random, these results present quite steady positive results (16 out of 18 are positive). The best momentum factor (in terms of less noisy one)  $M_{10\%,21}$  and its combined portfolio with value  $MV_{10\%,21}$  provide actually statistically significant result with both of the  $LS_{TO}$  measures. These results are not yet robust but provide a clear road sign on what to look at.

### 5.3 From present to the past: lagged connections

Up to this point, all of the results presented study the co-movement of daily momentum and value returns with the daily liquidity factors during the same day. From this point forward the fundamental viewpoint changes.

The following chapter focuses on the affect that the past liquidity changes have on these investment results. In addition to the practical reasoning that some portfolio allocation forcing events, such as margin calls for leveraged traders, might take some time to take effect (next day) and the possibility of slow moving prices (from several possible market dynamic reasons), the most practically interesting part is: are there any arbitrage profits to be made or are the markets efficient. If the past liquidity changes can actually forecast the future returns for these investment strategies, this could be another small blow to the efficient market hypothesis and quite profitable news for arbitrageurs.

---

<sup>26</sup> This portfolio uses no lag period before investing and is hence more likely to suffer from different kinds of distorting effects and also, the one-third portfolio has less weight on the stocks most heavily presenting the past momentums (positives or negatives).

### 5.3.1 Uncontrolled correlations

This section is similar to the Section 5.2.1 with one difference. Instead of using the day t's liquidity measures, the day t-1's measures are used instead. One could assume that the lagged liquidity changes would have lower impacts on investment returns but this section and the next one presents quite the opposite to be actually true.

**Table 10**

**Regression coefficients between momentum, value and combination portfolios with t-1 market liquidity factor (L), proportional liquidity change factor (LC) and liquidity shock factor (LS).**

This table presents the results from the Regressions 18, 19 and 20 (with one day lack) where portfolio returns (M, MV and V) are explained by the t-1 liquidity factors (L, LC and LS). The regression uses today's portfolio returns as explained variable and the yesterdays liquidity factor as an explanatory factor without any controlling variables.

Portfolio	L <sub>TV</sub>	L <sub>TO</sub>	LC <sub>TV</sub>	LC <sub>TO</sub>	LS <sub>TV</sub>	LS <sub>TO</sub>
M <sub>10%, 0</sub>	0.769** (2.82)	108.828** (3.64)	3.681 (0.67)	0.389 (1.35)	0.732* (2.07)	149.483** (3.70)
M <sub>10%, 21</sub>	0.666* (2.40)	107.012** (3.54)	2.485 (0.45)	0.357 (1.23)	0.630 (1.76)	147.954** (3.61)
M <sub>1/3, 0</sub>	0.585* (2.58)	84.823** (3.41)	3.212 (0.70)	0.324 (1.35)	0.570 (1.94)	121.103** (3.60)
M <sub>1/3, 21</sub>	0.529* (2.32)	86.074** (3.46)	2.475 (0.54)	0.307 (1.28)	0.511 (1.73)	122.642** (3.64)
MV <sub>10%, 0</sub>	0.309* (2.12)	46.472** (2.91)	1.861 (0.64)	0.191 (1.25)	0.333 (1.77)	70.649** (3.28)
MV <sub>10%, 21</sub>	0.258 (1.73)	45.564** (2.80)	1.264 (0.42)	0.176 (1.12)	0.282 (1.46)	69.884** (3.18)
MV <sub>1/3, 0</sub>	0.217 (1.75)	34.469* (2.53)	1.627 (0.65)	0.159 (1.22)	0.252 (1.56)	56.459** (3.07)
MV <sub>1/3, 21</sub>	0.189 (1.50)	35.095* (2.55)	1.258 (0.50)	0.151 (1.14)	0.222 (1.36)	57.228** (3.08)
V	-0.151 (-1.93)	-15.885 (-1.85)	0.042 (0.03)	-0.006 (-0.07)	-0.066 (-0.65)	-8.185 (-0.70)

When we compare the results from the Table 10 (with the t-1 lagged liquidity) to the earlier Table 8 (with the no lag period liquidity t) we can observe both the clear increase in the affect that the liquidity seems to have on momentum (increased correlation) and clearly improved statistical significance.

The relationship between market liquidity factors (L) and momentum factors are statistically significant with both liquidity proxies and with all four momentum portfolios studied. The lagged market liquidity clearly forecasts a part of the future momentum profits. The results from the value portfolio still stay statistically insignificant. These results are even more interesting since the results in Table 10 are obtained from the non-controlled regressions. The next section adds the control variables to this regression and demonstrates further improvement in the explanatory power.

### 5.3.2 Controlled correlations: strong evidence

This section follows the same structure as section 5.2.2 in all other details than the similar t-1 time period used for liquidity factors as in the last part 5.3.1. This section presents the strong relations between momentum portfolio returns and both market liquidity (L) and liquidity shocks (LS).

**Table 11**

**Regression coefficients between momentum, value and combination portfolios with t-1 market liquidity factor (L), proportional liquidity change factor (LC) and liquidity shock factor (LS) with Fama French two factors ( $R_{m-f}$  and SMB) as controlling variables.**

This table presents the results from the Regressions 21, 22 and 23 (with one day lack) where portfolio returns (M, MV and V) are explained by the t-1 liquidity factors (L, LC and LS). The regression uses today's portfolio returns as explained variable and the yesterdays liquidity factor as an explanatory factor with the today's two Fama French factors ( $R_{m-f}$  and SMB) as controlling variables.

Portfolio	$L_{TV}$	$L_{TO}$	$LC_{TV}$	$LC_{TO}$	$LS_{TV}$	$LS_{TO}$
$M_{10\%, 0}$	0.864** (3.23)	113.428** (3.89)	5.980 (1.11)	0.505 (1.79)	0.867* (2.50)	162.568** (4.11)
$M_{10\%, 21}$	0.801** (3.05)	113.528** (3.96)	5.772 (1.09)	0.522 (1.88)	0.825* (2.42)	166.387** (4.29)
$M_{1/3, 0}$	0.644** (2.87)	87.696** (3.57)	4.644 (1.03)	0.397 (1.68)	0.654* (2.24)	129.326** (3.89)
$M_{1/3, 21}$	0.623** (2.83)	90.607** (3.77)	4.755 (1.07)	0.422 (1.82)	0.645* (2.26)	135.501** (4.17)
$MV_{10\%, 0}$	0.376** (2.69)	49.777** (3.26)	3.504 (1.25)	0.276 (1.88)	0.427* (2.36)	80.009** (3.87)
$MV_{10\%, 21}$	0.345* (2.49)	49.827** (3.30)	3.400 (1.22)	0.286 (1.95)	0.406* (2.26)	81.919** (4.01)
$MV_{1/3, 0}$	0.266* (2.21)	36.911** (2.80)	2.836 (1.17)	0.221 (1.75)	0.32* (2.05)	63.389** (3.55)
$MV_{1/3, 21}$	0.255* (2.15)	38.367** (2.95)	2.892 (1.21)	0.234 (1.87)	0.316* (2.05)	66.476** (3.79)
V	-0.112 (-1.53)	-13.874 (-1.73)	1.029 (0.70)	0.046 (0.60)	-0.014 (-0.14)	-2.549 (-0.23)



The Table 11 verifies the earlier findings and provides extremely strong results for momentum returns. First focusing on the momentum (M) and combination (MV) portfolios shows that all of the regression coefficients between these portfolios and market liquidity factors (both  $L_{TV}$  and  $L_{TO}$ ) are positive and statistically significant. All of the results from momentum portfolios (M) are actually significant with the 1% level. Second, the results for liquidity change factors (LC) are all statistically insignificant. Third, the results from liquidity shock factors (LS) are all significant, especially the relationship with  $LS_{TO}$  where the significance level is 1% with all of the studied momentum (M) and combination portfolios (MV).

The results presented in Table 11 can be viewed as the main results from this study. First, the evidence clearly supports the hypothesis of link between momentum investment returns and market liquidity. Second, unexpected shocks (LS) rather than the expected liquidity changes (LS) seem to contribute to the momentum returns. Third, there seems to be an opposite signed relation between value portfolio (V) and liquidity factors (L) than between the momentum portfolios (M) and liquidity factors (L). This relationship is however much weaker and still statistically insignificant.

The first two results are in line with the previous study by Lee and Swaminathan (2000) who present that the past trading volume predicts the magnitude of the momentum effect and that most of the excess returns in volume-based investment strategies rise due to the changes in trading volume, rather than its static levels itself.

Another interesting detail is the positive correlation between momentum returns and market liquidity as it's actually the contrary than the results from Chordia, Roll and Subrahmanyam (2008) who found the predictability to diminish as liquidity improves. They conclude that these results are in line with the hypothesis of increasing arbitrage activity during liquid times and the enhancement of market efficiency. Also the results from Roll, Schwartz and Subrahmanyam (2007) present evidence that suggests that the liquidity enhances the future-cash pricing systems efficiency i.e. the improvement in liquidity decreases the profitable arbitrage situations. It seems that the daily correlations might actually differ from the longer time horizon correlations.

One possible explanation for these differences in the results could be the, almost self evident, intuition that if market liquidity is considered to consist of two parts, real friction and informational friction, presented by Stoll (2000), there should also be two different "categories" of liquidity: constant (or changeable in the long run) and marginal. If this holds, the relationship between daily

liquidity and arbitrage returns should differ from the relationship with the longer time periods (monthly, quarterly etc.). In practice this means that in the short run market makers only focus on the marginal costs when balancing their positions, but on the long run they can exit the markets if the marginal profitability doesn't cover the long run costs (computers, offices, staff etc.). This setting gives the findings from this study a slightly different undertone than the previous studies with monthly time horizon. As the affect from the short term liquidity shocks are studied here, the market makers actually reveal their marginal costs in this setting unlike the longer time periods overall costs studied in most of the previous studies.

#### **5.4 Prolonged effect: evidence for lagged relation**

Based on the earlier results it seems clear that there is some time varying effects between the factors studied. It seems reasonable to study the lagged effects little closer and this section studies the lagged effect that liquidity changes have on momentum and value investment returns. Four new lag periods are introduced:  $t-2$ ,  $t-3$ ,  $t-4$  and  $t-5$  and hence, the effects of daily liquidity and its changes are studied up to a one week time period.

Three tables present these results. The first table (Table 12) presents the results from the daily liquidity (L), the second table (Table 13) presents the results from the proportional liquidity changes (LC) and the third table (Table 14) presents the results from the liquidity shock factor (LS).

Table 12

**Market liquidity's (L) prolonged effects on momentum (M), value (V) and combination (MV) portfolio returns.**

This table presents the results from the Regressions 21, 22 and 23 (with zero to five day lags) where momentum (M), value (V) and combination (MV) portfolios returns are studied against lacked liquidity (L) while the two Fama French factors ( $R_{m,t}$  and SMB) are used as controlling variables. First columns present the regression coefficient between today's portfolio returns and the t-1, t-2, t-3, t-4 and t-5 present the past liquidity of previous five trading dates.

Portfolio	$L_{TV}(t)$	$L_{TV}(t-1)$	$L_{TV}(t-2)$	$L_{TV}(t-3)$	$L_{TV}(t-4)$	$L_{TV}(t-5)$	$L_{TO}(t)$	$L_{TO}(t-1)$	$L_{TO}(t-2)$	$L_{TO}(t-3)$	$L_{TO}(t-4)$	$L_{TO}(t-5)$
$M_{10\%, 0}$	0.593* (2.21)	0.864** (3.23)	0.597* (2.22)	0.271 (1.00)	0.346 (1.28)	0.092 (0.33)	85.265** (2.88)	113.428** (3.89)	48.465 (1.64)	2.843 (0.10)	-5.913 (-0.20)	-26.654 (-0.90)
$M_{10\%, 21}$	0.742** (2.81)	0.801** (3.05)	0.543* (2.06)	0.213 (0.80)	0.334 (1.25)	0.088 (0.32)	113.449** (3.91)	113.528** (3.96)	46.352 (1.60)	-1.227 (-0.04)	-1.617 (-0.06)	-22.996 (-0.79)
$M_{1/3, 0}$	0.317 (1.4)	0.644** (2.87)	0.436 (1.93)	0.205 (0.90)	0.232 (1.02)	0.037 (0.16)	52.582* (2.11)	87.696** (3.57)	33.407 (1.35)	2.439 (0.10)	-6.510 (-0.26)	-23.677 (-0.95)
$M_{1/3, 21}$	0.475* (2.14)	0.623** (2.83)	0.409 (1.85)	0.187 (0.84)	0.267 (1.20)	0.071 (0.31)	80.869** (3.32)	90.607** (3.77)	32.925 (1.36)	1.511 (0.06)	0.908 (0.04)	-17.238 (-0.70)
$MV_{10\%, 0}$	0.301* (2.14)	0.376** (2.69)	0.220 (1.57)	0.066 (0.47)	0.170 (1.20)	0.034 (0.24)	42.29** (2.73)	49.777** (3.26)	15.543 (1.01)	-6.940 (-0.45)	-5.003 (-0.32)	-14.237 (-0.92)
$MV_{10\%, 21}$	0.375** (2.7)	0.345* (2.49)	0.193 (1.39)	0.037 (0.26)	0.164 (1.17)	0.032 (0.23)	56.382** (3.7)	49.827** (3.30)	14.487 (0.95)	-8.975 (-0.59)	-2.856 (-0.19)	-12.408 (-0.81)
$MV_{1/3, 0}$	0.162 (1.34)	0.266* (2.21)	0.140 (1.15)	0.033 (0.27)	0.113 (0.93)	0.007 (0.05)	25.949 (1.94)	36.911** (2.80)	8.014 (0.60)	-7.142 (-0.54)	-5.302 (-0.40)	-12.748 (-0.95)
$MV_{1/3, 21}$	0.241* (2.02)	0.255* (2.15)	0.126 (1.06)	0.024 (0.20)	0.131 (1.09)	0.024 (0.19)	40.092** (3.05)	38.367** (2.95)	7.773 (0.59)	-7.606 (-0.58)	-1.593 (-0.12)	-9.529 (-0.72)
V	0.008 (0.1)	-0.112 (-1.53)	-0.157* (-2.13)	-0.139 (-1.89)	-0.006 (-0.08)	-0.023 (-0.31)	-0.685 (-0.08)	-13.874 (-1.73)	-17.378* (-2.16)	-16.723* (-2.08)	-4.094 (-0.51)	-1.820 (-0.22)

The Table 12 above presents a very interesting picture on the nature of market liquidity's explanatory power over the studied momentum (M), value (V) and combination (MV) portfolios.

There are clear peaks in regression coefficient and the statistical significance in all of the portfolios. With the momentum (M) and combination (MV) portfolios there is a clear increase in the explanatory power that starts immediately at the time t, peak at the lag period t-1, diminishes at the t-2 and turns practically to a random variable after that. Value (V) on the other hand, starts to show the connection in the t-1, peak at the t-2, still somewhat persist in to t-3 and vanish completely only at the t-4. More interestingly, the t-2 and t-3 periods are actually able to produce statistically significant results for the value portfolio (V), something that was not observed in previous chapters.

These results are remarkable in two ways. First, there seems to be clear lagged relationship between these factors and second, the relation is opposite for the momentum (M) and value (V) portfolios. Figure 1 and Figure 2, present the results from the Table 12 in a graphical form.

**Figure 1****Prolonged effects of market liquidity ( $L_{TV}$ )**

This figure presents the correlations from today's and five previous days' market liquidity measure ( $L_{TV}$ ) from the Regressions 21, 22 and 23. The momentum portfolios (M) are blue, combination portfolios (MV) are red and the value portfolio (V) is the black line.

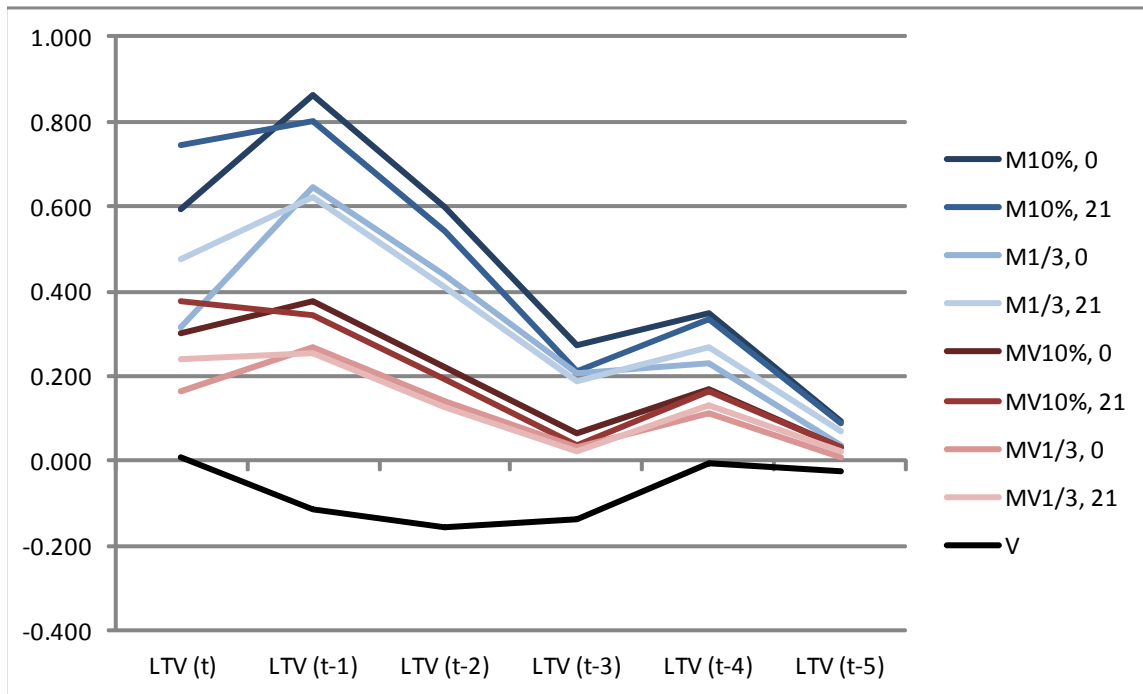
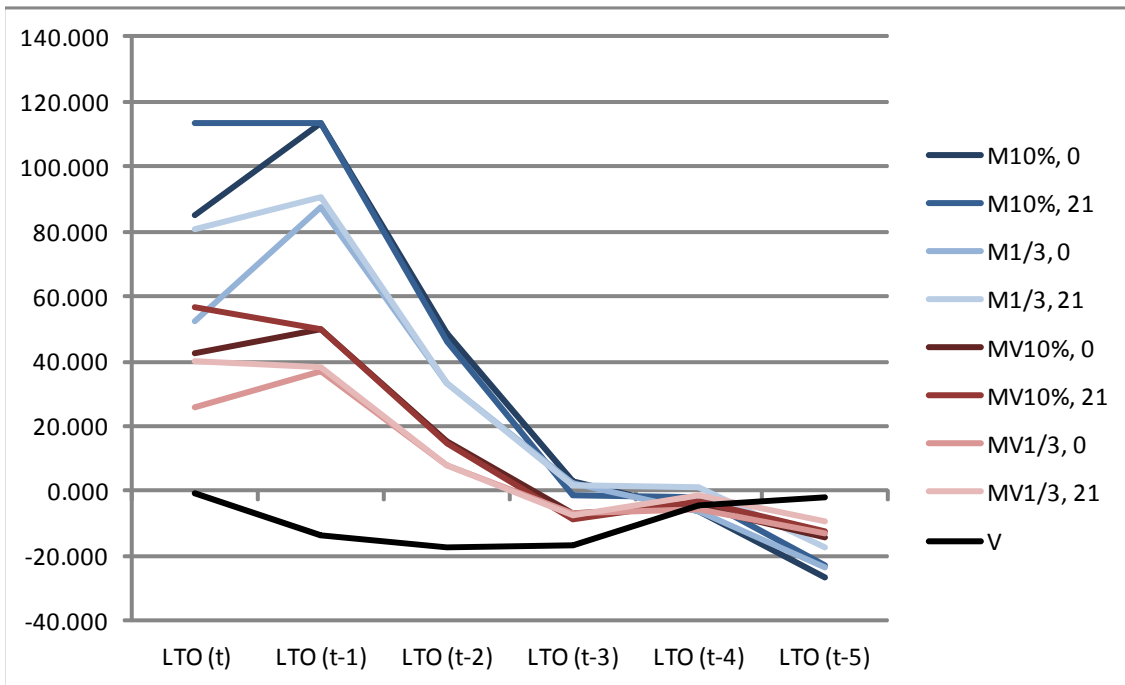


Figure 2

### Prolonged effects of market liquidity ( $L_{TO}$ )

This figure presents the correlations from today's and five previous days' market liquidity measure ( $L_{TO}$ ) from the Regressions 21, 22 and 23. The momentum portfolios (M) are blue, combination portfolios (MV) are red and the value portfolio (V) is the black line.



These two figures above (Figure 1 and Figure 2) show the difference in the regression coefficients between market liquidity factors ( $L_{TV}$  and  $L_{TO}$ ) and the nine portfolio returns studied. Both of the tables show the same two major effects. First, the significant positive connection between momentum (M) and combination (MV) portfolios with the liquidity factors  $L_{TV}$  and  $L_{TO}$  that starts at the same day  $t$  and diminishes after  $t-2$ . And second, the negative connection between value (V) returns and the liquidity factors  $L_{TV}$  and  $L_{TO}$  that starts in the  $t-1$  and peaks at the  $t-3$ .

An explanation for the lag period presented can be derived from Stoll (2000) where market friction is divided into two parts: real friction and informational friction. Since the real friction takes some time to adapt to, it should cause some time lag to the net profitability changes for the market makers. For example, the increase in market liquidity can increase their ability to borrow cheaper or the decrease in market liquidity can trigger marking calls. Both of these effects may however take some time to take place and lead to lagged reaction to market liquidity changes.

The following table, Table 13, presents the results from the prolonged affect from proportional liquidity changes (LC).

Table 13

**Proportional liquidity changes (LC) prolonged effects on momentum (M), value (V) and combination (MV) portfolio returns.**

This table presents the results from the Regressions 21, 22 and 23 (with zero to five days lack) where momentum (M), value (V) and combination (MV) portfolios returns are studied against lacked proportional liquidity change factor (LC) while the two Fama French factors (Rm-f and SMB) are used as controlling variables. First columns present the correlation between today's portfolio returns and the t-1, t-2, t-3, t-4 and t-5 present the past liquidity of previous five trading dates.

Portfolio	LC <sub>TV</sub> (t)	LC <sub>TV</sub> (t-1)	LC <sub>TV</sub> (t-2)	LC <sub>TV</sub> (t-3)	LC <sub>TV</sub> (t-4)	LC <sub>TV</sub> (t-5)	LC <sub>TO</sub> (t)	LC <sub>TO</sub> (t-1)	LC <sub>TO</sub> (t-2)	LC <sub>TO</sub> (t-3)	LC <sub>TO</sub> (t-4)	LC <sub>TO</sub> (t-5)
M <sub>10%, 0</sub>	-6.351 (-1.18)	5.980 (1.11)	7.208 (1.34)	-1.918 (-0.36)	5.797 (1.07)	1.224 (0.21)	-0.376 (-1.33)	0.505 (1.79)	0.312 (1.10)	-0.231 (-0.82)	0.125 (0.44)	0.052 (0.18)
M <sub>10%, 21</sub>	-1.593 (-0.30)	5.772 (1.09)	7.242 (1.37)	-2.897 (-0.55)	5.582 (1.05)	-0.058 (-0.01)	-0.126 (-0.45)	0.522 (1.88)	0.271 (0.98)	-0.267 (-0.96)	0.126 (0.45)	0.002 (0.01)
M <sub>1/3, 0</sub>	-7.607 (-1.69)	4.644 (1.03)	5.041 (1.11)	-0.823 (-0.18)	4.417 (0.97)	0.695 (0.14)	-0.458 (-1.93)	0.397 (1.68)	0.151 (0.64)	-0.165 (-0.70)	0.086 (0.36)	0.017 (0.07)
M <sub>1/3, 21</sub>	-3.592 (-0.81)	4.755 (1.07)	4.780 (1.08)	-1.958 (-0.44)	4.465 (1.00)	-0.232 (-0.05)	-0.236 (-1.01)	0.422 (1.82)	0.110 (0.47)	-0.216 (-0.93)	0.094 (0.40)	-0.029 (-0.12)
MV <sub>10%, 0</sub>	-1.834 (-0.65)	3.504 (1.25)	3.380 (1.20)	-2.443 (-0.87)	3.103 (1.10)	1.834 (0.62)	-0.128 (-0.87)	0.276 (1.88)	0.141 (0.95)	-0.170 (-1.16)	0.066 (0.44)	0.076 (0.50)
MV <sub>10%, 21</sub>	0.545 (0.20)	3.400 (1.22)	3.397 (1.22)	-2.933 (-1.06)	2.996 (1.07)	1.194 (0.40)	-0.003 (-0.02)	0.286 (1.95)	0.120 (0.82)	-0.188 (-1.29)	0.066 (0.45)	0.051 (0.34)
MV <sub>1/3, 0</sub>	-2.462 (-1.02)	2.836 (1.17)	2.296 (0.95)	-1.896 (-0.78)	2.413 (0.99)	1.570 (0.61)	-0.169 (-1.32)	0.221 (1.75)	0.060 (0.47)	-0.137 (-1.08)	0.046 (0.36)	0.058 (0.45)
MV <sub>1/3, 21</sub>	-0.454 (-0.19)	2.892 (1.21)	2.166 (0.91)	-2.463 (-1.03)	2.437 (1.01)	1.107 (0.44)	-0.058 (-0.46)	0.234 (1.87)	0.040 (0.32)	-0.163 (-1.30)	0.051 (0.40)	0.036 (0.28)
V	2.683 (1.83)	1.029 (0.70)	-0.448 (-0.30)	-2.969* (-2.02)	0.409 (0.28)	2.445 (1.57)	0.121 (1.56)	0.046 (0.60)	-0.031 (-0.40)	-0.109 (-1.42)	0.007 (0.09)	0.100 (1.27)

The results from Table 13 stands as an evidence for the second hypothesis studied in this thesis. There seems to be no clear connection between the expected liquidity changes (LC) and momentum (M), value (V) and combination (MV) portfolios. These results are very well in line with the theoretical framework of the "liquidity anomaly" i.e. the autoregressive cyclical nature of liquidity (e.g. Chowdhry and Nanda, 1991; Admati and Pfleiderer, 1988). They argue that the liquidity anomaly is in matter of a fact self-perpetuating, as if when investors find out about the lower liquidity they should rationally avoid trading during those times, which would even further reduce the liquidity. This can lead to market dynamics where the expected liquidity changes (LC) can be anticipated and priced beforehand and only the unexpected liquidity shocks (LS) will trigger an immediate price reaction.

Table 14

**Liquidity shocks (LS) prolonged effects on momentum (M), value (V) and combination (MV) portfolio returns.**

This table presents the results from the Regressions 21, 22 and 23 (with zero to five day lags) where momentum (M), value (V) and combination (MV) portfolios returns are studied against lacked liquidity shock factor (LS) while the two Fama French factors (Rm-f and SMB) are used as controlling variables. First columns present the regression coefficient between today's portfolio returns and the t-1, t-2, t-3, t-4 and t-5 present the past liquidity of previous five trading dates.

Portfolio	LS <sub>TV</sub> (t)	LS <sub>TV</sub> (t-1)	LS <sub>TV</sub> (t-2)	LS <sub>TV</sub> (t-3)	LS <sub>TV</sub> (t-4)	LS <sub>TV</sub> (t-5)	LS <sub>TO</sub> (t)	LS <sub>TO</sub> (t-1)	LS <sub>TO</sub> (t-2)	LS <sub>TO</sub> (t-3)	LS <sub>TO</sub> (t-4)	LS <sub>TO</sub> (t-5)
M <sub>10%, 0</sub>	0.078 (0.22)	0.867* (2.50)	0.664 (1.91)	0.140 (0.40)	0.484 (1.39)	0.008 (0.02)	29.397 (0.72)	162.568** (4.11)	88.487* (2.22)	21.436 (0.54)	26.098 (0.65)	-21.866 (-0.53)
M <sub>10%, 21</sub>	0.397 (1.16)	0.825* (2.42)	0.626 (1.83)	0.054 (0.16)	0.452 (1.32)	-0.104 (-0.29)	82.726* (2.07)	166.387** (4.29)	86.589* (2.21)	8.601 (0.22)	28.005 (0.71)	-31.508 (-0.78)
M <sub>1/3, 0</sub>	-0.148 (-0.51)	0.654* (2.24)	0.486 (1.66)	0.139 (0.48)	0.351 (1.20)	-0.017 (-0.06)	-0.380 (-0.01)	129.326** (3.89)	61.561 (1.84)	20.033 (0.60)	20.477 (0.61)	-19.265 (-0.56)
M <sub>1/3, 21</sub>	0.143 (0.5)	0.645* (2.26)	0.444 (1.55)	0.071 (0.25)	0.360 (1.26)	-0.093 (-0.31)	49.748 (1.49)	135.501** (4.17)	58.465 (1.78)	8.944 (0.27)	24.045 (0.73)	-27.402 (-0.81)
MV <sub>10%, 0</sub>	0.118 (0.65)	0.427* (2.36)	0.259 (1.43)	-0.040 (-0.22)	0.265 (1.46)	0.062 (0.32)	24.444 (1.15)	80.009** (3.87)	36.888 (1.77)	-2.295 (-0.11)	12.784 (0.61)	-3.760 (-0.18)
MV <sub>10%, 21</sub>	0.277 (1.54)	0.406* (2.26)	0.240 (1.34)	-0.083 (-0.46)	0.249 (1.39)	0.006 (0.03)	51.109* (2.44)	81.919** (4.01)	35.939 (1.75)	-8.712 (-0.42)	13.737 (0.67)	-8.581 (-0.41)
MV <sub>1/3, 0</sub>	0.004 (0.03)	0.32* (2.05)	0.170 (1.09)	-0.040 (-0.25)	0.199 (1.27)	0.049 (0.30)	9.556 (0.52)	63.389** (3.55)	23.425 (1.30)	-2.996 (-0.17)	9.974 (0.56)	-2.459 (-0.13)
MV <sub>1/3, 21</sub>	0.150 (0.97)	0.316* (2.05)	0.149 (0.97)	-0.074 (-0.48)	0.203 (1.32)	0.011 (0.07)	34.620 (1.92)	66.476** (3.79)	21.877 (1.24)	-8.541 (-0.48)	11.757 (0.66)	-6.528 (-0.36)
V	0.157 (1.65)	-0.014 (-0.14)	-0.145 (-1.53)	-0.219* (-2.31)	0.047 (0.49)	0.115 (1.16)	19.492 (1.76)	-2.549 (-0.23)	-14.711 (-1.35)	-26.026* (-2.40)	-0.530 (-0.05)	14.347 (1.28)

The third table from the prolonged affect, the Table 14 above, demonstrates similar relations as the Table 12 from the market liquidity (L) part. There are statistically significant results between the liquidity shocks (LS) and all of the portfolios studied.

The regression coefficient peaks at the t-1 for the momentum (M) and combination (MB) portfolios and at t-3 for the value (V) portfolio. The results are statistically significant and of opposite direction for the momentum (M) and value (V) portfolios. It seems that the liquidity shocks (LS) increase the momentum returns (M) at first and then diminish the value returns (V).

The importance of studying the prolonged (or lagged) affect of these factors is clear. When a one day lag period is added, the results from momentum returns rise significantly, but only after studying the 5 day prolonged affect we discover the significant results from the value returns.

These findings are in line with the results from Asness, Moskowitz and Pedersen (2013) as the liquidity shocks seem to correlate positively with momentum returns and negatively with value returns. These results therefore confirm the monthly results (ibid.) also in the daily level.

One explanation for these findings could be that the unexpected increase in liquidity allows the arbitrageurs to enter momentum investments as the net profitability of these investments increases.

This sudden flow of arbitrage money can then drive up prices for these stocks and thus cause this phenomenon.

The opposite reactions for momentum and value returns can be explained by simple portfolio overlapping. Since both momentum and value investment portfolios are built using market prices, the changes in these prices affect the allocation for both of these strategies and this effect is in the opposite direction. The increase (decrease) in market value of a stock increase its past returns and lead to a long (short) position in momentum investment strategy. Similar increase (decrease) in market value will on the other hand decrease the book-to-market ratio and lead to a short (long) position in the value investment portfolio. The negative correlation between liquidity shocks and value returns can therefore be caused by the negatively overlapping portfolio allocation.

Another explanation might be that value returns rise from an unobserved rational risk factor (Zhang, 2005). This removes the anomaly state from the value effect and verify its rationality as a part of the efficient markets. The reasoning is quite straightforward, if value returns are not an anomaly and should be present at the markets but the momentum returns are an anomaly, the increase of market efficiency (and liquidity) should diminish the momentum returns but actually increase the value returns.

More questions rise when comparing these results to the results by Amihud (2002) as it presents that the expected illiquidity has a positive effect on expected stock returns but the unexpected changes has a negative effect. The results present the correlation from daily liquidity and liquidity shocks to be of the same direction (positive with the momentum returns and negative with the value returns). This difference in returns can be due to the fact that this study focuses on studying the market anomaly returns where Amihud (2002) studies the individual stock returns. One possible explanation can be derived from results from Pastor Stambaugh (2003) where the stock returns in general are found to be cross-sectionally related to their sensitivity in aggregate market liquidity. This can lead to market dynamics where the changes in liquidity can cause short term price movements in stock prices that can induce these interestingly spurious results.

The following two figures, Figure 3 and Figure 4, present the results from Table 14 in a graphical form and demonstrate the lagged and prolonged affect that the liquidity shocks (LS) have on the momentum (M), value (V) and combination (MV) portfolios.



Figure 3

### Prolonged effects of liquidity shocks ( $LS_{TV}$ )

This figure presents the correlations from today's and five previous days' liquidity shock measure ( $LS_{TV}$ ) from the Regressions 21, 22 and 23. The momentum portfolios (M) are blue, combination portfolios (MV) are red and the value portfolio (V) is the black line.

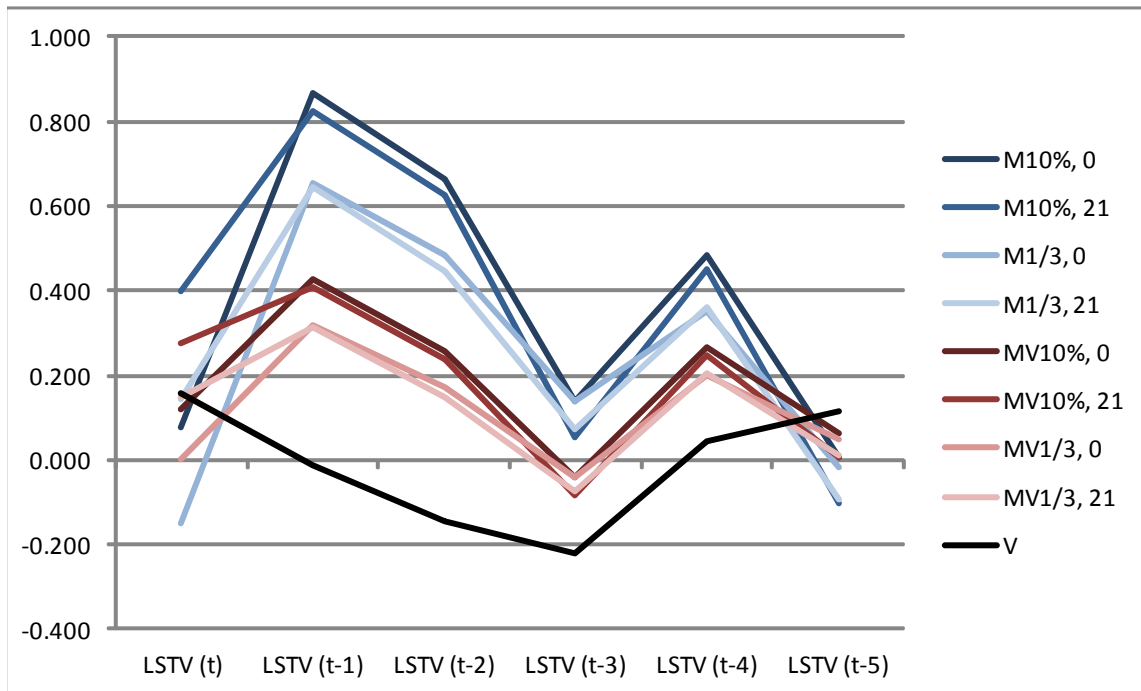
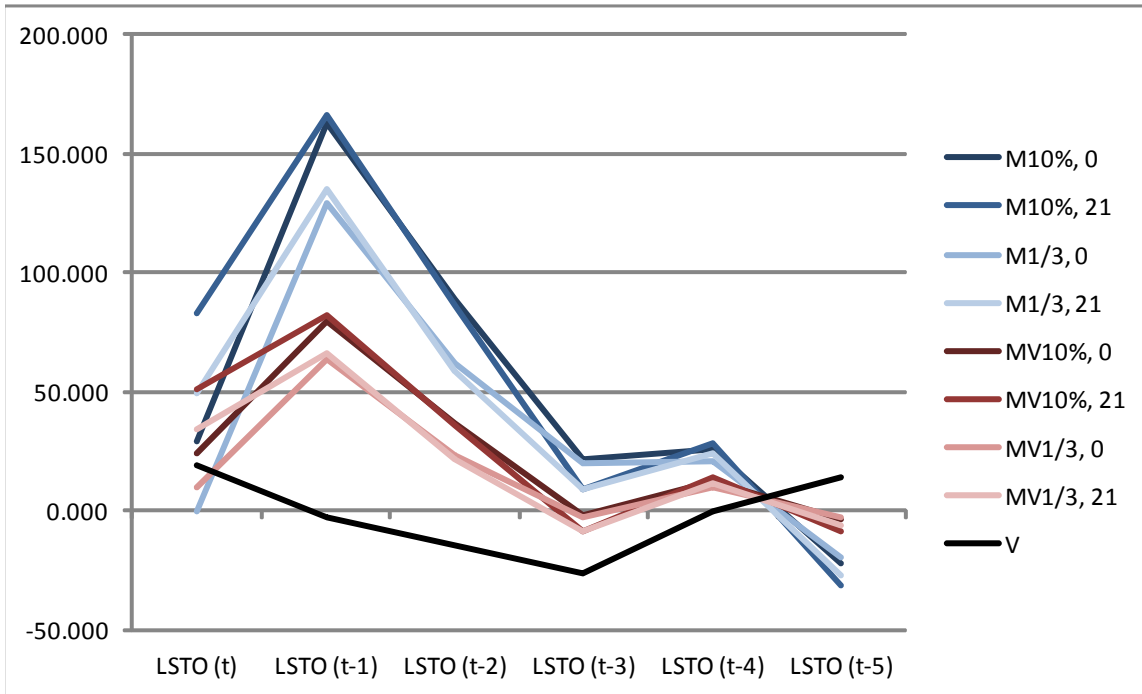


Figure 4

### Prolonged effects of liquidity shocks ( $LS_{TO}$ )

This figure presents the correlations from today's and five previous days' liquidity shock measure ( $LS_{TO}$ ) from the Regressions 21, 22 and 23. The momentum portfolios (M) are blue, combination portfolios (MV) are red and the value portfolio (V) is the black line.



These figures above, Figure 3 and Figure 4, present the slow moving, lagged and prolonged, affect that the liquidity shocks (LS) have on momentum (M), value (V) and combination (MV) portfolios. The same time structure, of instantaneous positive effect on momentum and two to three days lagged negative effect on value, are observable as in the Figures 1 and 2 presenting the effects on market liquidity's (L) parts.

The evidence for slowly moving price effect seems quite clear, but what really drives these effects? The next section divides the liquidity shock (LS) factors to six parts and demonstrates that the positive liquidity shocks are the driving force behind this phenomenon.

## 5.5 The dummy approach: the positive shocks dominate

This section studies the liquidity shocks (LS) effect more closely and reveals that the positive liquidity shocks, rather than the negative ones, are the driving force behind the results presented in the previous sections. A new dummy variable is introduced for the liquidity shocks (LS).

The dummy variables are obtained by ranking the liquidity shocks (LS) into six categories:  $D_{-2}$  dummy for the major negative shocks,  $D_{-1}$  for the minor negative shock,  $D_{-0}$  for all the negative shocks,  $D_{+0}$  for all of the positive shocks,  $D_{+1}$  for the minor positive shocks and  $D_{+2}$  for the major positive shocks. The cut-off values for these shocks are set ex-post as roughly one standard deviation and half of the standard deviation apart from the zero<sup>27</sup>. This division is made to study more closely which kind of shocks contribute to the results.

The following two tables, Table 15 and Table 16, present the explanatory power of the most effective liquidity shock (LS) measures obtained in the previous sections. The t-1 time period is used for the momentum (M) and combination (MV) portfolios and t-3 for the value portfolio (V) as the liquidity shocks (LS) affect on these portfolio returns occurs during these time periods.

---

<sup>27</sup> The dummy variables got the value 1 if the liquidity shock exceeded their cut-off value i.e. the minor shock factors include also the major shock factors as it also exceeds the minor shock cut-off etc. The twelve dummy variables got the value 1 in the following percentages of times: trading volume dummies,  $D_{TV-2}$  10%,  $D_{TV-1}$  24%,  $D_{TV-0}$  50%,  $D_{TV+0}$  50%,  $D_{TV+1}$  25% and  $D_{TV+2}$  12%. And the turnover dummies  $D_{TO-2}$  9%,  $D_{TO-1}$  26%,  $D_{TO-0}$  56%,  $D_{TO+0}$  44%,  $D_{TO+1}$  22% and  $D_{TO+2}$  12%.

**Table 15****Explanatory power of the dummy variables ( $D_{TV}$ ).**

This table presents the regression coefficients between the six different dummy variables ( $D_{TV}$ ) and the momentum (M), value (V) and combination portfolio (MV) returns. The dummy variables used here are obtained from the liquidity shock (LS) factor from the trading volume factor (TV). They rank from the -2 to the +2 where the -2 includes the most extreme negative shocks and the +2 the most extreme positive shocks, as defined earlier in this chapter.

Portfolio	$D_{TV-2}$	$D_{TV-1}$	$D_{TV-0}$	$D_{TV+0}$	$D_{TV+1}$	$D_{TV+2}$
$M_{10\%, 0}$	-0.345 (-1.87)	-0.239 (-1.80)	-0.225* (-1.99)	0.225* (1.99)	0.297* (2.28)	0.535** (3.07)
$M_{10\%, 21}$	-0.293 (-1.61)	-0.249 (-1.92)	-0.216 (-1.94)	0.216 (1.94)	0.270* (2.11)	0.393* (2.29)
$M_{1/3, 0}$	-0.275 (-1.77)	-0.166 (-1.50)	-0.148 (-1.56)	0.148 (1.56)	0.217* (1.98)	0.404* (2.76)
$M_{1/3, 21}$	-0.266 (-1.75)	-0.185 (-1.70)	-0.147 (-1.57)	0.147 (1.57)	0.204 (1.90)	0.290* (2.02)
$MV_{10\%, 0}$	-0.172 (-1.78)	-0.114 (-1.65)	-0.123* (-2.09)	0.123* (2.09)	0.161* (2.37)	0.244** (2.68)
$MV_{10\%, 21}$	-0.146 (-1.53)	-0.119 (-1.75)	-0.119* (-2.04)	0.119* (2.04)	0.148* (2.20)	0.119 (1.91)
$MV_{1/3, 0}$	-0.137 (-1.64)	-0.078 (-1.31)	-0.085 (-1.67)	0.085 (1.67)	0.121* (2.06)	0.178* (2.27)
$MV_{1/3, 21}$	-0.133 (-1.62)	-0.087 (-1.49)	-0.084 (-1.68)	0.084 (1.68)	0.115* (1.98)	0.121 (1.56)
V	-0.042 (-0.82)	0.077* (2.15)	0.079* (2.58)	-0.079* (-2.58)	-0.096** (-2.71)	-0.098* (-2.06)

**Table 16****Explanatory power of the dummy variables ( $D_{TO}$ ).**

This table presents the regression coefficients between the six different dummy variables ( $D_{TO}$ ) and the momentum (M), value (V) and combination portfolio (MV) returns. The dummy variables used here are obtained from the liquidity shock (LS) factor from the turnover factor (TO). They rank from the -2 to the +2 where the -2 includes the most extreme negative shocks and the +2 the most extreme positive shocks, as defined earlier in this chapter.

Portfolio	$D_{TO-2}$	$D_{TO-1}$	$D_{TO-0}$	$D_{TO+0}$	$D_{TO+1}$	$D_{TO+2}$
$M_{10\%, 0}$	-0.258 (-1.32)	-0.226 (-1.76)	-0.279* (-2.45)	0.279* (2.45)	0.429** (3.12)	0.612** (3.50)
$M_{10\%, 21}$	-0.296 (-1.54)	-0.250* (-1.98)	-0.246* (-2.20)	0.246* (2.20)	0.416** (3.08)	0.561** (3.26)
$M_{1/3, 0}$	-0.171 (-1.04)	-0.182 (-1.69)	-0.215* (-2.25)	0.215* (2.25)	0.331** (2.86)	0.447** (3.04)
$M_{1/3, 21}$	-0.222 (-1.38)	-0.208* (-1.97)	-0.187* (-1.99)	0.187* (1.99)	0.315** (2.78)	0.406** (2.81)
$MV_{10\%, 0}$	-0.114 (-1.11)	-0.110 (-1.65)	-0.161** (-2.71)	0.161** (2.71)	0.225** (3.13)	0.296** (3.24)
$MV_{10\%, 21}$	-0.132 (-1.32)	-0.122 (-1.85)	-0.144* (-2.45)	0.144* (2.45)	0.218** (3.07)	0.270** (2.99)
$MV_{1/3, 0}$	-0.070 (-0.80)	-0.088 (-1.53)	-0.129* (-2.52)	0.129* (2.52)	0.176** (2.83)	0.213** (2.70)
$MV_{1/3, 21}$	-0.095 (-1.10)	-0.102 (-1.79)	-0.115* (-2.27)	0.115* (2.27)	0.168** (2.75)	0.193* (2.47)
V	0.015 (0.28)	0.060 (1.71)	0.036 (1.16)	-0.036 (-1.16)	-0.114** (-3.03)	-0.121* (-2.54)

Both of the tables above, Table 15 and Table 16, provide the same picture. The positive liquidity shocks forecast the future returns (t+1 for momentum and t+3 for value). These positive shocks seem to anticipate positive momentum (M) returns for the next trading date and negative returns for the value (V) investments for the third trading date after the liquidity shock (LS).

The relationship between the negative liquidity shocks (LS) seems to be much lower both in the magnitude of the correlation and the statistical significance. However, the regression coefficients

with the negative shocks are opposite than the positive shocks for both momentum (M) and value (V) and over a quarter of the negative shocks are statistically significant (15 out of 54).

The explanatory power of the liquidity shock dummy variable reach statistically significant levels with the combination portfolio (MV), especially for the positive shock parts where 20 out of 24 results are statistically significant.

The following two figures, Figure 5 and Figure 6, present the regression coefficients from the dummy variables in a graphical form.

**Figure 5**

**Explanatory power of trading volume dummies ( $D_{TV}$ )**

This figure presents the correlation coefficients between the six dummy variables for market liquidity shocks ( $LS_{TV}$ ):  $D_{TV-2}$ ,  $D_{TV-1}$ ,  $D_{TV-0}$ ,  $D_{TV+0}$ ,  $D_{TV+1}$  and  $D_{TV+2}$ . The momentum portfolios (M) are blue, combination portfolios (MV) are red and the value portfolio (V) is the black line.

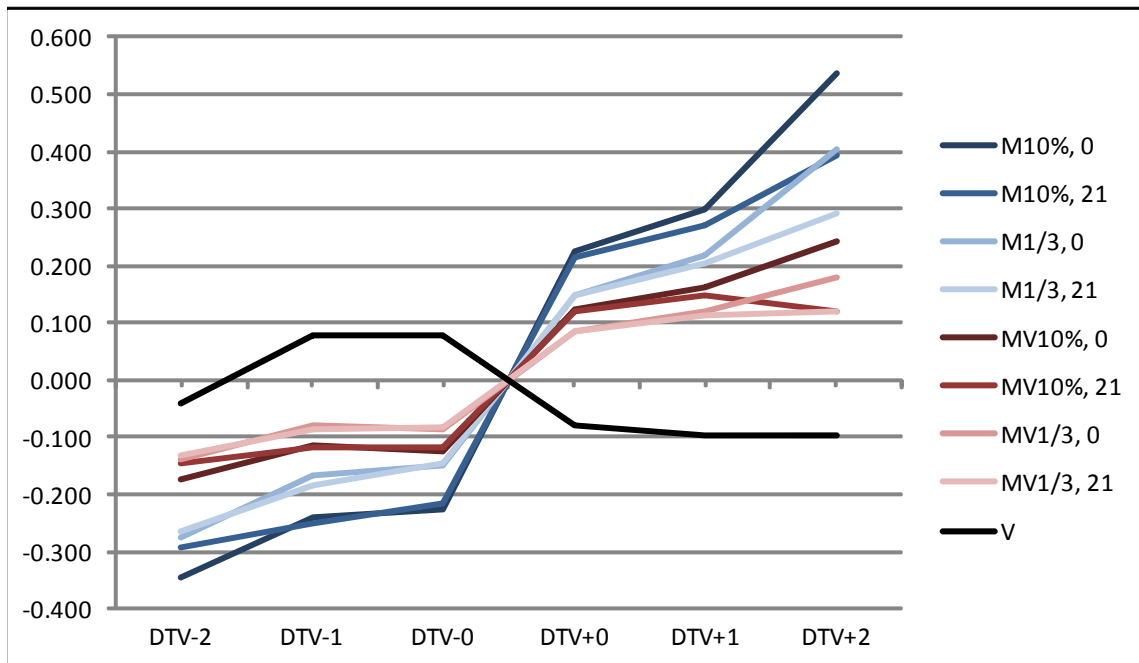


Figure 6

### Explanatory power of turnover dummies ( $D_{TO}$ )

This figure presents the correlation coefficients between the six dummy variables for market liquidity shocks ( $LS_{TO}$ ):  $D_{TO-2}$ ,  $D_{TO-1}$ ,  $D_{TO-0}$ ,  $D_{TO+0}$ ,  $D_{TO+1}$  and  $D_{TO+2}$ . The momentum portfolios (M) are blue, combination portfolios (MV) are red and the value portfolio (V) is the black line.

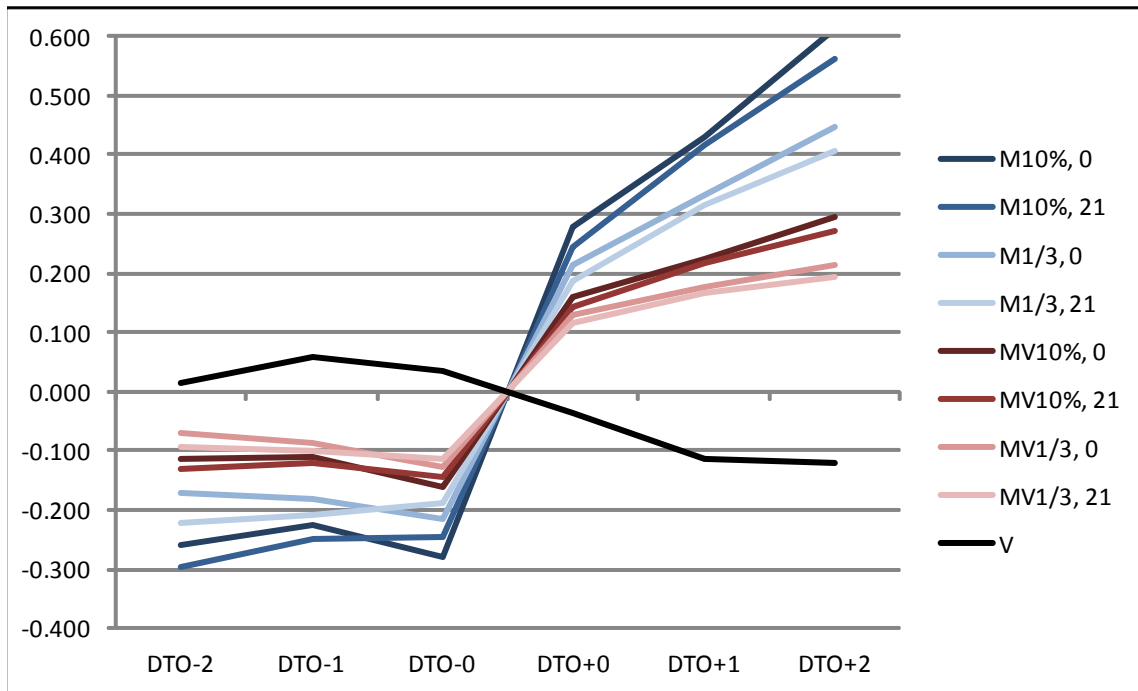


Figure 5 and Figure 6 present clear positive connection with momentum (M) and combination (MV) portfolios and a negative connection with value portfolio (V). These regression coefficients are strongest with positive liquidity shocks and also the most statistically significant.

These results contribute to the earlier results by Asness, Moskowitz and Pedersen (2013) by demonstrating the very same relationship between these measures, but from the daily data instead of the monthly data, and by showing that these results are mainly driven by positive liquidity shocks rather than the negative ones.

If the positive liquidity shocks are the driving force behind these relations, what is the market dynamic that causes it? The results could rise due to several reasons. The most practical explanation is a small capital buffer used by arbitrage investors. If the capital flow to arbitrage investors is the fundamental reason behind these changes, a simple risk buffer by these investors

can explain the results that these effects are driven by positive liquidity shocks. If investors keep some excess capital buffer they can avoid forced sell-offs which were offered as an explanation by Asness, Moskowitz and Pedersen (2013). In this setting, increase in their capital allows an immediate increase in their investments and the small negative shocks can be absorbed by their capital buffers and won't force them into immediate sell-offs. This leads to a dynamic where positive shocks cause immediate reaction but negative shocks are mostly absorbed by capital buffers.

## 6 Conclusion

This study focus on the links between market liquidity and two of the most studied stock market anomalies: momentum effect and value effect.

First, there are no positive alphas for momentum or value investment strategies during the post 2008 financial crisis period. This is in line with the previous findings of diminishing anomaly investment strategy returns (Chordia, Subrahmanyam and Tong, 2013).

Second, the results from Asness, Moskowitz and Pedersen (2013) are confirmed using the daily stock market data and similar negative relationship between liquidity shocks and value investment returns, and a positive relationship between liquidity shocks and momentum investment returns are confirmed.

Third, the unexpected liquidity shocks, rather than the expected ones, forecast the value and momentum investment returns. The unexpected liquidity shocks correlate positively with momentum returns. This connection starts to show immediately, peaks at the t-1 and diminishes after the t-2. Value, on the other hand, correlates negatively with the unexpected liquidity shocks and this effect is not realized immediately. This effect is statistically significant only at the t-2 and t-3 days.

And finally, positive liquidity shocks seem to be the driving force behind these phenomena. This disproves the forced sell-off argumentation offered by Asness, Moskowitz and Pedersen (2013) and raises a question on the exact market dynamic causing this effect. One explanation could be the



capital flows to arbitrage investors who keep some capital buffer. This would allow them to absorb some of the negative shocks but to invest immediately after most of the positive ones.

All in all, the results clearly show that unexpected liquidity shocks predict both momentum and value investment returns. These results open up many new directions for future studies. First, there seems to be obvious new avenues for both daily and intraday data usage when analyzing the role that stock market liquidity plays in explaining different market anomalies. Second, the time structure in the relationship between stock market liquidity raises the need for further studies on slow moving prices. And finally, the further studies to clarify the role of arbitrage investors and the effect of capital flows to these investors.

## References

### Articles:

Acharya, V., Pedersen, L., 2005, Asset pricing with liquidity risk, *Journal of Financial Economics* 77, 375-410.

Admati, R., Pfleiderer, P., 1988, A theory of intraday patterns: Volume and price variability, *Review of Financial Studies* 1, 3-40.

Admati, R., Pfleiderer, P., 1989, Divide and conquer: A theory of intraday and day-of-the-week mean effects, *Review of Financial Studies* 2, 189-223.

Ahn, D.H., Boudoukh, J., Richardson, M., Whitelaw., R.F., 2002, Partial adjustment or stale prices? Implications from stock index and futures return autocorrelations, *Review of Financial Studies* 15, 655–689.

Amihud, Y., 2002, Illiquidity and stock returns: cross-section and time-series effects, *Journal of Financial Markets* 5, 31–56.

Amihud, Y., Mendelson, H., 1980, Dealership market: market making with inventory, *Journal of Financial Economics* 8, 311–353.

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

Amihud, Y., Mendelson, H., 1989, The effects of beta, bid-ask spread, residual risk and size on stock returns, *Journal of Finance* 44, 479-486.

Amihud, Y., Mendelson, H., 1991, Liquidity, maturity, and the yields on U.S. treasury securities, *Journal of Finance* 46, 1411-1425.

Asness, C., Moskowitz T.J., Pedersen, L., 2013, Value and momentum everywhere, *Journal of Finance*, forthcoming.

Avramov, D., Cheng, S., Hameed, A., 2013, Time-varying momentum payoffs and illiquidity, *Working Paper*.

- Avramov, D., Chordia, T., 2006, Asset pricing models and financial market anomalies, *Review of Financial Studies* 19, 1001-1040.
- Avramov, D., Chordia, T., Goyal, A., 2006, Liquidity and autocorrelation in individual stock returns, *Journal of Finance* 61, 2365-2394.
- Avramov, D., Chordia, T., Jostova, G., Philipov, A., 2007, Momentum and credit rating, *Journal of Finance* 62, 2503-2520.
- Ball, R., Kothari, S., 1989, Nonstationary expected returns: Implications for tests of market efficiency and serial correlation in returns, *Journal of Financial Economics* 25, 51-74.
- Ball, R., Kothari, S., Wasley, C., 1995, Can we implement research on stock trading rules?, *Journal of Portfolio Management* 21, 54-63.
- Banerjee, S., Gatchev, V., Spindt, P., 2007, Stock market liquidity and firm dividend policy, *Journal of Financial Quantitative Analysis* 42, 369-397.
- Banz, R., 1981, The relationship between return and market value of common stocks, *Journal of Financial Economics* 9, 3-18.
- Barberis, N. Shleifer, A., Vishny, R., 1998, A Model of Investor Sentiment, *Journal of Financial Economics* 49, 307-343.
- Basu, S., 1977, Investment performance of common stocks in relation to their price earnings ratios: A test of the efficient market hypothesis, *Journal of Finance* 32, 663-682.
- Berk, J., Green, R. Naik, V., 2002, Optimal investment, growth options, and security returns, *Journal of Finance* 54, 1553-1607.
- Bhootra, A., 2011, Are momentum profits driven by the cross-sectional dispersion in expected stock returns?, *Journal of Financial Markets* 14, 494-513.
- Brav, A., Heaton, J., 2002, Competing theories of financial anomalies, *Review of Financial Studies* 15, 575-606.

- Breen, W., Hodrick, L., Korajczyk, R., 2002, Predicting equity liquidity, *Management Science* 48, 470-483.
- Bremer, M., Sweeney, R., 1991, The reversal of large stock-price decreases, *Journal of Finance* 46, 747-754.
- Brennan, M., Subrahmanyam, A., 1996, Market microstructure and asset pricing: on the compensation for illiquidity in stock returns, *Journal of Financial Economics* 41, 441-464.
- Brown, K., Harlow, W., 1988, Market overreaction: Magnitude and intensity, *Journal of Portfolio Management* 14, 6-13. --- Brown, K., Harlow, W., Tinic, S., 1988, Risk aversion, uncertainty information, and market efficiency, *Journal of Financial Economics* 22, 355-385.
- Campbell, J., Grossman, S., Wang, J., 1993, Trading volume and serial correlation in stock returns, *Quarterly Journal of Economics* 108, 905-939.
- Carhart, M., 1997, On persistence in mutual fund performance, *Journal of Finance* 52, 57-82.
- Chan, K., 1988. On the contrarian investment strategy, *Journal of Business* 61, 147-163.
- Chan, W., 2003, Stock price reaction to news and no-news: Drift and reversal after headlines, *Journal of Financial Economics* 70, 223-260.
- Chan, L., Hamao, Y., Lakonishok, J., 1991, Fundamentals and stock returns in Japan, *Journal of Finance* 46, 1739-1764.
- Chordia, T., Subrahmanyam, A., Anshuman, V., 2001, Trading activity and expected stock returns, *Journal of Financial Economics* 59, 3-32.
- Chordia, T., Subrahmanyam, A., Tong, Q., 2013, Trends in Capital Market Anomalies, *Working Paper*.
- Chordia, T., Shivakumar L., 2002, Momentum, business cycle, and time-varying expected returns, *Journal of Finance* 57, 985-1019.
- Chordia, T., Roll, R., Subrahmanyam, A., 2000, Commonality in liquidity, *Journal of Financial Economics* 56, 3-28.

- Chordia, T., Roll, R., Subrahmanyam, A., 2001, Market liquidity and trading activity, *Journal of Finance*, 56, 501-530.
- Chordia, T., Roll, R., Subrahmanyam, A., 2008, Liquidity and market efficiency, *Journal of Financial Economics* 87, 249-268.
- Chowdhry, B., Nanda, K., 1991, Multimarket trading and market liquidity, *Review of Financial Studies* 24, 483-511.
- Ciccone, S., 2003, Does analyst optimism about future earnings distort stock prices?, *Journal of Behavioral Finance* 4, 59-64.
- Conrad, J., Gultekin, M., Kaul, M., 1997, Profitability of short-term contrarian strategies: implications for market efficiency, *Journal of Business and Economic Statistics* 15, 379-386.
- Conrad, J., Kaul, G., 1998, An anatomy of trading strategies. *Review of Financial Studies* 11, 489-519.
- Copeland, T., Galai, D., 1983, Information effects of the bid-ask spread, *Journal of Finance* 38, 1457-1469.
- Cox, P., Peterson, D., 1994, Stock returns following large one-day declines: Evidence on short-term reversals and longer-term performance, *Journal of Finance* 49, 255-267.
- Daniel, K., Hirshleifer, D., Subrahmanyam, A., 1998, A theory of overconfidence, self-attribution, and security market under- and over-reactions, *Journal of Finance* 53, 1839-1885.
- Daniel, K., Moskowitz, T., 2012, Momentum crashes, *Working paper*.
- Dann, L., Mayers, D., Raab, R., 1977, Trading rules, large blocks and the speed of price adjustment, *Journal of Financial Economics* 4, 2-33.
- Datar, V., Naik, N., Radcliffe, R., 1998, Liquidity and stock returns: An alternative test, *Journal of Financial Markets* 1, 203-219.
- De Bondt, W., Thaler, R., 1985, Does the stock market overreact?, *Journal of Finance* 40, 793-805.

- De Bondt, W., Thaler, R., 1987, Further evidence of investor overreaction and stock market seasonality, *Journal of Finance* 42, 557-581.
- Demsetz, H., 1968, The cost of transacting, *Quarterly Journal of Economics* 82, 33-53.
- Diether, K., Malloy, C., Scherbina, A., 2002, Differences of opinion and the cross-section of stock returns, *Journal of Finance* 57, 2113-2141.
- Fama, E., 1965, The behavior of stock-market prices, *Journal of Business* 38, 35-105.
- Fama, E., 1970, Efficient capital markets: A review of theory and empirical work, *Journal of Finance* 25, 383-417.
- Fama, E., French, K., 1993, Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics* 33, 3-56.
- Fama, E., French, K., 1996, Multifactor explanations of asset pricing anomalies, *Journal of Finance* 51, 55-84.
- Fama, E., French, K., 1988, Permanent and temporary components of stock prices, *Journal of Political Economy* 96, 246-273.
- Foster, D., Viswanathan, S., 1990, A theory of the interday variations in volume, variance, and trading costs in securities markets, *Review of Financial Studies* 3, 593-624.
- Frazzini, A., Israel, R., Moskowitz, T., 2012, Trading costs of asset pricing anomalies, *Working Paper*.
- Garman, M., 1976, Market microstructure, *Journal of Financial Economics* 3, 257-275.
- Glosten, L., Harris, L., 1988, Estimating the components of the bid-ask spread, *Journal of Financial Economics* 21, 123-142.
- Glosten, L., Milgrom, P., 1985, Bid, ask and transaction prices in a specialist market with heterogeneously informed traders, *Journal of Financial Economics* 14, 71-100.
- Goyenko, R., Holden, C., Trzcinka, C., 2009, Do liquidity measures measure liquidity?, *Journal of Financial Economics* 92, 153-181.

- Grinblatt, M., Moskowitz, T., 2004, Predicting stock price movements from past returns: The role of consistency and tax-loss selling, *Journal of Financial Economics* 71, 541-579.
- Grinblatt, M., Han, B., 2005, Prospect theory, mental accounting and momentum, *Journal of Financial Economics* 78, 311-339.
- Groot, W., Huij, J., Zhou, W., 2012, Another look at trading costs and short-term reversal profits, *Journal of Banking and Finance* 36, 371-382.
- Grossman, S., Miller, M., 1988, Liquidity and market structure, *Journal of Finance* 43, 617-633.
- Grundy, B., Martin, J., 2001, Understanding the nature of the risks and the source of the rewards to momentum investing, *Review of Financial Studies* 14, 29-78.
- Gutierrez, R. Jr., Kelley, E., 2008, The long-lasting momentum in weekly returns, *Journal of Finance* 63, 415-447.
- Hasbrouck, J., 1991, Measuring the information content of stock trades, *Journal of Finance* 46, 179-207.
- Hasbrouck, J., Seppi, D., 2001, Common factors in prices, order flows and liquidity, *Journal of Financial Economics* 59, 383-411.
- Hong, H., Lim, T., Stein, J., 2000, Bad news travels slowly: Size, analyst coverage, and the profitability of momentum strategies, *Journal of Finance* 55, 265-295.
- Huberman, G., Halka, D., 2001, Systematic liquidity, *Journal of Financial Research* 24, 161-178.
- Jacoby, G., Fowler, D., Gottesman, A., 2000, The capital asset pricing model and the liquidity effect: A theoretical approach, *Journal of Financial Markets* 3, 69-81.
- Jaffe, J., Keim, D., Westerfield, R., 1989, Earnings yields, market values, and stock returns, *Journal of Finance* 44, 135-148.
- Jegadeesh, N., 1990, Evidence of predictable behavior of security returns, *Journal of Finance* 45, 881-898.

- Jegadeesh, N., Titman, S., 1993, Returns to buying winners and selling losers: Implications for stock market efficiency, *Journal of Finance* 48, 35-91.
- Jegadeesh, N., Titman, S., 2001, Profitability of momentum strategies: An evaluation of alternative explanations, *Journal of Finance* 56, 699-720.
- Jegadeesh, N., Titman, S., 1995, Short-horizon return reversals and the bid-ask spread, *Journal of Financial Intermediation* 4, 116-132.
- Jegadeesh, N., Titman, S., 2002, Cross-sectional and time-series determinants of momentum Returns, *Review of Financial Studies* 15, 143-157.
- Jensen, M., Bennington, G., 1970, Random walks and technical theories: Some additional evidence, *Journal of Finance* 25, 469-482.
- Jiang, G., Lee, C., Zhang, Y., 2005, Information uncertainty and expected returns. *Review of Accounting Studies* 10, 185-221.
- Kaul, G., Nimalendran, M., 1990, Price reversals: Bid-ask errors or market overreaction?, *Journal of Financial Economics* 28, 67-93.
- Keim, D, Madhavan, A., 1997, Transaction costs and investment style: An interexchange analysis of institutional equity trades, *Journal of Financial Economics* 46, 265-292.
- Kendal, M., 1953, The analysis of economic time series, part I. Prices, *Journal of Royal Statistical Society* 96, 11-25.
- Kogan, L., 2001, An equilibrium model of irreversible investment, *Journal of Financial Economics* 62, 201-245.
- Korajczyk, R., Sadka, R., 2004, Are momentum profits robust to trading costs?, *Journal of Finance* 59, 1039-1082.
- Kyle, A., 1985, Continuous auctions and insider trading, *Econometrica* 53, 1315-1336.
- Lakonishok, J., Shleifer, A., Vishny, R., 1994, Contrarian investment, extrapolation, and risk, *Journal of Finance* 49, 1541-1578.



- Lee, C., Swaminathan, B., 2000, Price momentum and trading volume, *Journal of Finance* 5, 2017-2069.
- Lehmann, B., 1990, Fads, martingales, and market efficiency, *Quarterly Journal of Economics* 105, 1-28.
- Lesmond, D., Schill, M., Zhou, C., 2004, The illusionary nature of momentum profits, *Journal of Financial Economics* 71, 349-380.
- Levy, R., 1967, Relative strength as a criterion for investment selection, *Journal of Finance* 22, 595-610.
- Lewellen, J., Shanken, J., 2002, Learning, asset-pricing tests, and market efficiency, *Journal of Finance* 57, 1113-1145.
- Lippman, S., McCall, J., 1986, An operational measure of liquidity, *American Economic Review* 76, 43-55.
- Lintner, J., 1965, The valuation of risk assets and the selection of risky investments in stock portfolios and capital budgets, *Review of Economics and Statistics* 47, 13-37.
- Lo, A., MacKinlay, C., 1988, Stock prices do not follow random walks: evidence from a simple specification test, *Review of Financial Studies* 1, 41-66.
- Lo, A., MacKinlay, A., 1990, When are contrarian profits due to stock market overreaction?, *Review of Financial Studies* 3, 175-205.
- McNichols, M., O'Brien, P., 1997, Self-selection and analyst coverage, *Journal of Accounting Research* 35, 167-199.
- Mitchell, M., Pedersen, L., Pulvino, T., 2007, Slow moving capital, *American Economic Review* 97, 215-220.
- Moskowitz, T., Grinblatt, M., 1999, Do industries explain momentum?, *Journal of Finance* 54, 1249-1290.

- Moskowitz, T., Ooi, Y., Pedersen, L., 2012, Time series momentum, *Journal of Financial Economics* 104, 228-250.
- Pastor, L., Stambaugh, R., 2003, Liquidity risk and expected stock returns, *Journal of Political Economy* 111, 642–85.
- Poterba, J., Summers, L., 1988, Mean reversion in stock prices: evidence and implications, *Journal of Financial Economics* 22, 27–59.
- Reinganum, M., 1981, Misspecification of capital asset pricing: Empirical anomalies based on earning yields and market values, *Journal of Financial Economics* 9, 19-46.
- Roll, R., Schwartz, E., Subrahmanyam, A., 2007, Liquidity and the Law of One Price: The Case of the Futures-Cash Basis, *Journal of Finance* 62, 2201-2234.
- Rosenberg, B., Reid, K., Lanstein, R., 1985, Persuasive evidence of market inefficiency, *Journal of Portfolio Management* 11, 9-17.
- Sadka, R., 2006, Momentum and post-earning-announcement drift anomalies: The role of liquidity risk, *Journal of Financial Economics* 80, 309-349.
- Sadka, R., Scherbina, A., 2007, Analyst disagreement, mispricing, and liquidity, *Journal of Finance* 62, 2367-2403.
- Schultz, P., 1983, Transaction costs and small firm effect, *Journal of Financial Economics* 12, 81-88.
- Sharpe, W., 1964, Capital Asset Prices: A theory of market equilibrium under conditions of risk, *Journal of Finance* 19, 425-442.
- Shleifer, A., Vishny, R., 1997, The limits of arbitrage, *Journal of Finance*, 52, 35-55.
- Stattman, D., 1980, Book values and stock returns. *The Chicago MBA: A journal of selected papers* 4, 25-45.
- Stoll, H., Whaley, R., 1983, Transaction costs and the small firm effect, *Journal of Financial Economics* 12, 57-79.

Stoll, H., 2000, Presidential address: friction. *The Journal of Finance* 55, 1479-1514.

Summers, H., 1986, Does the stock market rationally reflect fundamental values?, *Journal of Finance* 41, 591-601.

Veronesi, P., 1999, Stock market overreactions to bad news in good times: a rational expectations equilibrium model, *Review of Financial Studies* 12, 975-1007.

Watkins, B., 2003, Riding the wave of sentiment: An analysis of consistency as a predictor of future returns, *Journal of Behavioral Finance* 4, 191-200.

Zhang, L., 2005, The Value Premium, *Journal of Finance* 60, 67-103.

Zhang, X., 2006, Information uncertainty and stock returns, *Journal of Finance* 61, 105-137.

#### Books:

Brealey, R., Myers, S., Allen F., 2008, Principles of corporate finance, *McGraw-Hill/Irwin*, Singapore.

Boulding, K., 1955, Economic analysis, 3rd ed., *Harper and Brothers*, New York, USA.

Graham, B., Dodd, D., 1934, Security analysis, *McGraw-Hill Companies*, New York, USA.

Grinblatt, M., Titman, S., 2001, Financial markets and corporate strategy, 2nd Edition. *McGraw-Hill/Irwin*, Singapore.

Schwert, G., 2003, Anomalies and market efficiency. --- Constantinides, G., Harris, H., Stulz, R., eds., *Handbook of the Economics of Finance*, North-Holland, Amsterdam, Netherlands.

Shleifer, A., 2000, Inefficient markets, an introduction to behavioral finance. *Oxford University Press*, Oxford, UK.