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Pricing of Risk Factors at Various Horizons

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PREFACE AND ACKNOWLEDGEMENTS

Starting, I would like to express my delight of studying at the Erasmus University Rotterdam over the last five years. I can certainly say that I developed myself on an academic and personal level, and look forward of applying my knowledge into practice. For me, this thesis marks the end of five fruitful and enjoyable years that I have spent at the Erasmus University, but also marks the beginning of the next step in my life, whatever this may be.

I would like to start with thanking my thesis supervisor Dr. Jan Lemmen. I am sure that everybody writing their thesis is experiencing the same struggles along the road of completing it. However, with the guidance of Dr. Lemmen I was able to overcome most, if not all of these struggles. I am grateful that Dr. Lemmen was always really timely with his feedback, which provided me with the opportunity to keep making progress with the Master Thesis. In this preface I want to emphasize my gratitude of how Dr. Lemmen helped me at one critical moment in the Master Thesis process. During the official holidays of Dr. Lemmen, I noticed that a wrong version was reviewed, despite his holidays Dr. Lemmen reviewed the right version the day after.

I would also like to thank my (grand)parents for providing me with their help on multiple aspects. The times that I was at the bottom of my confidence of finishing the Master Thesis in time, they always found the right words to keep me going. I can honestly say, that I could not have finished both my Bachelor and Master studies without their unconditional love and support.

I considered writing the Master Thesis as really challenging. However, it was a meaningful experience to explore the academic field and improve my academic writing. I am happy to present, the result of 5 months of determination, countless hours behind computers, blood, sweat and tears. I am really proud of what I have accomplished and I hope you will enjoy reading this Master Thesis.

ABSTRACT

Using a sample of 3045 Chinese firms over the period between June 1995 and December 2015, this study investigates whether systematic risk factors (i.e. market, size, value, momentum, profitability and investment factors) are priced differently over various horizons ranging from 1 month to 5 years. This is done by forming portfolios based on pre-ranked betas for each of the six factors and for each horizon examined. The results indicate that when looking at both excess returns and alphas relative to a benchmark (which is the Fama-French five-factor model + momentum), there is dispersion observable for all the systematic risk factors across horizons. Adding illiquidity and opacity as control variables to the regression does not explain the dispersion in how the systematic risk factors are priced, but generally widens the dispersion over investment horizons.

Keywords: Asset pricing, horizon, risk factors, international financial markets

JEL Classification: G12, G15

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CHAPTER 1: Introduction

There is a consensus among academics on the existence of certain macroeconomic variables that are classified as systematic priced risk factors. Risk factors are defined as characteristics relating to a group of securities that is important in explaining their return and risk. Such factors have historically earned a risk premium and represent exposure to systematic sources of risk. However, a shortcoming in the vast majority of prior academic research regarding systematic risk factors, is that they solely focuses on a single-period analysis. Whereas, in practice different investors have various horizons. The importance of incorporating various horizons in the research to the pricing of systematic risk factors is significant, because recent literature showed that systematic risk factors can be priced differently over time.

1.1 Research question

This study will incorporate various horizons and tests whether there is dispersion in the pricing of systematic risk factors over those horizons. In the study six equity systematic risk premia factors are examined: market, value, size, momentum, profitability and investment. The abovementioned factors will be priced at various horizons ranging from 1 month to 5 years (60 months). This study will be performed by looking at data from the equity market in the People's Republic of China (henceforth mentioned as China). The main question that this study will try to answer is the following:

''Are there systematic risk factors that can explain the cross-sectional return at one horizon, where it does not at another horizon?''

If there is indeed dispersion in how systematic risk factors are priced over various horizons two control variables will be introduced that might explain this dispersion. These control variables are illiquidity and opaqueness (transparency).

1.2 Scientific Relevance

Until recently, most research of the pricing of systematic risk factors has been based on an one-period horizon, neglecting other horizons. There is an upcoming stream of literature that does incorporate different horizons in their study for the pricing of systematic risk factors (see e.g., Kamara, Korajczyk, Lou, and Sadka, 2015; Gilbert, Hrdlicka, Kalodimos, and Siegel, 2014). However, horizon pricing is still a relatively recent topic, wherein there is still a lot of room for additional research.

This study is - to my knowledge - the first to study multiple systematic risk factors over different horizons in China. China is chosen as the reference country, because China is the biggest emerging market, meaning a country that is in the process of rapid growth and development, with lower per capita incomes, less mature capital markets and with a lower market liquidity relative to a developed market. It might be interesting to see whether the results from this study differ from the results that are previously found in developed markets. There are more distinctive characteristics that distinguish the Chinese stock market from other countries (e.g. weak legal framework, heavy government involvement such as regulation and central bank intervention, and a relatively high level of state owned enterprises). Demirer & Kutan (2006) hypothesize that due to the abovementioned distinctive characteristics investors are more likely to act like speculators and follow the market consensus. Therefore, traders in China tend to behave more like positive feedback traders: they sell when prices fall and buy when prices rise. Another distinctive characteristic of the Chinese stock market is the fact that the Chinese stock market is fuelled by undereducated and inexperienced traders. New data from the China Household Finance Survey, a large-scale survey of household income and assets headed by Professor Li Gan of Southwestern University of Finance and Economics, shows that two thirds of new equity investors excited the education system by middle school (Orlik, 2015). As a result of these distinctive characteristics, trading behaviour in Chinese markets may differ significantly from other markets.

1.3 Social Relevance

Hence, besides the relevance of being the first study, outcomes of this study can be socially relevant as well. For example, it can be used in the relative new approach of investing: factor investing. Factor investing describes the investment process that aims to harvest risk premia through exposure to systematic risk factors. Factor investing has become an investment strategy that is a more widely used approach for various forms of financial institutions like hedge funds, mutual funds, pension funds etc. Incorporating horizons to price risk factors can give important implications for the implementation of the factor investing approach. Pension funds, for instance, are established to invest the employees' retirement savings, and therefore expect to grow over the long term. Therefore, for pension funds it is more likely to invest in systematic risk factors that are priced in the long run. The opposite would apply for financial institutions such as hedge funds and mutual funds.

However, China lacks in the number of investors with long-term investment horizons, such as pension funds, which may also explain the existence of so many speculators in China. If several systematic risk factors appear to be priced over the longer term, increasing the participation of long-term investors (e.g. experienced foreign pension funds, insurance companies, and long-term investment funds in domestic markets) seems like a good way to make capital markets more efficient (Pettis, 2013). China has already made their first steps towards increasing the participation of long-term investors by implementing the Qualified Foreign Institutional Investor program, wherein China allows global institutional investors, on a selective basis, to invest in its capital markets.

1.4 Preliminary results

Using a portfolio analysis, the results show that there is dispersion in how the six systematic risk factors used in this study are priced at different horizons. This is done by obtaining the spread in excess returns and alphas (relative to the Fama-French five-factor model + momentum) between the portfolio decile wherein stocks have the most exposure to a particular factor and the portfolio decile wherein stocks have the least exposure to a particular factor. The excess returns appear to be especially significant at relative intermediate-term horizons for the market, value and profitability factors. However, despite the excess returns being significant, they are also negative. This means that an intermediate horizon investor that purely looks at generating excess returns, may consider a strategy wherein it takes a long position in stocks with high exposure to the market/value/profitability factor and a short position in stocks with low exposure to the market/value/profitability factor as unattractive. The size factor has significant positive excess returns for all horizons, nevertheless, the short horizons are most significant. Therefore, the size factor seems to be priced explicitly at short-term horizons. The momentum factor exhibits significant excess returns for all horizons. Meanwhile, the investment factor has is just priced significantly and positively over longer horizons.

When looking at alpha the market and value factors seem to be priced over relatively longer horizons, implying the more significant coefficients at longer horizons. The alphas are positive at longer horizons for the market and value factor. A long-term horizon investor that purely looks at beating the benchmark (FF5-factor model + momentum) and generating alpha may consider a strategy where it takes a long position in stocks with high exposure to the market/value factor and a short position in stocks with low exposure to the market/value factor as attractive. The size factor has significant alphas over the 1 month and 36 months horizons, it is therefore hard to draw a conclusion on what term the size factor is priced. The same applies to the momentum factor that has significant alphas for the 1, 3, 12, and 48 months horizons. However, with the 1 and 3 months horizon being priced it seems that the momentum factor is priced at short-term horizons. The profitability factor has positive alphas for all horizons. The investment factor has significant alphas for short and long-term horizons. Therefore, the investment factor is priced at short and long-term horizons, however not for intermediate horizons.

With the aim to explain the dispersion in returns over various horizons two control variables are added. The first is illiquidity measured by the Amihud illiquidity measure (2002), the second is opacity measured by the variance in discretionary accruals. Both control variables have no significant impact in the explanation of the dispersion in the pricing of the systematic risk factors over various horizons.

1.5 Outline of the paper

The remainder of the paper is organized as follows. Chapter 2 provides a literature review in which the risk factors are introduced and the pricing of the systematic risk factors over different horizons are discussed in an academic context. Chapter 3 describes the data-gathering process, provides information how respectively the factors and betas are constructed, and introduces the proxies for the control variables. Chapter 4 discusses the results. It looks for each individual systematic risk factor whether there is dispersion in the pricing over various horizons, and whether this dispersion can be explained by two control variables: illiquidity and opacity. Chapter 5 will give a brief summary of the results and discusses the limitations of this paper and provides possible directions for future research.

CHAPTER 2: Literature Review

2.1 Introduction of Risk Factors

The mean-variance portfolio theory developed by Markowitz (1952, 1959) has been considered as the cornerstone for the many asset pricing models that are known nowadays. The mean-variance portfolio theory of Markowitz states that investors select a portfolio at t-1 that produces a random return at t. In the model it is assumed that investors are risk averse, that investors maximize one-period expected utility, and that investors care only about the expected return and the variance of return, where the expected return is desirable and variance of return an undesirable.

The Capital Asset Pricing Model (henceforth mentioned as CAPM) of Sharpe (1964), Lintner (1965), and Black (1972) builds on the mean-variance portfolio theory, and is considered as the first asset pricing model with clear testable predictions about risk and return (Fama & French, 2004). The central prediction of the CAPM is that the market portfolio of invested wealth is mean-variance efficient in the sense of Markowitz (1952, 1959). The efficiency of the market portfolio implies that (i) expected returns on securities are a positive linear function of their market betas (the slope in the regression of a security's return on the market's return), and (ii) market betas suffice to describe the cross-section of expected returns (Fama & French, 1992). Hence, with the market factor (MKT) the CAPM introduced the first systematic risk factor that tried to capture the excess returns of securities.

Many authors criticized the CAPM, by arguing that the cross-section of average returns on stocks showed little relation to the market betas (see e.g., Reinganum, 1981; Breeden, Gibbons, and Litzenberger, 1989). Therefore, several other macroeconomic variables have been proposed in the asset pricing literature as systematic priced risk factors.

The first extension on the CAPM model came from the work of Fama & French (1993), who have proposed a three-factor model. The model says that expected return on a portfolio in excess of the risk free rate is not just explained by the market factor (i.e. the excess return on a broad market portfolio), the expected return is as well explained by the sensitivity of its return to two other factors: (i) size, the difference between the return on a portfolio of small stocks and the return of a portfolio of large stocks (SMB, small minus big); and (ii) value, the difference between the return on a portfolio of high-book-to-market stocks and the return on a portfolio of low-book-to-market stocks (HML, high minus low).

In reaction to the three-factor model proposed by Fama and French (1993), Carhart (1997) stresses the three-factor model inability to explain cross-sectional variation in momentum-sorted portfolio returns. Therefore, he constructs a four-factor model using Fama and French three-factor model plus an additional factor capturing Jegadeesh and Titman's (1993) one-year momentum anomaly. This momentum factor is the difference between the return on a portfolio of stocks that have performed well over the prior year and the return on a portfolio of stocks that performed poorly over the prior year.

Besides Carhart (1997) there was more criticism regarding the three-factor model of Fama & French (1993). For example, Novy-Marx (2013), Titman, Wei, and Xie (2004), and others state that the three-factor model is an incomplete model for expected returns, because the three factors miss much of the variation in average returns related to profitability and investment. Therefore, Fama & French (2015) add profitability and investment to the three-factor model. The profitability factor displays the difference between returns on diversified portfolios of stocks with robust and weak profitability (RMW), and the investment factor displays the difference between returns on diversified portfolios of the stocks of low and high investment firms, which the authors call conservative and aggressive (CMA).

2.2 Incorporating Horizons

In single-period models, like the CAPM, it is assumed that investors do only care about the mean and variance of their one-period investment return. The theory remains silent about the investment horizons of investors. Where, in practice, investors have different investment horizons. For instance, leveraged quantitative hedge funds are more likely to have short investment horizons in order to reap benefits to deliver returns from arbitrage opportunities, compared to pension funds, who are emerged in more responsible investment strategies to generate stable growth on the long term. However, it is not just the CAPM that remains silent about the investment horizons, in by far the majority of the asset pricing tests the horizon is taken as one month and returns are measured over monthly intervals (Brennan, and Zheng, 2012). This while the difference in investment horizons across different investors or investment institutions is of significant importance, because there could be a change in risk dynamics across different horizons.

A recent stream of literature stress the importance of incorporating different horizons in their research to examine the risk of risk factors. Kamara, Korajczyk, Lou, and Sadka (2015), for example, examine whether systematic risk factors can explain the differences in cross-sectional returns for one horizon while the risk measured over another horizon does not. The authors find that the liquidity risk factor seems to capture a short-horizon risk, implying that liquidity risk is priced on the short term. However, at longer horizons the risk premium of the liquidity beta falls substantially to insignificant levels. In contrast, the market, and the value factors seem to behave like intermediate-horizon systematic risk factors. Market risk is priced at the 6 and the 12 months horizon, while the value factor is priced at the 2 year and 3 year horizon. For the momentum and the size risk factors no significant values are found by the authors, from which they insinuate that both risk factors are not able to explain excess returns for any of their formulated horizons.

Gilbert, Hrdlicka, Kalodimos, and Siegel (2014) test whether the CAPM is able to explain the differences in cross-sectional returns. They use both daily and quarterly return data over the previous five years to estimate lagged CAPM-betas. They then sort stocks into five quantile portfolios based on the difference between daily and quarterly CAPM-betas. The alphas are than estimated by going long in portfolio 5 and short in portfolio 1. It appears that at the daily frequency, the alphas (i.e. the pricing error relative to the CAPM) for almost all portfolios are positive and significantly different from zero (except for the top decile portfolio which is insignificant). At the quarterly frequency, the alphas are insignificant and generally lower relative to the daily frequency. This translates in a significant difference in the alphas between daily and quarterly frequencies. The results tell that CAPM can explain excess returns at the quarterly frequency, due to its insignificant alphas. However, at the daily frequency the CAPM cannot fully explain excess returns and the market factor seems to outperform the CAPM benchmark. This suggest that at daily frequency, taking exposure to the market factor delivers a higher alpha and is therefore positively priced. Short-term investors can reap benefits from investment strategies wherein it takes a long position in high exposure to the market factor.

Boons and Tamoni (2016) highlight the importance to account for horizon-specific exposures to macroeconomic risk when connecting the prices to the real economy. The authors' test at which horizon macroeconomic growth and volatility risk provide the strongest determination of asset returns. Boons and Tamoni show that long-term risk, measured as the covariance between four year returns with innovations in economic growth and volatility with matching half-life (i.e. the authors scale the returns based on how far in the past this returns occurred, for each day/month the returns get weighted by a multiplier of a number less than 1. The half-life is the sum of all past returns divided by the sum of the weights, which gives a weighted average of the past returns), is priced. Whereas, short-term risk appears not to be priced. Therewith, the results in their study strongly support using long-horizon betas to measure systematic risks in asset returns.

Kang et al. (2002) examine the behaviour of stock returns in the Chinese stock market. They try to find momentum (i.e. past winners are bought and past losers are shorted) profits and contrarian momentum (i.e. past losers are bought and past winners are shorted) profits at different holding periods. The authors find statistically significant profits for the momentum strategy at the intermediate-term horizon and statistically significant profits for the contrarian momentum strategy at the short-term horizon. The contrarian momentum profits appear more distinct, the authors explain this due to the dominance of overreaction to firm-specific information. This excessive overreaction can be attributed due to the dominance of individual investors in the Chinese stock market, the lack of reliable information on firms, and the dominance of speculators in the Chinese stock market who favour to create a bullish sentiment on small stocks.

2.3 Control Variables

The studies of Kamara et al. (2015), Gilbert et al. (2014), Boons and Tamoni (2016), and Kang et al. (2002) infer coinciding results regarding their findings that systematic risk factors are priced differently over various horizons. For example, Kamara et al. find that market and value factor are just priced at intermediate horizons, where the liquidity factor is priced at the short-term horizon. The existing literature provides us with explanations why there is dispersion in the way various horizons are priced.

2.3.1 Opacity

One often mentioned explanation is the opaqueness of firms. Gilbert et al. (2014) pose that additional risk arises because the systematic news of opaque firms is revealed with a delay. In a situation where an opaque firm receives better than expected systematic news, opaque firms have higher risk and hence higher expected returns. However, due to the delay in the revealing of the better than expected systematic news, the short-term realized returns are lower than the expected returns. In contrast, for transparent firms the revelation of the impact of systematic news is immediate. Therefore, the riskiness and expected returns does not vary from realized returns with either good or bad systematic news. Transparent firms generally make up for most of the market, the realized returns of opaque firms co-move less with the market on shorter term horizons, and the opposite being true for realized returns of transparent firms, that co-move more with the market on shorter term horizons. This dampens the betas for opaque firms and enlarges the betas for transparent firms at shorter horizons. These differences in betas are expected to lead to differences in alphas. For example, when the market is going down alphas are positive for opaque firms and negative for transparent firms at short horizons and zero for both transparent and opaque firms at the longer term horizons.

The opacity effect is expected to be especially pronounced in the Chinese stock market, since one of the biggest problems in China facing investors is the transparency of Chinese stocks. Reporting requirements for listed Chinese companies are neither well developed and less comprehensive in comparison to the stock markets of more developed countries (Demirer & Kutan, 2006).

2.3.2 Illiquidity

Amihud and Mendelson (1986) provide an explanation based on liquidity. They model a market where rational traders differ in their expected holding periods and where assets have different bid-ask spreads. Their equilibrium has the following characteristics: (i) market-observed average returns are an increasing function of the spread; (ii) the asset return of equity holders, net of trading costs, increase with a higher bid-ask spread (due to investors demanding a higher liquidity premium); (iii) there is a clientele effect, whereby stocks with higher spreads are held by investors with longer holding periods; and (iv) due to the clientele effect, returns on higher-spread stocks are less spread-sensitive. The model of Amihud and Mendelson (1986) implies that the dispersion between short-term and long-term risk could be due to liquidity.

Illiquidity is expected to be especially pronounced in the Chinese stock market, because the Chinese stock market is dominated by positive feedback traders. When positive feedback traders dominate the market, market prices are liable to be unstable and the market may become one-sided and illiquid. A reduction in the price of an asset causes the trader to sell. This results in prices falling further and more selling. The opposite applies when asset prices increase which causes traders to buy. This results in the price of the asset increasing further and more buying (Hull, 2015).

In Table 1 there is an overview of the literature that is most relevant for this research.

Table 1: This table contains a literature table, which gives a brief summarization of all the main findings that are relevant for the research.

Literature Table

Authors	**Region**	**Time period**	**Result**
Fama and French (1992)	United States	1962 - 1989	Significant evidence that size and value factors explain cross-sectional variation in excess returns.
Jegadeesh and Titman (1993)	United States	1965 - 1989	Strategy of buying stocks that performed well in the past and sell stocks that performed poorly, is a profitable strategy that are not due to their systematic risk or to delayed stock price reactions to common factors.
Carhart (1997)	United States	1962 - 1993	Consistent with Jegadeesh and Titman (1993), Carhart also found that momentum strategies are profitable, and he added the momentum factor to the existing three-factor model of Fama and French (1992).
Fama and French (2015)	United States	1963 - 2013	Finds that adding profitability and investment factors leads to a better performing model in capturing the cross-sectional variation in excess returns.
Kamara, Korajczyk, Lou, and Sadka (2015)	United States	1962 – 2013	Finds that the liquidity, market, value, size and momentum factors are priced differently over different time horizons.
Boons and Tamoni (2016)	United States	1962 - 2011	The results favour using long-horizon betas to measure macroeconomic risk in asset returns.
Gilbert, Hrdlicka, Kalodimos, and Siegel (2014)	United States	1969 - 2010	Shows that CAPM works better at longer horizons, and therefore for low-frequency traders. The results also indicate that the dispersion of beta can be explained by the opaqueness or transparency of a firm.
Amihud and Mendelson (1986)	United States	1960 – 1979	Their model implies that the difference in risks for short and long-term horizons can be explained by liquidity.

CHAPTER 3: Data & Methodology

3.1 Sample and criteria

The sample consists of Chinese companies listed on the two main stock exchanges in China: the Shanghai Stock Exchange and the Shenzhen Stock Exchange, and a minority of Chinese firms listed on three stock exchanges outside China: the Hong Kong Stock Exchange, the Singapore Stock Exchange and the Taiwan Stock Exchange. The firms' fundamentals are collected from Compustat Global Fundamentals Annual. The monthly stock prices, the risk free rate, turnover per value, and the index constituents are obtained from Datastream (see Appendix A for description of all variables used). The sample runs from June 1995 to December 2015. The proxy for the risk free rate is the China 3-months' time deposit rate, it was difficult to find a proxy with a time series of length that did stroke with the period investigated, the China 3-months' time deposit therefore seemed the best fit to satisfy this condition.

To overcome issues with the data several criteria were applied. Firstly, penny stocks (i.e. stocks with a price below 1 Yuan) were excluded. This is because, penny stocks are mostly neglected by financial institutions. Due to their low price, penny stocks have a high price sensitivity to the level of trading, which makes them highly speculative. Secondly, also the fundamentals that were reported in another currency than the Chinese Yuan, which is the main currency for China, were excluded. After these criteria were applied the final dataset contains of 3045 firms.

3.2 Returns

The monthly stock prices for the Chinese firms and the risk free rate can be used for calculating the monthly excess returns. This can be done by using the following formula:

$$R_{i,t} = \frac{p_{i,t} - p_{i,t-1}}{p_{i,t-1}} - rf_{i,t},$$

Where $R_{i,t}$ is the excess return for firm *i* at time *t*, $p_{i,t}$ is the closing price of firm *i* at time *t* adjusted for dividends, $p_{i,t-1}$ is the closing price of firm *i* at time t-1 adjusted for dividends, and $rf_{i,t}$ is the risk free rate of firm *i* at time *t*. The excess returns will be used in creating the market, size, value, momentum, profitability, and investment factors.

3.3 Creating Factors

To create the abovementioned factors the methods described on the website of Ken French[1] were followed. The explanations how to define and calculate the factors are also employed in Fama & French (1992, 2015). The fundamentals and monthly prices are used to define the variables that later will be

[1] I thank Ken French, for the extensive description of the variables, and how the factors are formed. http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

used to construct the factors. The market equity is the monthly price times the number of shares outstanding. The book equity is the book value of stockholders' equity plus balance sheet deferred taxes and investment tax credit. With the market and book value defined, it is possible to define the book-to-market ratio, which is the book value for the fiscal year ending in calendar year t-1, divided by market equity at the end of December of t-1. The operating profitability ratio is defined as the annual revenues minus the cost of goods sold interest expense, and the selling, general, and administrative expenses divided by book equity for the last fiscal year end in t-1. The investment ratio is the change in assets from the fiscal year ending in year t-2 to the fiscal year ending in year t-1.

At the end of June for each year, stocks are sorted and allocated to their respective portfolios This allocation is done based on four variables, respectively market equity (size), market-to-book ratio (value), operating profitability ratio (profitability) and investment ratio (investment). In contrast, the allocation based on momentum is done for each month of each year. To obtain the factors Fama & French use a double sorting approach.

The size factor (SMB – small minus big) is constructed by first use two value-weighted portfolios on size (i.e. split the sample in the 50% stocks of the smallest companies and the 50% stocks of the biggest companies), and use three value-weighted portfolios over the two size portfolios formed on the book-to-market ratio. Which provides six (2x3) value-weighted portfolios formed on size and book-to-market:

$$
\begin{aligned}
SMB_{(B/M)} = {}^{1}/_{3} * (&Small\ Value + Small\ Neutral + Small\ Growth) \\
&- {}^{1}/_{3} * (Big\ Value + Big\ Neutral + Big\ Growth)
\end{aligned}
$$

After, the double sorting approach is also used to create six value-weighted portfolios formed on size and momentum, size and profitability, and size and investment.

$$
\begin{aligned}
SMB_{(MOM)} &= {}^{1}/_{3} * (Small\ Up + Small\ Medium + Small\ Down) \\
&\quad - {}^{1}/_{3} * (Big\ Up + Big\ Medium + Big\ Down) \\
SMB_{(OP)} &= {}^{1}/_{3} * (Small\ Robust + Small\ Neutral + Small\ Weak) \\
&\quad - {}^{1}/_{3} * (Big\ Robust + Big\ Neutral + Big\ Weak) \\
SMB_{(B/M)} &= {}^{1}/_{3} * (Small\ Conservative + Small\ Neutral + Small\ Aggressive) \\
&\quad - {}^{1}/_{3} * (Big\ Conservative + Big\ Neutral + Big\ Aggressive)
\end{aligned}
$$

The size factor is then simply obtained by taking the average return of the twelve small stock portfolios (e.g. small value, small neutral, small growth, small robust, etc.) minus the average return of the twelve big stock portfolios (e.g. big value, big neutral, big growth, big robust, etc.).

$$SMB = {}^{1}/_{4} * \left(SMB_{(B/M)} + SMB_{(MOM)} + SMB_{(OP)} + SMB_{(B/M)}\right)$$

A similar way is used to calculate the value factor (HML – high minus low), the profitability factor (RMW – robust minus weak) and the investment factor (CMA – conservative minus aggressive). The six value-weighted portfolios formed on size and book-to-market, size and profitability, and size and investment were calculated to create the three abovementioned systematic risk factors.

$$\begin{aligned} HML &= {}^{1}/_{2} * (Small\ Value + Big\ Value) \\ &\quad - {}^{1}/_{2} * (Small\ Growth + Big\ Growth) \\ RMW &= {}^{1}/_{2} * (Small\ Robust + Big\ Robust) \\ &\quad - {}^{1}/_{2} * (Small\ Weak + Big\ Weak) \\ CMA &= {}^{1}/_{2} * (Small\ Conservative + Big\ Conservative) \\ &\quad - {}^{1}/_{2} * (Small\ Aggressive + Big\ Aggressive) \end{aligned}$$

In determining the value, profitability and investment factors, the neutral portfolios are neglected. The value factor is obtained by taking the average return of two value portfolios minus the average return on two growth portfolios. Similarly, the profitability and investment factors are determined by taking the average return of two robust/conservative portfolios minus the average return on two weak/aggressive portfolios. Momentum is defined as the return of a company over the prior 12 months excluding the most recent month. To construct the momentum factor, six-value weighted portfolios are formed on size and momentum. The neutral portfolios are again neglected, and the momentum factor is constructed by taking the average return on two highest momentum portfolios minus the average return on two low momentum portfolios.

$$\begin{aligned} UMD &= {}^{1}/_{2} * (Small\ Up + Big\ Up) \\ &\quad - {}^{1}/_{2} * (Small\ Down + Big\ Down) \end{aligned}$$

The construction of the market factor is somewhat more intuitive. It is simply the difference between the percentage change in the market index from the stock exchange where the company is listed minus the risk free rate. Since in the sample companies are listed on five different stock exchanges, there are also five market indices used to determine the market factor.

3.4 Horizon factors

The monthly factors can be used to determine factors of horizon *k*. The method to construct factors of horizon *k* is similar to Kamara et al. (2015). First it is important to note that each of the factors represent an excess return portfolio. For example, the market factor is the excess return of the market index over the risk free rate and the size factor is the excess return of a small company portfolio over a big company portfolio. Similarly, the *k*-month factors are the excess return in the *k*-period of a long portfolio over a short portfolio. For example the size factor of horizon *k* is the *k*-period return of small company portfolios minus the *k*-period return of big company portfolios. This can be denoted with the following formula:

$$f_{k,t}^{SMB} = \prod_{k=0}^{k-1}(1 + r_{1,t-k}^{s}) - \prod_{k=0}^{k-1}(1 + r_{1,t-k}^{b}) ,$$

where $k_{1,t}^{s}$ is the monthly return for the small company portfolio at time *t*, and $k_{1,t}^{b}$ is the monthly return for the big portfolio company at time *t*. The formula will be applied to calculate the size factors for the 1, 3, 6, 9, 12, 18, 24, 36, 48, 60 months horizons. Note that the same formula can be used for determining the other systematic risk factors at various horizons as well.

3.5 Betas

After the factors are obtained for different horizons, portfolios are formed based on pre-ranked betas for the six systematic risk factors at the end of each month for each firm. Betas are estimated for various horizons by using overlapping *k*-months returns and factors in the five years prior to the portfolio-formation month. The beta estimation requires at least 24 observations for both the factors and the returns. For example, the beta of the market factor is calculated as follows:

$$\beta_k^{MKT} = \frac{Cov\ (r_{k,t}^{e}, f_{k,t}^{MKT})}{Var(f_{k,t}^{MKT})}$$

The pre-ranked betas will be used in an portfolio analysis, where the pricing of a factor at a particular horizon will be derived by taking a long position in the top decile portfolio, and a short position in the bottom decile portfolio. The top decile portfolio represents the 10% of stocks with the biggest exposure to a particular factor, meaning the 10% stocks which returns co-move most with the factor. The bottom decile portfolio represents the 10% of stocks with the lowest exposure to a particular factor, meaning the 10% stocks which returns co-move least with the factor.

3.6 Illiquidity

Two control variables are introduced that might explain why dispersion in the pricing of the factors at various horizons can be observed. The first control variable is illiquidity. However, illiquidity is an elusive concept, and cannot be observed directly. Therefore, a proxy needs to be found that does well in capturing illiquidity. Numerous of proxies for illiquidity have been proposed in the literature. The most used proxy is Amihud’s illiquidity measure (Amihud, 2002), which is defined as the average ratio of the daily absolute return to the dollar trading volume on that day. The Amihud illiquidity measure has two main advantages over other measures: 1) the Amihud illiquidity measure has a simple construction and it relies on the wide availability of data for its computation; 2) the measure has a strong positive relation to expected stock return. The Amihud illiquidity measure can be defined as follows:

$$ILLIQ_{iy} = 1/D_{iy} \sum_{t=1}^{D_{iy}} \left|R_{iyd}\right| /VOL_{iyd},$$

where $1/D_{iy}$ is the number of days for which data was available for stock *i* in year y, $\left|R_{iyd}\right|$ is the return on stock *i* on day *d*, and VOL_{iyd} is the respective daily volume in dollars. However, since monthly returns are used in the sample of this study, the Amihud illiquidity measure can be rewritten in such a way that it can applied it on the data.

$$ILLIQ_{iy} = 1/M_{iy} \sum_{t=1}^{M_{iy}} \left|R_{iym}\right| /VOL_{iym},$$

where $1/M_{iy}$ is the number of months for which data was available for stock *i* in year y, $\left|R_{iym}\right|$ is the return on stock *i* in month *m*, and VOL_{iym} is the respective monthly volume in Yuan (Chinese currency).

3.7 Opacity

The other control variable is opacity, or the transparency of financial disclosure of a firm. Same as illiquidity, also opacity is a difficult variable to grasp. Gilbert et al. (2014) try to explain dispersion in the pricing of the CAPM (market factor) at daily return data and quarterly return data by looking to opacity as well. One of the measures they use to proxy opacity is the variance in discretionary (abnormal) accruals. Discretionary accruals are non-mandatory expenses/assets which are recorded within the accounting system but still need to be realized. According to Healy (1996), discretionary accruals are the accruals that can be influenced by the management. So for example, a manager can influence earnings by choosing a general accepted procedure defined by accounting standard-setting bodies, that maximizes the earning for that particular year. So discretionary accruals can be used by managers to manipulate earnings. High discretionary accruals indicate that managers manipulate accruals in such a way that the earnings in the accounting year are higher than the actual earnings, and low discretionary accruals indicate that managers manipulate accruals in such a way that earnings in the accounting year are lower than the actual earnings. Manipulating accruals so that earnings are lower than the actual earnings is done to carry the earnings over to the following years. The question that remains is, how does the variance of discretionary accruals relate to the opaqueness of a firm. Gilbert et al. (2014) explain that the more managers make use of accruals to manage the firms' earnings, the harder it will be for investors to understand the impact of systematic news on the value of the firm. A firm that has a high variance of discretionary accruals is more opaque in the sense that investors require more information and hence more time to price the impact of news because, the production function is more difficult to discern.

In the academic literature there is a variety of models that try to measure discretionary accruals. The models that will be briefly discussed are: the Healy model, the DeAngelo model, the Jones models, and the modified-Jones model. These models are discussed in an attempt to give a better understanding of why a particular model that measures discretionary accruals is chosen in this study. The Healy model (1985) does measure non-discretionary accruals (note: the difference between accruals and non-discretionary accruals are the discretionary accruals), by comparing the mean of total accruals scaled by lagged total assets. In the Healy model the non-discretionary accruals follow a mean-reverting process. The DeAngelo model (1986) differs from the Healy model, in that it uses the total accruals of the previous period to estimate non-discretionary accruals, and in that the non-discretionary accruals follow a random process. The Jones model (1991) relaxes the assumption that was made in the models of Healy and DeAngelo, and states that non-discretionary accruals are constant. The Jones model attempts to control the non-discretionary accruals for a changing economic environment. Also, the Jones Model assumes that revenues are non-discretionary, which implies that the Jones model removes a part of the discretionary accruals, or the accruals that can be managed. Dechow et al. (1995) did make a modification to the Jones model by correcting the Jones model for the error when measuring discretionary accruals for when discretion is exercised over revenue recognition, this model is known as the modified-Jones model. To determine the discretionary accruals in this paper, the modified-Jones model will be used. The advantages of the modified-Jones model is that it is easy to implement, and a lot of variables are used to determine the discretionary accruals. The discretionary accruals according to the modified-Jones model are calculated by obtaining the regression residuals of the following regression:

$$TA_{it} = \alpha_0 + \alpha_1 (1/Assets_{\,it-1}) + \alpha_2 (\Delta REV - \Delta REC)_{it} + \alpha_3 PPE_{it} + \epsilon_{it},$$

where TA_{it} are the total accruals of firm *i* at time *t*, $Assets_{\,it-1}$ are the assets of firm *i* from the previous period, $(\Delta REV - \Delta REC)_{it}$ is the difference in the change of revenues and the change of receivables of firm *i* at time *t*. and PPE_{it} is the gross property, plant and equipment of firm *i* at time *t*. The regression is performed by industry. After the discretionary accruals are computed, the variance of the discretionary accruals is taken for each firm in the sample.

CHAPTER 4: Results

In this section I will discuss the results and try to determine whether risk factors are priced differently over various horizons. However, to get a better overview of the data it is relevant to first look at the descriptive statistics of the sample used in this study.

Table 2 reports that on average a Chinese firm has a monthly excess return of 1.73% over the period of June 1995 to December 2015. Over the same period China experienced huge economic and industrial growth, and also the stock markets in China grew enormously. This lead to the excess returns being positive on average for Chinese firms. Table 2 also reports the average levels of illiquidity and the variance of discretionary levels, so that the levels of illiquidity and the variance of discretionary accruals at the different deciles, that will be reported in a later stage of the paper, are comparable.

Table 2: This table shows the average levels of the monthly excess returns, illiquidity and the variance in discretionary accruals over the entire sample of 3045 Chinese firms. The sample period is June 1995 – December 2015.

Descriptive Statistics

Variable	Mean	Standard Deviation
Excess Return	1.73%	15.56%
Illiquidity	0.4343	0.8762
Variance of Discretionary Accruals	0.0070	0.0084

4.1 Dispersion in Excess Returns

Table 3 displays the dispersion in excess returns for six systematic risk factors. The coefficients represent the monthly excess return on a portfolio that goes long in the 10% stock portfolio with the highest exposure over n-months to a particular risk factor, and goes short in the 10% stock portfolio with the lowest exposure over n-months to a particular risk factor. This is done to create an equity market neutral position. So for example the coefficient of the market factor at 12 months ($\beta_{12}^{\mathrm{MKT}}$) is -2.99. This means that a strategy wherein a long position is taken in a portfolio that represent the 10% stocks with the highest exposure to the market factor over the last 12 months, and a short position is taken in a portfolio that represent the 10% stocks with the lowest exposure to the market factor over the last 12 months, does deliver an excess return of -2.99%. I will discuss how the systematic risk factors are priced at different horizons by looking at each systematic risk factor individually.

4.1.1 Market Factor

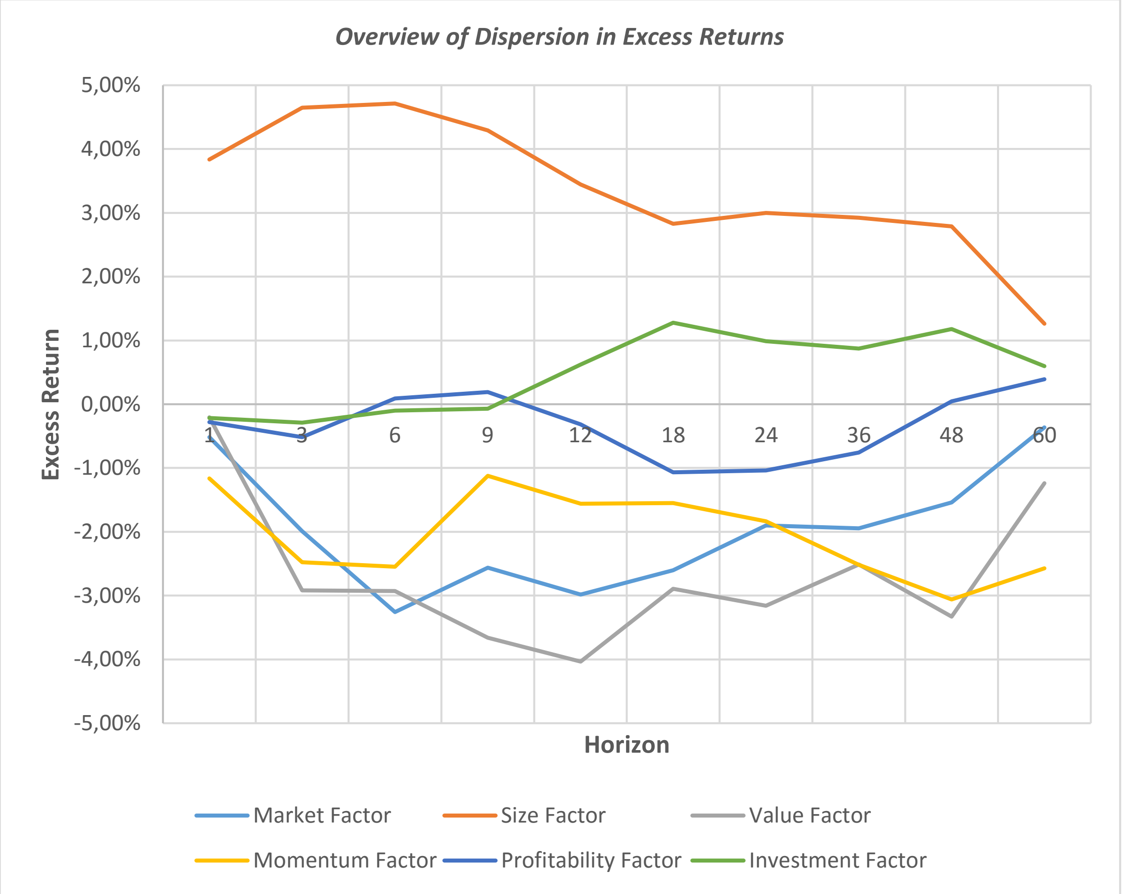
Table 3 shows that the market factor exhibits an insignificant negative excess return at the 1 month horizon. At the 3, 6, 9, and 12 months horizons the excess return level gradually decreases and excess

Table 3: At the beginning of each month in year *y*, stocks are sorted in 10 portfolios based on each of the six k-month pre-ranked betas (*e.g.* β_k^{MKT}, β_k^{SMB}, β_k^{HML}, β_k^{UMD}, β_k^{RMW}, β_k^{CMA}), where *k* is the horizon. The return spread is then calculated by subtracting the excess return of the bottom decile portfolio from the excess return of the top decile portfolio. For example, the column labelled β_k^{MKT} represents the spread in excess returns for a portfolio that is long in 10% of the stocks with the highest exposure to the market factor and short 10% of the stocks with the lowest exposure to the market factor. I report the excess returns for horizons (*k*) of 1, 3, 6, 9, 12, 18, 24, 36, 48, and 60 months. The coefficients represent monthly excess returns. The corresponding t-statistics are reported in brackets after the coefficients. * shows whether the coefficients are significant at a 1%-level. The sample period is June 1995 – December 2015.

Overview of Dispersion in Excess Returns

Excess Return Horizon (k)	$\boldsymbol{\beta_k^{MKT}}$		$\boldsymbol{\beta_k^{SMB}}$		$\boldsymbol{\beta_k^{HML}}$		$\boldsymbol{\beta_k^{UMD}}$		$\boldsymbol{\beta_k^{RMW}}$		$\boldsymbol{\beta_k^{CMA}}$	
1	-0.51	[-1.83]	3.83*	[8.06]	-0.21	[-0.81]	-1.16*	[-3.58]	-0.28	[-0.93]	-0.21	[-0.80]
3	-1.99*	[-5.43]	4.65*	[10.20]	-2.92*	[-6.02]	-2.48*	[-6.75]	-0.52	[-1.63]	-0.29	[-0.99]
6	-3.26*	[-8.25]	4.71*	[10.48]	-2.93*	[-6.69]	-2.55*	[-6.47]	0.09	[0.34]	-0.10	[-0.35]
9	-2.56*	[-7.55]	4.29*	[10.52]	-3.66*	[-8.47]	-1.12*	[-4.12]	0.19	[0.59]	-0.07	[-0.28]
12	-2.99*	[-8.16]	3.44*	[9.28]	-4.03*	[-9.19]	-1.56*	[-5.50]	-0.32	[-1.37]	0.62	[1.94]
18	-2.60*	[-7.78]	2.83*	[7.83]	-2.89*	[-8.42]	-1.55*	[-5.57]	-1.07*	[-3.59]	1.28*	[4.14]
24	-1.90*	[-6.31]	3.00*	[7.96]	-3.16*	[-8.32]	-1.83*	[-6.41]	-1.04*	[-3.29]	0.99*	[3.11]
36	-1.95*	[-5.69]	2.92*	[7.67]	-2.51*	[-6.30]	-2.52*	[-8.06]	-0.76*	[-2.76]	0.87*	[2.69]
48	-1.54*	[-3.94]	2.79*	[6.64]	-3.33*	[-7.77]	-3.06*	[-8.83]	0.04	[0.18]	1.18*	[4.17]
60	-0.36	[-1.26]	1.26*	[4.38]	-1.24*	[-3.62]	-2.57*	[-8.07]	0.39	[1.92]	0.60*	[2.40]

Figure 1: This figure summarizes Table 3, and give a graphical depiction of the excess return at each horizon for each systematic risk factor. The y-axis displays monthly excess returns in percentages and the x-axis displays horizons in months. The legend shows which systematic risk factor belongs to which line. The sample period is June 1995 – December 2015.



returns become significant. After the 12 months horizon the excess returns for the market factor remain significantly negative. However, the excess return level does slowly recover and excess returns increase with the horizon becoming longer, ending at the 60 months horizon which still captures negative excess returns, thus not significant.

The results show that looking at the excess returns, the market factor is negatively priced and investing in stocks with a high exposure to the market factor is not profitable. The market factor is especially unprofitable at relative intermediate horizons, implied by the 6 and 12 months horizons exhibiting the lowest excess returns with the highest significance. For example, an investor with a 6 months horizon that follows an investment strategy where it goes long in the 10% stocks with the highest exposure to the market factor and goes short in the 10% stocks with the lowest exposure to the market factor, will generate a negative excess return of approximately 3.26%. The results do not coincide with Kamara et al. (2015), who did find that in the United States the market factor is priced positive and significant at intermediate-term horizons.

4.1.2 Size Factor

When looking in Table 3 the size factor seems to have positive significant excess returns for every horizon examined. The 1 month horizon captures an excess return of 3.83%. The excess return does increase over the 3 and 6 months horizons, reaching an ultimately high excess return level of 4.71% at the 6 months horizon. For longer horizons the excess returns remain positively significant. However, the excess returns pattern is slowly decreasing after the 6 months horizon reaching an excess return level of 1.26% at the 60 months horizon.

The results show that the size factor is significantly and positively priced over all the horizons examined. However, short-term horizons seem to capture a higher level of excess returns relative to long-term horizons, which can be underpinned by Figure 1 that shows a decreasing patterns of the excess returns when the horizon becomes longer. Based on the results, an investment strategy for an investor where it takes a long position in the 10% stocks with the highest exposure to the size factor and a short positon in the 10% stocks with the lowest exposure to the size factor, is proving to be profitable, irrelevant for which horizon the investor invests in. An economic rationale behind the decreasing level of excess returns for longer horizons could be due to illiquidity. Illiquidity is naturally higher at shorter horizons, which translates into a higher illiquidity premium at shorter horizons.

4.1.3 Value Factor

The dispersion in excess returns for the value factor do act quite similarly as the dispersion in excess returns for the market factor. The excess return for the value factor at the 1 month horizon is negative, however not significant. When looking at the excess returns at the 3, 6, 9, and 12 months horizons it is again observable that there is a gradually decrease in the excess returns, reaching an ultimate low at a monthly excess return of -4.03%. When looking at horizons longer than 12 months the excess returns remain significantly negative. However, moving over longer horizons after the 12 months horizon the level of excess returns does get steadily less negative over time, ending at a -1.24% monthly excess return at the 60 months horizon.

When looking at the value factor in Figure 1 it can be detected that the excess returns follow a u-shaped pattern across horizons, with the excess returns all being negative. This means that following a strategy where an investor goes long in the 10% stocks with the highest exposure to the value factor and short in the 10% stocks with the lowest exposure to the value factor, proves to be a significantly unprofitable strategy at every horizon, except for the 1 month horizon which is not significantly priced. That value stocks seems to underperform growths stocks in China can be intuitively argued, since China is an emerging market growth stocks are expected to perform better.

4.1.4 Momentum Factor

Table 3 does report that as are the market and value factor, the momentum factor is also negatively priced over all the horizons examined. At the 1 month horizon the momentum factor delivers an excess return of -1.16%, which decreases at the 3 and 6 months horizons. At the 9 months horizon the excess return level moves back to the same level as the 1 month horizon, where after the excess returns further decreases at horizons longer than the 9 months horizon, reaching a low at the 48 months horizon with an excess return of -3.01%.

Looking at Figure 1 it can be observed that the level of negative excess returns is relatively constant over the horizons, with the longer horizons being somewhat lower priced relative to shorter and intermediate-term horizons. It may be clear that an investment strategy where an investor goes long in stocks with high exposure to the momentum factor and short in stocks with low exposure to the momentum factor, is an unprofitable strategy irrelevant of the horizon of the investor. When comparing the results relative to the research of Kang et al. (2002), who find that the momentum factor is profitable at the intermediate-term horizon, the results in this study indeed show generally higher returns at intermediate horizons. However, despite of the returns being higher, the returns are still negative and do not provide evidence for the profitable nature of the momentum factor at intermediate-term horizons.

4.1.5 Profitability Factor

It can be seen from Table 3 that the profitability factor is not priced over the short and long-term horizons, implied by the t-statistics that show that the excess returns are not significant over the 1, 3, 6, 9, 12, 48 and 60 months. The 18, 24, and 36 months horizons do hold significantly negative excess returns, with the 18 months horizon being priced lowest with a monthly excess return of -1.07%.

In Figure 1 it becomes clear that the dispersion in the pricing of different horizons of the profitability factor is not as pronounced as for example the market factor. However, it still can be observed that the profitability factor is significantly and negatively priced at intermediate term horizons (i.e. 18, 24, and 36 months horizons), while the profitability factor is not priced at other horizons.

Therefore, the conclusion can be made that for intermediate term investors taking a long position in the 10% stocks with the highest exposure to the profitability factor and a short position in stocks with the lowest exposure to the profitability factor, is not a profitable strategy. Such a strategy is not priced at the other horizons.

4.1.6 Investment Factor

Table 3 shows that the investment factor is not priced at the short-term horizons, but becomes priced at longer horizons. At the 1, 3, 6, and 9 months horizons the excess returns are negative, however not significant. Where at the longer horizons, starting from the 12 months horizon the investment factor holds excess returns that are positive and significant. The highest excess return is generated at the 18 months horizon with a monthly excess return of 1.28%.

The dispersion of excess returns at different horizons is also visible in Figure 1, where for the short-term horizons the excess returns fluctuate around zero, where after an increase can be observed in the excess returns for longer horizons. This implies that a strategy where an investor takes a long position in the 10% stocks with the highest exposure to the investment factor and a short position in the 10% stocks with the lowest exposure to the investment factor, is a profitable strategy for investors that do invest over longer horizons.

4.2 Dispersion in Alpha

So far the study just focused on excess returns. However, for investors it might be more interesting to look how well the strategy, wherein a long position is taken in the highest exposure to a risk factor and a short position is taken in the lowest exposure to the risk factor, performs when returns are benchmarked. So instead of looking at the excess returns, this section looks at the alphas, where a significant alpha denotes risk-adjusted excess returns relative to a benchmark. The benchmark that will be used consists of the 6 factors that were previously introduced, which are the market, size, value, momentum, investment and profitability factors. So the benchmark is the Fama & French five-factor model (2015) + momentum. The alphas are calculated using the following regression:

$$R_t = \alpha_t + \beta_1 MKT_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 MOM_t + \beta_5 RMW_t + \beta_6 MKT_t + \epsilon_t,$$

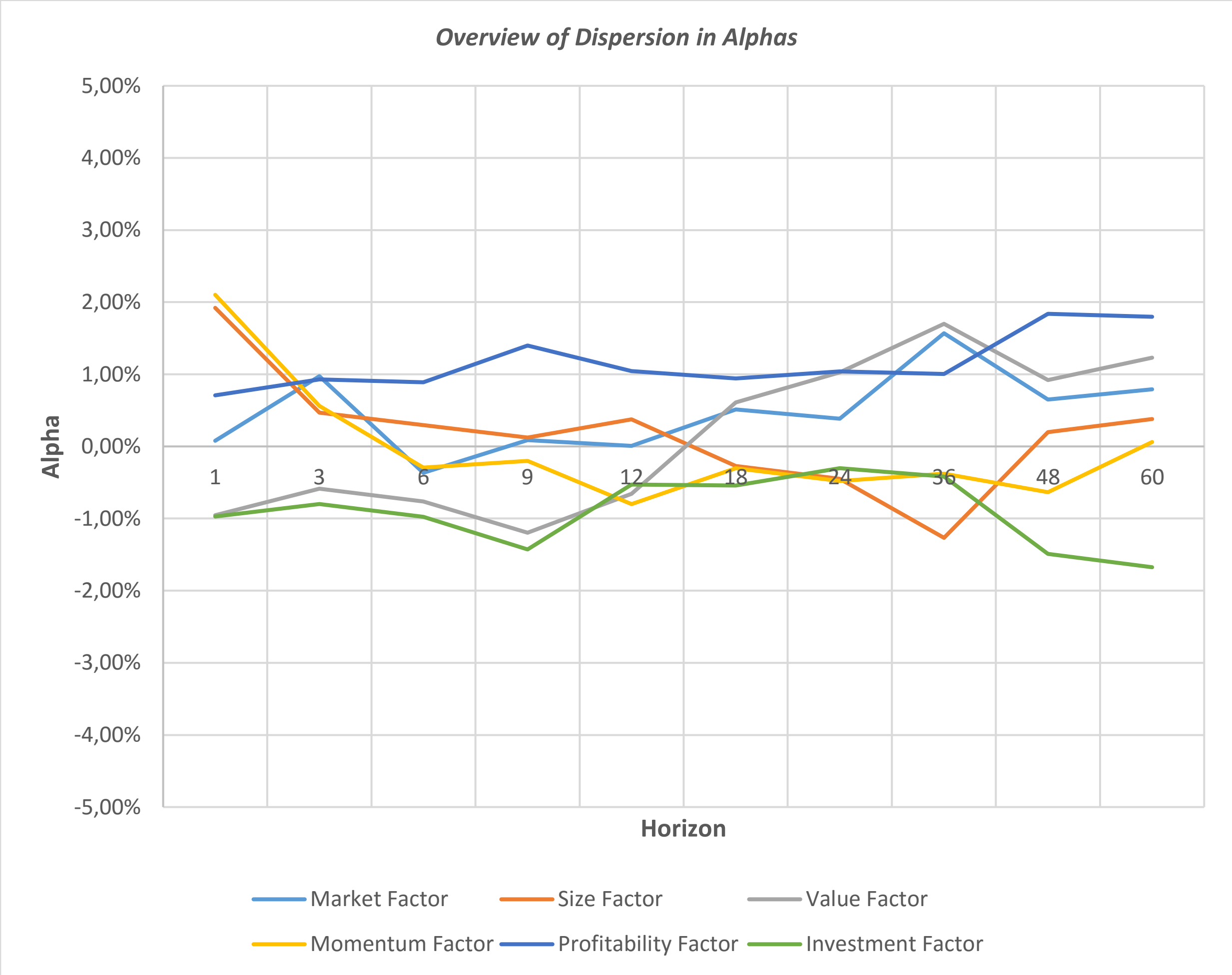
where α_t is the alpha at time *t*. What directly becomes clear when looking at Figure 2 is that in general the alphas have less dispersion over various horizons, and are closer to zero relative to the excess returns. This implies that the Fama & French five-factor model + momentum, tends to explain a part of the excess return at most horizons. It will be discussed whether taking exposure to the six previously introduced systematic risk factors is profitable across various horizons, by looking at alpha instead of excess returns for each individual systematic risk factor.

Table 4: At the beginning of each month in year *y*, stocks are sorted in 10 portfolios based on each of the six k-month pre-ranked betas (*e.g.* β_k^{MKT}, β_k^{SMB}, β_k^{HML}, β_k^{UMD}, β_k^{RMW}, β_k^{CMA}), where *k* is the horizon. The alpha spread is then calculated by subtracting the alpha of the bottom decile portfolio from the alpha of the top decile portfolio. For example, the column labelled β_k^{MKT} represents the spread in alpha for a portfolio that is long in 10% of the stocks with the highest exposure to the market factor and short 10% of the stocks with the lowest exposure to the market factor. The alphas are obtained relative to the Fama-French five-factor model (MKT, SMB, HML, RMW, CMA) + the momentum factor (MOM). I report the alphas for horizons (*k*) of 1, 3, 6, 9, 12, 18, 24, 36, 48, and 60 months. The coefficients represent monthly alphas. The corresponding t-statistics are reported in brackets after the coefficients. * shows whether the coefficients are significant at a 1%-level. The sample period is June 1995 – December 2015.

Overview of Dispersion in Alphas

Alpha Horizon (k)	$\boldsymbol{\beta_k^{MKT}}$		$\boldsymbol{\beta_k^{SMB}}$		$\boldsymbol{\beta_k^{HML}}$		$\boldsymbol{\beta_k^{UMD}}$		$\boldsymbol{\beta_k^{RMW}}$		$\boldsymbol{\beta_k^{CMA}}$	
1	0.08	[0.29]	1.92*	[6.54]	-0.95*	[-4.11]	2.10*	[9.60]	0.71*	[3.14]	-0.97*	[-4.42]
3	0.97*	[3.46]	0.47	[1.92]	-0.59	[-1.67]	0.56*	[2.46]	0.93*	[3.46]	-0.80*	[-3.36]
6	-0.37	[-1.24]	0.30	[1.00]	-0.76	[-2.27]	-0.29	[-1.04]	0.89*	[4.10]	-0.98*	[-3.82]
9	0.09	[0.33]	0.12	[0.44]	-1.20*	[-3.57]	-0.20	[-0.88]	1.40*	[4.74]	-1.43*	[-5.99]
12	0.01	[0.03]	0.38	[1.40]	-0.66	[-2.00]	-0.80*	[-3.41]	1.04*	[5.23]	-0..53	[-2.06]
18	0.51	[2.01]	-0.27	[-1.00]	0.61*	[2.46]	-0.30	[-1.28]	0.94*	[3.32]	-0.54	[-2.26]
24	0.39	[1.72]	-0.45	[-1.50]	1.03*	[3.86]	-0.48	[-2.02]	1.04*	[3.51]	-0.30	[-1.13]
36	1.57*	[6.07]	-1.27*	[-4.53]	1.70*	[5.53]	-0.38	[-1.52]	1.00*	[4.53]	-0.42	[-1.53]
48	0.65*	[2.34]	0.20	[0.67]	0.92*	[3.28]	-0.63*	[-2.33]	1.84*	[7.83]	-1.49*	-[6.32]
60	0.79*	[3.43]	0.38	[1.70]	1.23*	[4.61]	0.06	[0.22]	1.80*	[9.19]	-1.68*	[-7.71]

Figure 2: This figure summarizes Table 4, and give a graphical depiction of alpha at each horizon for each systematic risk factor. The y-axis displays monthly alphas in percentages and the x-axis displays horizons in months. The legend shows which systematic risk factor belongs to which line. The sample period is June 1995 – December 2015.



4.2.1 Market Factor

When looking at Table 4 there is not a discernible trend in the way the market factor is priced over different horizons. However, it seems that longer horizons are priced, proved by the significant alphas for the 36, 48, and 60 months horizons. These alphas all have positive coefficients proving that following a strategy where an investor takes exposure to the market factor pays off. Contrary, shorter horizons are not priced, except for the 3-months horizon that has a positive and significant alpha. Compared with the excess returns for the market factor that are all negative for every horizon examined, the alphas seem to be generally positive for the market factor. I will tend to explain how this is possible. As abovementioned, the excess returns for the market factor are negative at all horizons, which means that the stocks with a low exposure to the market factor generated higher excess returns than the excess returns of stocks with a high exposure to the market factor, at every single horizon examined. Contrary, the alphas for the market factor are generally positive. This is because the Fama-French five-factor model + momentum, which is the benchmark to obtain the alphas, requires the portfolio of stocks with low exposure to the market factor to realize a higher excess return than the portfolio of stocks with a high exposure to the market. In this way it is possible that the same portfolio with a positive excess return, also captures a negative alpha, or vice versa.

4.2.2 Size Factor

Based on Table 4 there are just two horizons with significant alphas, implying that the size factor is just priced at the 1 and 36 months horizon when looking at alpha. The size factor has a positive and significant alpha of 0.38% at the 1 month horizon, and a negative significant alpha of -1.27% at the 36 months horizon. Therefore, it is hard to draw conclusions whether a strategy that buys stocks with a high exposure to the size factor is profitable for an investor that tries to generate a positive alpha. Purely based on the results this might only be so for an investor that trades really frequently, which means an investor that has a holding period for less than a month.

4.2.3 Value Factor

Table 4 shows an interesting pattern wherein the value factor has a negative alpha at shorter horizons, and the longer horizons capture a positive alpha. The alphas are significant and negative between the 1 month horizon and the 12 months horizon, except for the 3 months horizon. Contrary, the alphas are significant and positive between the 18 months and the 60 months horizons. This implies that a strategy that goes long in the 10% stocks with the highest exposure to the value factor and short in 10% stocks with the lowest exposure to the value factor, is profitable for long-term horizon investors that aim to generate a positive alpha and negative for short-term horizon investors that aim to generate a positive alpha. This pattern can also be observed in Figure 2, where it can be noticed that there is a sudden increase in alpha after the 12 months horizon.

4.2.4 Momentum Factor

Table 4 displays positive and significant alphas for the 1 and 3 months horizons, implying that buying stocks with a high exposure to the momentum factor generates alpha at those particular horizons. However, this changes over longer horizons. The 6, 9, 18, 24, 36, and 60 months horizons are not significant and therefore not priced. The 12 months and the 48 months horizons also capture significant alphas, but contrary to the 1 and 3 months horizons those alphas are negative. In Figure 2 it can also clearly be observed that the momentum factor has positive alphas at the shorter horizons, but after the 3 month horizon the alphas drops to zero, where after it keeps fluctuating around the 0% alpha mark.

4.2.5 Profitability Factor

From Table 4 it can be seen that there is not that much dispersion observable in the profitability factor. An investment strategy where a long position is taken in the 10% stocks with the highest exposure to the profitability factor and a short position is taken in the 10% stocks with the lowest exposure to the profitability factor, seems to be a profitable strategy, regardless the investment horizon of an investor. However, it can be argued that the longer horizons, represented by the 48 and 60 months horizons are more profitable, while those horizons have higher alphas that also exhibit a higher significance. This can also be seen in Figure 2, where a significant increase is observable after the 36 months horizon.

4.2.6 Investment Factor

Table 4 shows that the investment factor is priced significantly and negative over the short-term horizons (i.e. the 1, 3, 6, and 9 months horizons). The alphas of the investment factor become insignificant at the intermediate-term horizons, and again significant and negative at the long-term horizons (i.e. the 48 and 60 months horizon). This would imply that a strategy of buying the 10% stocks with the highest exposure to the investment factor and shorting the 10% stocks with the lowest exposure to the investment factor, proves not to be a profitable strategy for short-term and long-term investors that aim to generate a positive alpha. Looking in Figure 2 it becomes clear that the alphas are generally lowest for the investment factor, which implies that an investor who wants to obtain a high alpha, should definitely not invest in stocks that have a high exposure to the investment factor.

4.3 Illiquidity

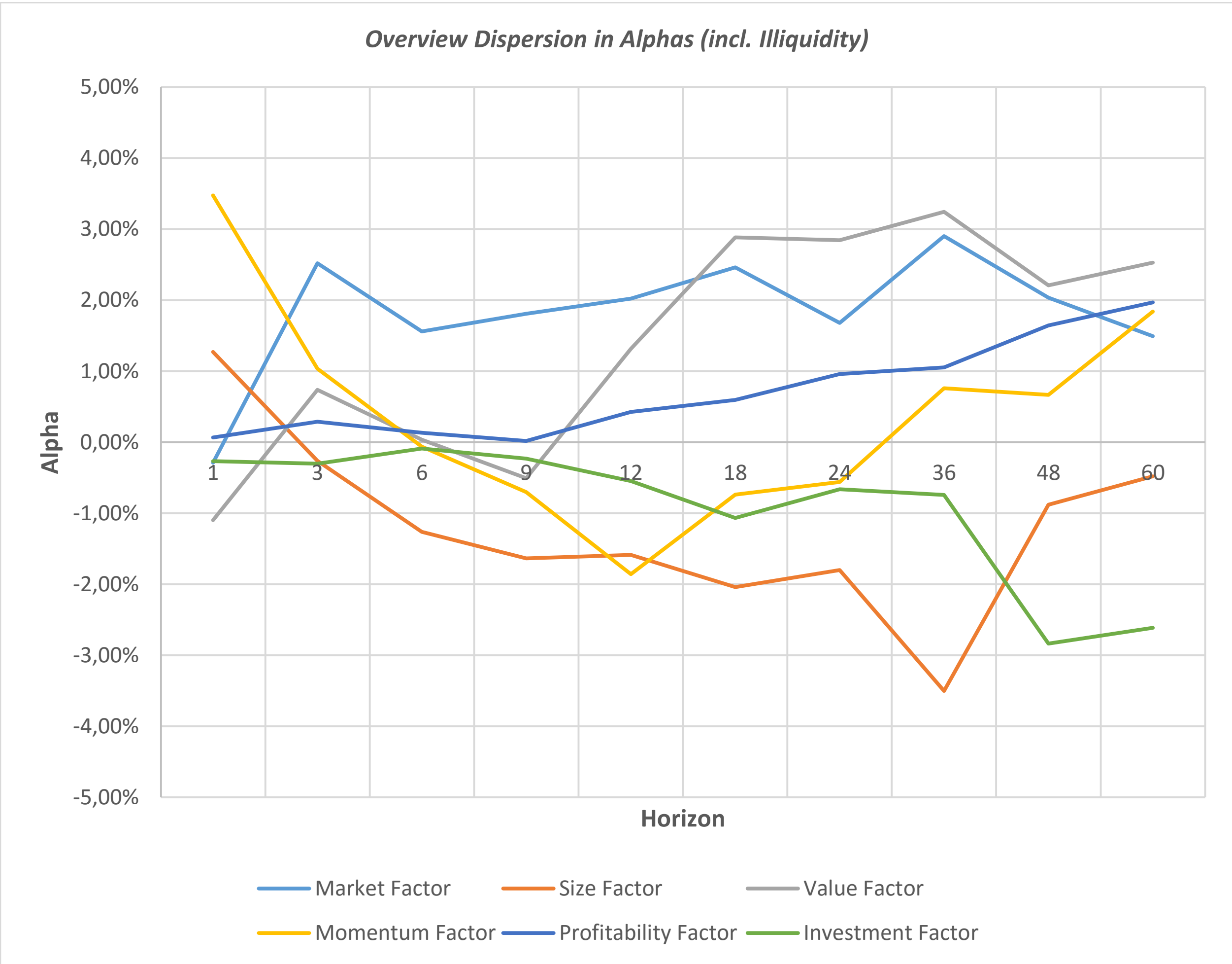
Both the excess returns and alphas display dispersion in how risk factors are priced over various horizons. Amihud and Mendelson (1986) provided an explanation based on liquidity, wherein they expect that more liquid stocks are held by short-term horizon investors, and the more illiquid stocks are held by long-term horizon investors. Amihud and Mendelson also state that it is highly expected that when equity holders hold more illiquid stocks, their asset returns normally increase because of the illiquidity premium. Therefore, illiquidity will be introduced in the regression as a control variable. Since illiquidity is now captured in the benchmark, it is expected that portfolios with more illiquid stocks

Table 5: At the beginning of each month in year *y*, stocks are sorted in 10 portfolios based on each of the six k-month pre-ranked betas (*e.g.* β_k^{MKT}, β_k^{SMB}, β_k^{HML}, β_k^{UMD}, β_k^{RMW}, β_k^{CMA}), where *k* is the horizon. The alpha spread is then calculated by subtracting the alpha of the bottom decile portfolio from the alpha of the top decile portfolio. For example, the column labelled β_k^{MKT} represents the spread in alpha for a portfolio that is long in 10% of the stocks with the highest exposure to the market factor and short 10% of the stocks with the lowest exposure to the market factor. The alphas are obtained relative to the Fama-French five-factor model (MKT, SMB, HML, RMW, CMA) + the momentum factor (MOM) + the Amihud illiquidity measure. I report the alphas for horizons (*k*) of 1, 3, 6, 9, 12, 18, 24, 36, 48, and 60 months. The coefficients represent monthly alphas. The corresponding t-statistics are reported in brackets after the coefficients. * shows whether the coefficients are significant at a 1%-level. The sample period is June 1995 – December 2015.

Overview Dispersion in Alphas (incl. Illiquidity)

Alpha incl. illiquidity Horizon (k)	$\boldsymbol{\beta_k^{MKT}}$		$\boldsymbol{\beta_k^{SMB}}$		$\boldsymbol{\beta_k^{HML}}$		$\boldsymbol{\beta_k^{UMD}}$		$\boldsymbol{\beta_k^{RMW}}$		$\boldsymbol{\beta_k^{CMA}}$	
1	-0.29	[-0.92]	1.27*	[3.15]	-1.10*	[-3.66]	3.48*	[10.13]	0.07	[0.26]	-0.27	[-1.08]
3	2.52*	[7.62]	-0.26	[-0.97]	0.74	[2.02]	1.04*	[3.67]	0.29	[1.10]	-0.30	[-0.99]
6	1.56*	[4.84]	-1.26*	[-3.45]	0.04	[0.10]	-0.06	[-0.20]	0.13	[0.53]	-0.09	[-0.28]
9	1.81*	[6.15]	-1.63*	[-4.95]	-0.50	[-1.31]	-0.70*	[-2.37]	0.02	[0.08]	-0.23	[-0.85]
12	2.02*	[7.27]	-1.58*	[-4.36]	1.31*	[3.79]	-1.86*	[-5.95]	0.43	[1.68]	-0.54	[-1.66]
18	2.46*	[8.43]	-2.04*	[-5.72]	2.88*	[10.73]	-0.74*	[-2.76]	0.60	[2.26]	-1.06*	[-3.70]
24	1.68*	[6.52]	-1.80*	[-4.60]	2.84*	[9.04]	-0.56	[-2.11]	0.96*	[3.53]	-0.66*	[-2.61]
36	2.90*	[9.96]	-3.50*	[-9.40]	3.24*	[9.47]	0.76*	[2.95]	1.06*	[4.36]	-0.74*	[-2.60]
48	2.03*	[6.11]	-0.88*	[-2.46]	2.21*	[6.43]	0.67	[1.94]	1.64*	[6.03]	-2.83*	[-11.92]
60	1.49*	[5.90]	-0.48	[-1.77]	2.53*	[7.67]	1.84*	[6.86]	1.97*	[7.97]	-2.61*	[-10.94]

Figure 3: This figure summarizes Table 5, and give a graphical depiction of alpha at each horizon for each systematic risk factor. The y-axis displays monthly alphas in percentages and the x-axis displays horizons in months. The legend shows which systematic risk factor belongs to which line. The sample period is June 1995 – December 2015.



obtain a lower alpha, since a part of their alpha will now be explained by illiquidity. So in short, it is expected that when a portfolio decile captures a high level of illiquidity, the alpha of this portfolio decile will be lower relative to the alpha in the Fama-French five-factor model + momentum. Illiquidity will be measured by the Amihud illiquidity measure (2002). And the regression that will be used is the following:

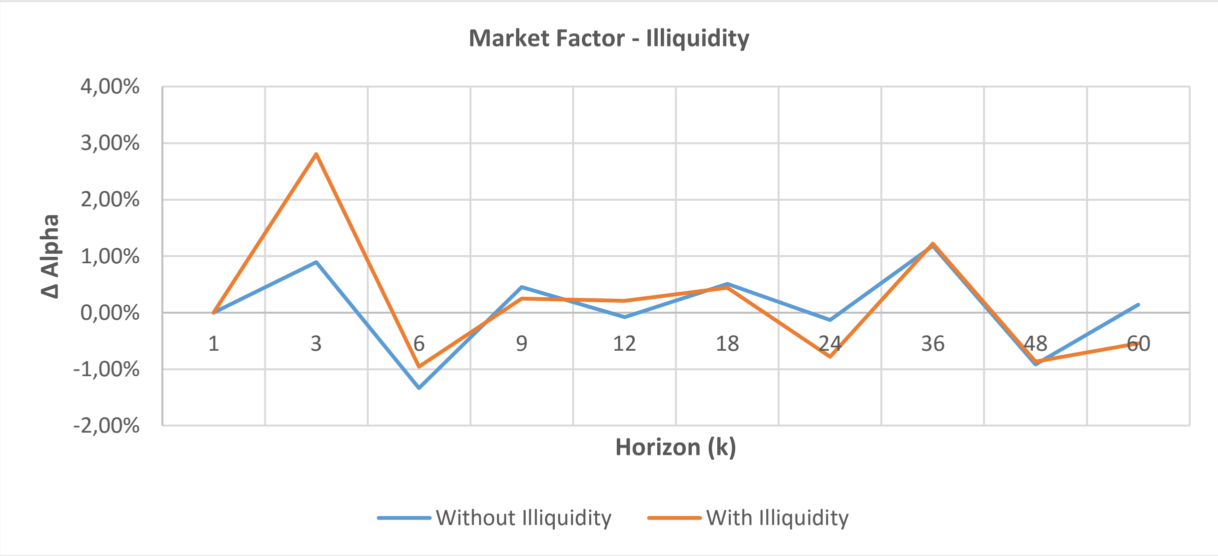
$$R_t = \alpha_t + \beta_1 MKT_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 MOM_t + \beta_5 RMW_t + \beta_6 CMA_t + \beta_7 ILLIQ_{it} + \in_t,$$

where $ILLIQ_{it}$ is the Amihud illiquidity measure at time t, for firm i. Also with including illiquidity, every systematic risk factor will be discussed individually. This is done by including a figure for every systematic risk factor that shows whether the illiquidity measure added as a control variable in the regression does a better job in explaining the dispersion of how risk factors are priced over various horizons. Besides the figures, also statistical proof is provided that can be find in Table 8 located in the attachment. Table 8 reports a z-test wherein the alpha of one horizon is tested against the alpha of the previous horizon to see whether there is statistical proof or these two alphas are significantly different from each other. When illiquidity would narrow the dispersion in how systematic risk factors are priced, the z-values of the alphas with illiquidity included in the regression should consistently be smaller over all horizons relative to the z-values of the alphas without illiquidity included in the regression. Additionally, in the attachment the interested reader can also find Table 10. This table displays the level of illiquidity in the top decile and bottom decile for every horizon and for every risk factor. However, it is difficult to draw a conclusion based on this table, since there are no patterns observable in the level of illiquidity over different horizons.

4.3.1 Market Factor

Adding illiquidity as a control variable does not seem to reduce the dispersion in how the market factor is priced at different horizons. Figure 4 shows the difference of the alpha of one horizon relative to the alpha of the previous horizon for the market factor. To minimize dispersion the line should stay close to a difference in alphas of zero. It is expected that the difference in alpha between two horizons stays closer to zero for regressions with illiquidity relative to regressions that do not include illiquidity, in the sense that illiquidity is better able to explain the dispersion in the pricing of risk factor over various horizons. However, overall this expectation does not hold for the market factor. The difference in alphas is lower for almost all horizons, except for the 6 and the 9 months horizons, for the regressions without illiquidity. Illiquidity appears not to be a good control variable for the market factor, this conclusion can also be made when looking at statistical evidence. Even though, in Table 8 there is more evidence that including illiquidity in the regression can explain the dispersion in how the market factor is priced over various horizons, relative to Figure 4, this evidence is far from convincing. The z-statistics are closer to zero for regression including illiquidity for the 6, 9, 18, 36, and 48 months horizons, but not for the 3, 12, 24, and 60 months horizons. The reason that statistical evidence is more favourable for the regressions with illiquidity is because the standard deviation of the alphas are somewhat higher for the regression with liquidity relative to the regressions without illiquidity. That illiquidity is not a good measure to explain the dispersion in how the market factors is priced can also be underpinned by Table 10. Table 10 displays no observable pattern in the level of illiquidity over different horizons. It is not the case that there is a higher level of illiquidity at longer horizons and lower levels of illiquidity at shorter horizons.

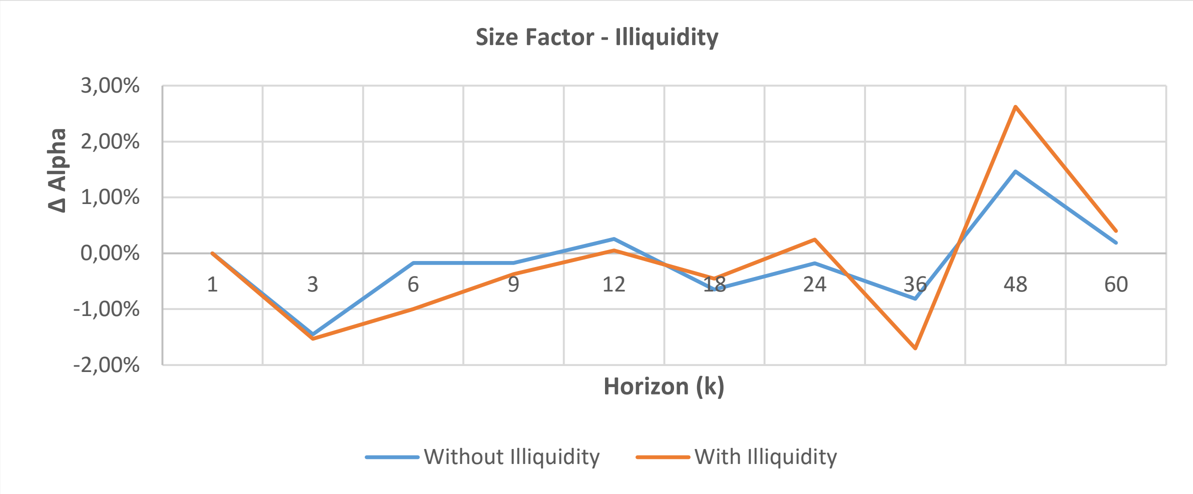
Figure 4: Displays the difference in alpha for horizon *k* relative to the previous horizon for the market factor



4.3.2 Size Factor

Figure 5 displays a pattern that is not in favour for illiquidity being a good control variable to explain dispersion of how horizons are priced for the size factor. Besides the 12 month horizon, the difference in alphas for regressions without the illiquidity measure is closer to zero than when the illiquidity measure would be included. This can be underpinned with statistical proof reported by Table 8, where most z-statistics are closer to zero when not including illiquidity in the regression. Additionally, in Table 10 we can see that overall the level of illiquidity is higher in the top decile portfolio, which makes sense because the stocks of small firms are represented in that portfolio. Since stocks of small stocks firms tend to get locked in by buy-and-hold portfolios more easily, reducing the tradable amount and thus their liquidity, higher levels of illiquidity for top decile portfolios are expected. However, there is not a pattern traceable in the difference in the level of illiquidity for short and long horizons

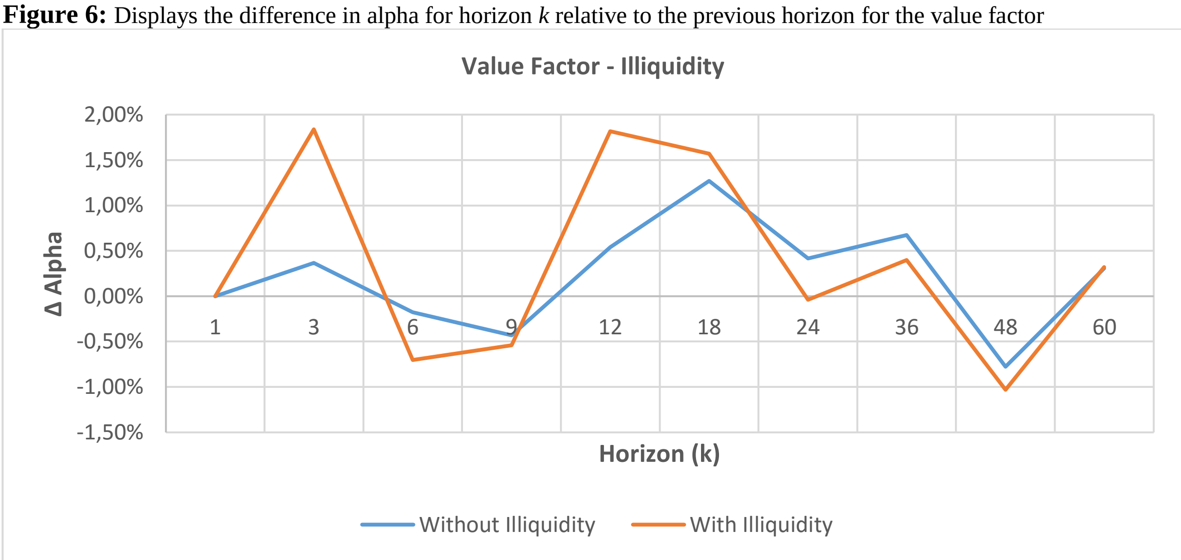
Figure 5: Displays the difference in alpha for horizon *k* relative to the previous horizon for the size factor



4.3.3 Value Factor

Based on Figure 6, proof is also lacking that illiquidity can explain the difference in the pricing of the value factor at various horizons. Only at the 24 and the 36 months horizons the difference in alphas compared to the previous period is closer to zero for the regression without illiquidity, where for the other horizons the difference in alphas is closer to zero when the alpha is determined for regressions without illiquidity as a control variable. Statistical proof from Table 8 also reports that including illiquidity in the regression explains the dispersion in how the value factor is priced better at the 24 and 36 months horizons, and additionally, also at the 60 months horizon. However, overall the regression without illiquidity as a control variable explains dispersion in how the value factor is priced better.

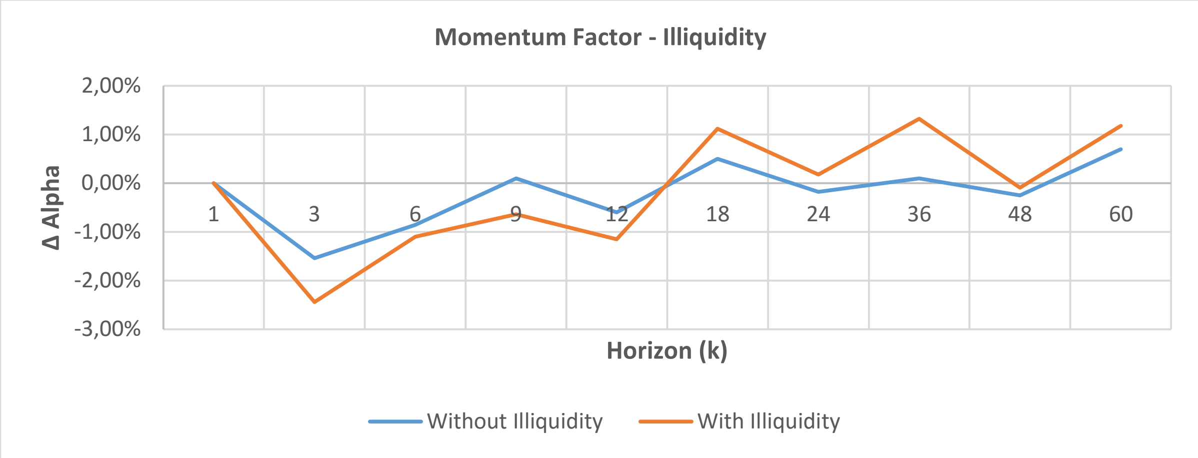
Figure 6: Displays the difference in alpha for horizon *k* relative to the previous horizon for the value factor



4.3.4 Momentum Factor

Figure 7 shows that including illiquidity in the regression results in a consistent bigger difference of the alpha relative to the alpha of the previous horizon for all horizons examined. So also for the momentum factor, illiquidity as a control variable that tries to explain the dispersion in the pricing of a risk factor over various horizon does a poor job. This is confirmed by Table 8 that displays generally lower z-statistics for regressions without including illiquidity.

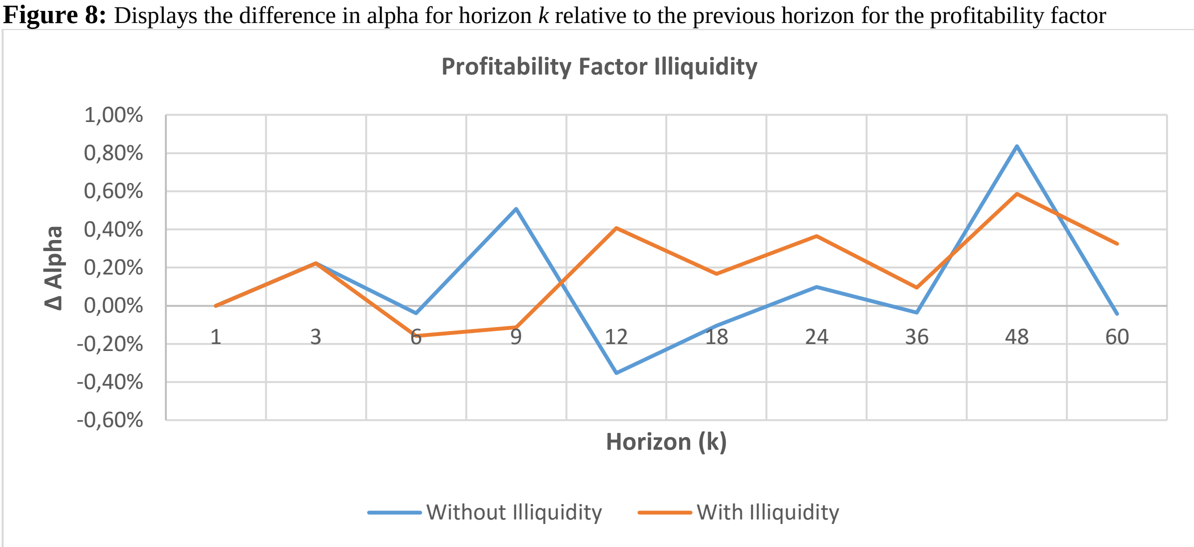
Figure 7: Displays the difference in alpha for horizon *k* relative to the previous horizon for the momentum factor



4.3.5 *Profitability Factor*

When looking at Figure 8 it becomes clear that illiquidity does also a poor job in explaining dispersion in horizon pricing for the profitability factor. Even though the difference in the alphas are closer to zero for the 9 months and 48 months horizons, the rest of the horizons perform better when illiquidity is not in the regression as a control variable. This is again affirmed by Table 8 that generally displays lower z-statistics for regressions that do not include illiquidity as a control variable.

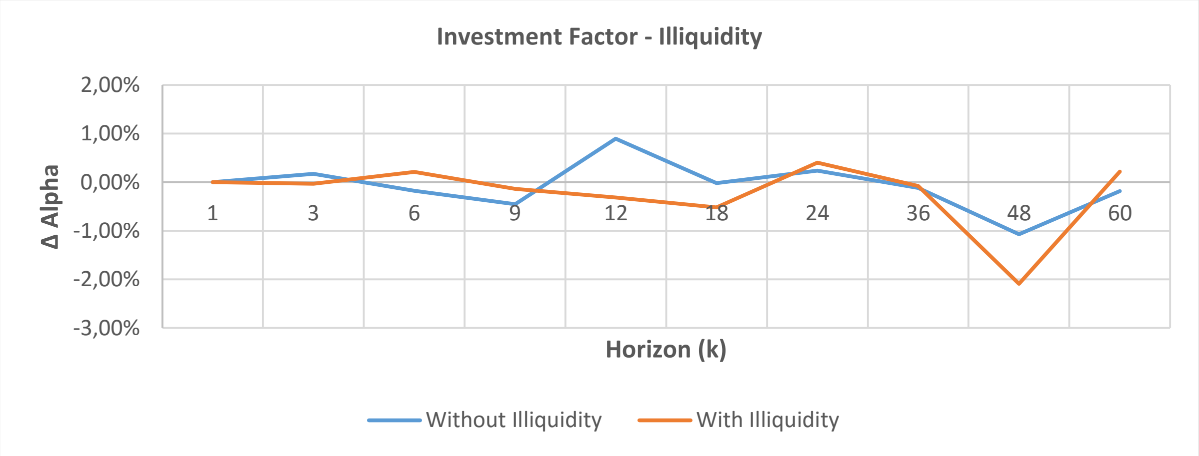
Figure 8: Displays the difference in alpha for horizon *k* relative to the previous horizon for the profitability factor



4.3.6 *Investment Factor*

Figure 9 displays evidence that is more in favour for illiquidity being able to explain why there is dispersion in the pricing of the profitability factor at different horizons. The figure shows that for the 3, 9, 12 and 36 months horizons the difference in the alphas of the regression that includes illiquidity is closer to zero relative to the regression that does not include illiquidity. However, there are still five horizons (the 6, 18, 24, 48 and 60 months horizons) where the regression without illiquidity has differences in the alphas that are closer to zero. So despite there being more evidence that illiquidity can explain dispersion in the pricing of the profitability factor, this evidence is not convincing. The same conclusion can be drawn when looking at statistical proof in Table 8. At the 3, 6, 9, 12, and 36 months horizons the regressions with illiquidity have z-statistics closer to zero. However, for the other horizons, the regressions with illiquidity are not closer to zero.

Figure 9: Displays the difference in alpha for horizon *k* relative to the previous horizon for the investment factor



4.4 Opacity

Illiquidity does not seem to explain the dispersion in the pricing of the systematic risk factors over various horizons. However, in the literature another explanation is given that can explain the dispersion in the pricing of a systematic risk factor over various horizon. The literature states that systematic risk factors are generally priced better over longer horizons. One of the reasons is the opaqueness or transparency of firms. For opaque firms there is a delay in the reaction of the prices of their stocks to systematic news. This is why on the short term systematic risk factors could be priced incorrectly, and this is also why opacity is introduced as a second control variable. Opacity is measured by the variance in discretionary accruals. The higher the variance of the discretionary accruals, the more opaque is a firm in the sense that investors require more information to price the impact of systematic news. The regression that will be used including the variance of discretionary accruals as a proxy for opacity is:

$$R_t = \alpha_t + \beta_1 MKT_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 MOM_t + \beta_5 RMW_t + \beta_6 CMA_t + \beta_7 VarACCRUALS_{it} + \epsilon_t,$$

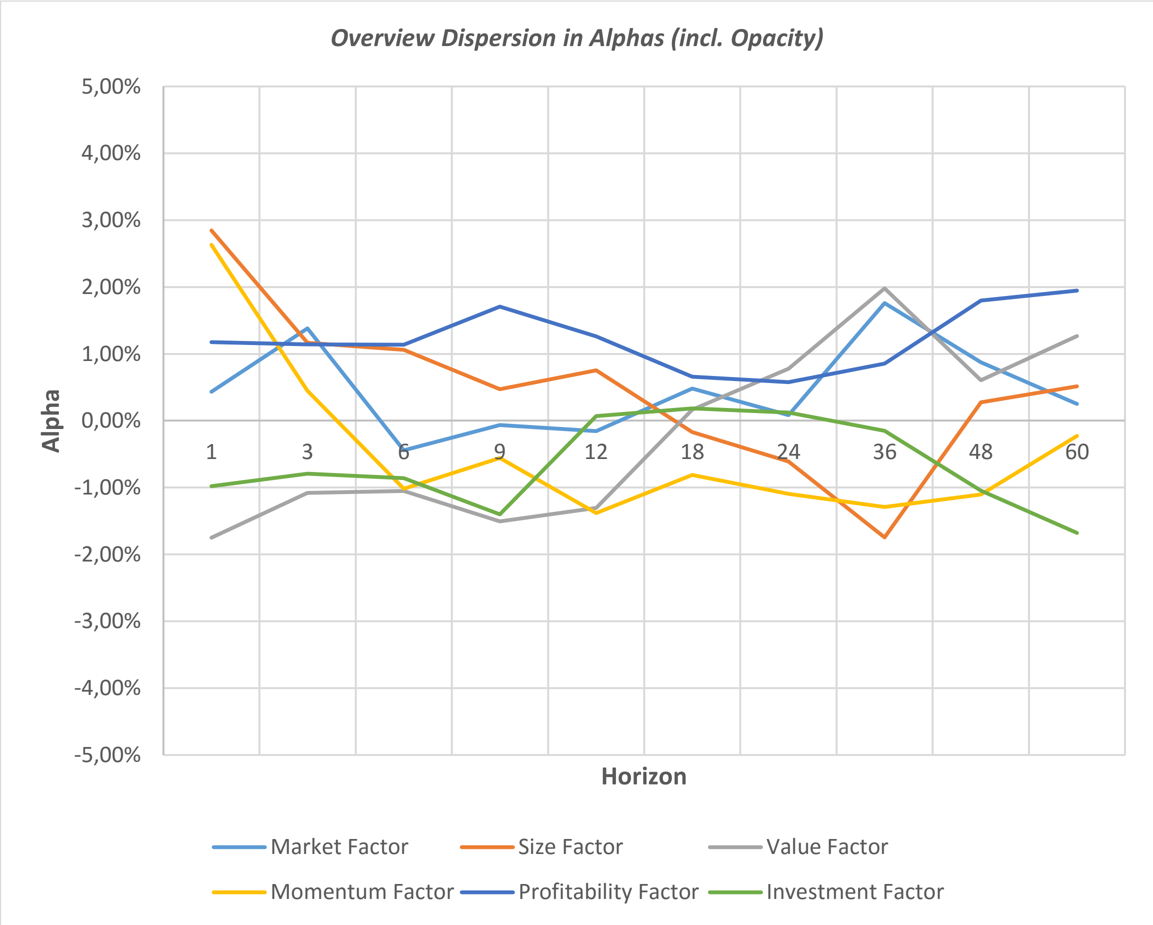
where $VarACCRUALS_{it}$ is the variance of the discretionary accruals at time *t*, for firm *i*. The equation shows that both opacity and the momentum factor are represented in the regressions. This can cause some problems, because both opacity and momentum arise due to the under reaction to new information.

Table 6: At the beginning of each month in year *y*, stocks are sorted in 10 portfolios based on each of the six k-month pre-ranked betas (*e.g.* β_k^{MKT}, β_k^{SMB}, β_k^{HML}, β_k^{UMD}, β_k^{RMW}, β_k^{CMA}), where *k* is the horizon. The alpha spread is then calculated by subtracting the alpha of the bottom decile portfolio from the alpha of the top decile portfolio. For example, the column labelled β_k^{MKT} represents the spread in alpha for a portfolio that is long in 10% of the stocks with the highest exposure to the market factor and short 10% of the stocks with the lowest exposure to the market factor. The alphas are obtained relative to the Fama-French five-factor model (MKT, SMB, HML, RMW, CMA) + the momentum factor (MOM) + the variance of discretionary accruals. I report the alphas for horizons (*k*) of 1, 3, 6, 9, 12, 18, 24, 36, 48, and 60 months. The coefficients represent monthly alphas. The corresponding t-statistics are reported in brackets after the coefficients. * shows whether the coefficients are significant at a 1%-level. The sample period is June 1995 – December 2015.

Overview Dispersion in Alphas (incl. Opacity)

Alpha incl. opacity Horizon (k)	β_k^{MKT}		β_k^{SMB}		β_k^{HML}		β_k^{UMD}		β_k^{RMW}		β_k^{CMA}	
1	0.43	[1.15]	2.85*	[7.06]	-1.75*	[-5.49]	2.63*	[8.55]	1.18*	[3.88]	-0.98*	[-3.64]
3	1.38*	[3.66]	1.17*	[3.56]	-1.08	[-2.22]	0.45	[1.51]	1.14*	[3.09]	-0.79*	[-2.37]
6	-0.44	[-1.16]	1.06*	[2.70]	-1.05	[-2.31]	-1.02*	[-2.71]	1.14*	[3.92]	-0.86*	[-2.44]
9	-0.06	[-0.18]	0.47	[1.31]	-1.51*	[-3.31]	-0.56	[-1.86]	1.71*	[4.21]	-1.40*	[-4.30]
12	-0.15	[-0.41]	0.75*	[2.15]	-1.31*	[-2.90]	-1.38*	[-4.36]	1.26*	[4.80]	0.07	[0.20]
18	0.48	[1.47]	-0.17	[-0.48]	0.17	[0.51]	-0.81*	[-2.56]	0.66	[1.69]	0.18	[0.55]
24	0.09	[0.30]	-0.61	[-1.53]	0.78	[2.24]	-1.09*	[-3.47]	0.58	[1.42]	0.12	[0.32]
36	1.76*	[5.18]	-1.74*	[-4.95]	1.98*	[4.87]	-1.29*	[-3.84]	0.85*	[2.83]	-0.15	[-0.40]
48	0.87*	[2.41]	0.28	[0.72]	0.61	[1.60]	-1.11*	[-3.15]	1.80*	[5.71]	-1.05*	[-3.23]
60	0.25	[0.87]	0.51	[1.77]	1.27*	[3.60]	-0.23	[-0.62]	1.95*	[7.54]	-1.68*	[-5.61]

Figure 10: This figure summarizes Table 6, and give a graphical depiction of alpha at each horizon for each systematic risk factor. The y-axis displays monthly alphas in percentages and the x-axis displays horizons in months. The legend shows which systematic risk factor belongs to which line. The sample period is June 1995 – December 2015.



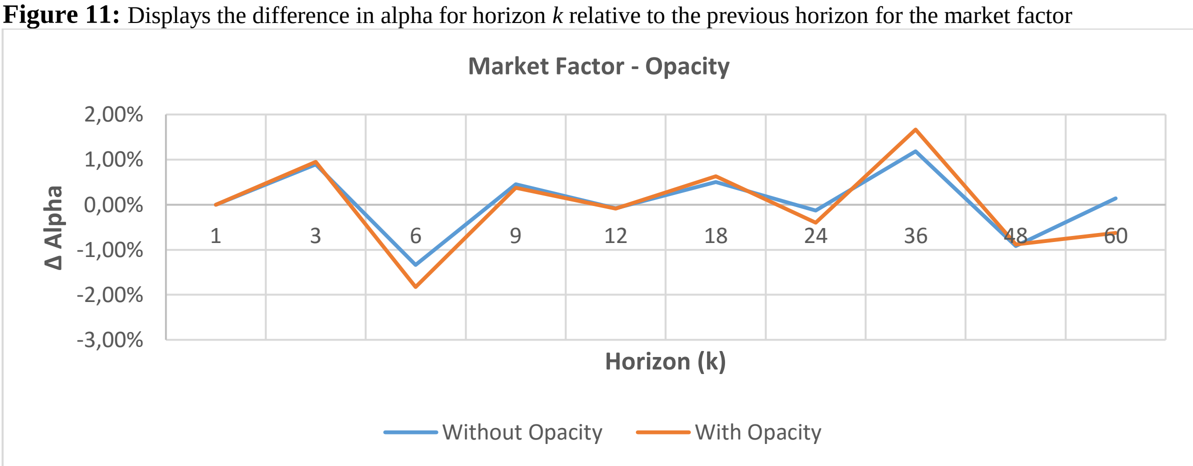
Therefore, there is a substantial chance that the two variables are correlated, which can lead to multicollinearity. However, the correlation between the momentum factor and opacity is only -0.0057. It appears that there is no correlation between the two variables, and thus opacity is an independent explanatory variable that can possibly explain dispersion in the pricing of systematic risk factors over various horizons, by itself.

In the subsequent sections, all risk factors will be again discussed individually. Also statistical evidence is provided in Table 9 that is located in the attachment. Table 9 displays the outcome of a z-test wherein the alpha of one horizon is tested against the alpha of the previous horizon to see whether there is statistical proof or these two alphas are significantly different from each other. A lower z-score indicates that there is less dispersion. For the interested reader the level of variance in discretionary accruals for the top and bottom decile for different risk factors over various horizons, are displayed in Table 11. This table can be found in the attachment as well.

4.4.1 Market Factor

The same figures as in the illiquidity section will be used to determine or including opacity in the regression will do a better job in explaining the dispersion in the pricing of a risk factor over various horizons. In Figure 11 it can be observed that even though the lines are almost the same, the differences in alpha are closer to zero for the regressions where opacity is not included for all horizons except the 9 and 48 months horizons. The difference in the alphas being closer to zero for regression where opacity is not included at other horizons, implies that opacity does not do a better job in explaining the dispersion in how the market factor is priced over various horizons. This can also be underpinned with statistical evidence displayed by Table 9. Even though the z-statistics for the regressions including opacity are closer to zero at the 3, 9, 12, 18, 48 months horizons, at the other horizons the z-statistics are closer to zero when opacity is not included as a control variable in the regressions. So there is no overwhelming statistical evidence that opacity does a better job in explaining dispersion in the market factor over various horizons. Also, from Table 11 it can be concluded that there is no discernible pattern in opacity over the top and bottom deciles.

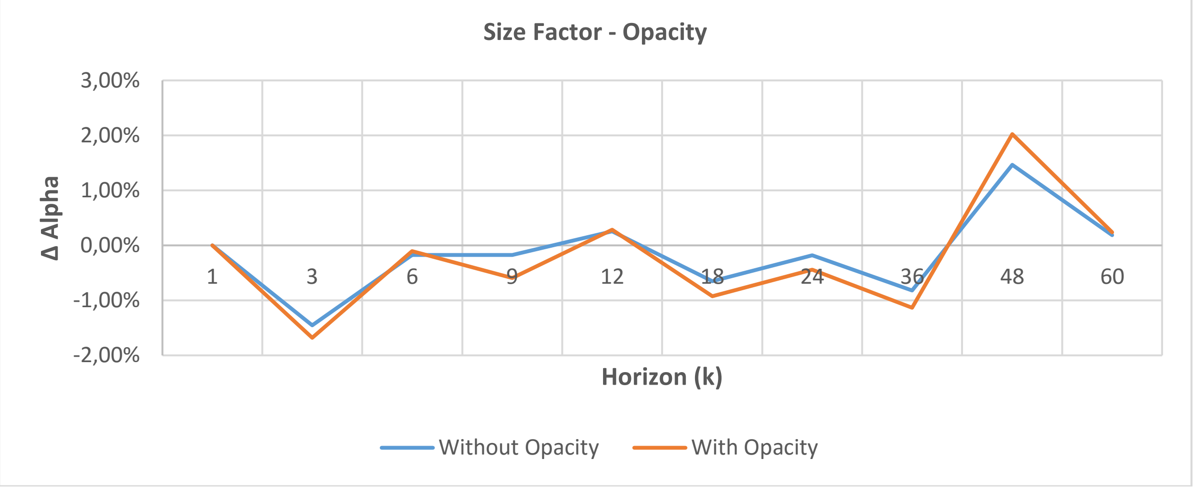
Figure 11: Displays the difference in alpha for horizon *k* relative to the previous horizon for the market factor



4.4.2 Size Factor

In Figure 12 it becomes clear that also for the size factor including opacity in the regression does not narrow the dispersion of the pricing of that particular size factor across horizons. Again, the difference in alphas are closer to zero for regressions when opacity is not included. This holds for all horizons. This is again affirmed by statistical proof, displayed in Table 9, wherein most horizons displays lower z-statistics for regressions that do not include illiquidity as a control variable.

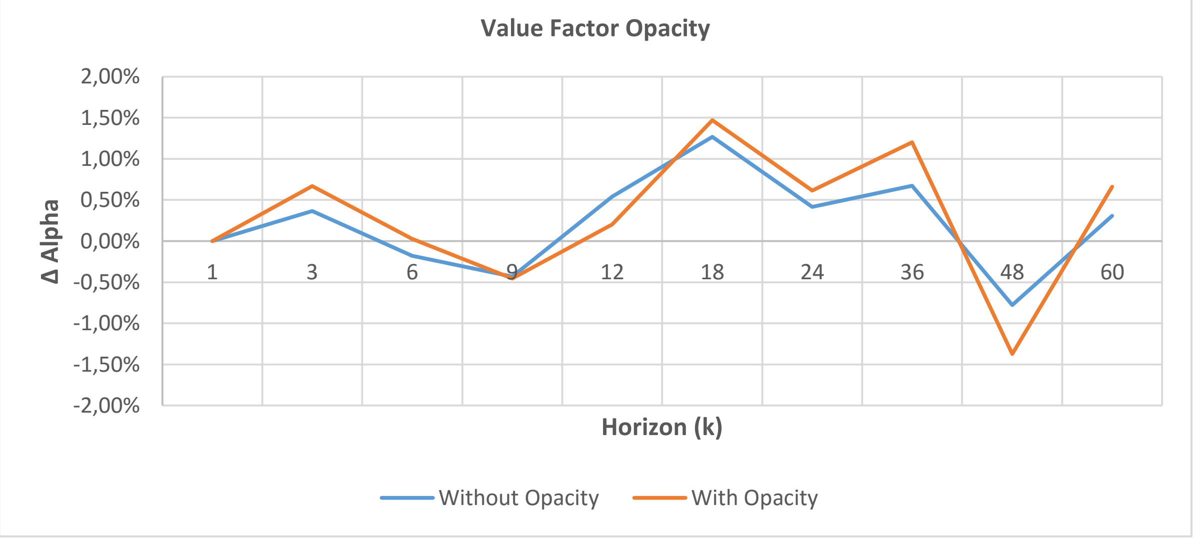
Figure 12: Displays the difference in alpha for horizon *k* relative to the previous horizon for the size factor



4.4.3 Value Factor

In Figure 13 it is shown that the dispersion in the pricing of the value factor at various horizon cannot be explained by opacity. The differences in the alpha are closer to zero for the regression without opacity as a control variable for all horizons, except for the 12 months horizon. This finding is supported by statistical proof in Table 9. Table 9 displays that for the value factor most of the horizons have z-statistics closer to zero for regressions where opacity is not included as a control variable.

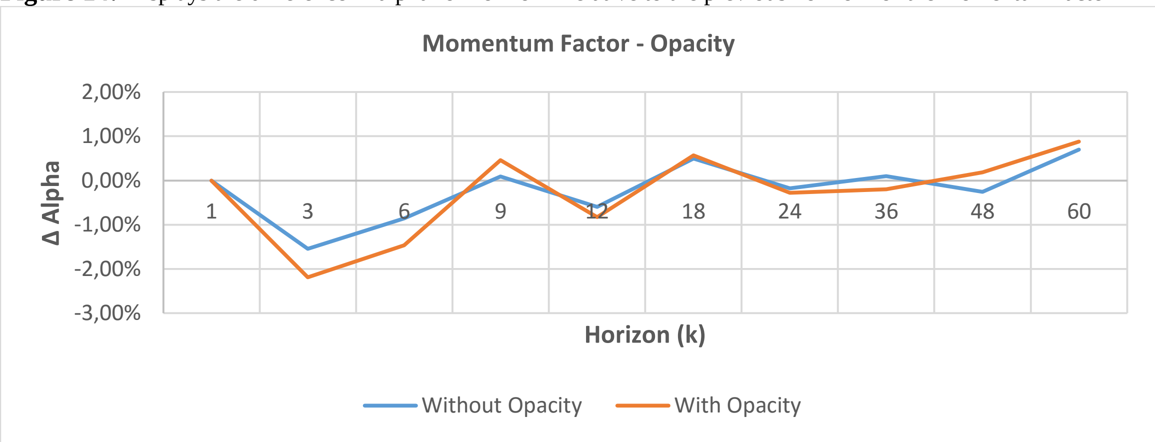
Figure 13: Displays the difference in alpha for horizon *k* relative to the previous horizon for the value factor



4.4.4 *Momentum Factor*

Figure 14 states that opacity does not help in explaining the dispersion of how the momentum factor is priced at different horizons. Again the difference in the alphas is closer to zero when opacity is not included in the regression. This holds for all horizons. The graphical results are again backed with statistical proof in Table 9. For most horizons of the momentum factor the z-statistics are lower for regressions without opacity as a control variable.

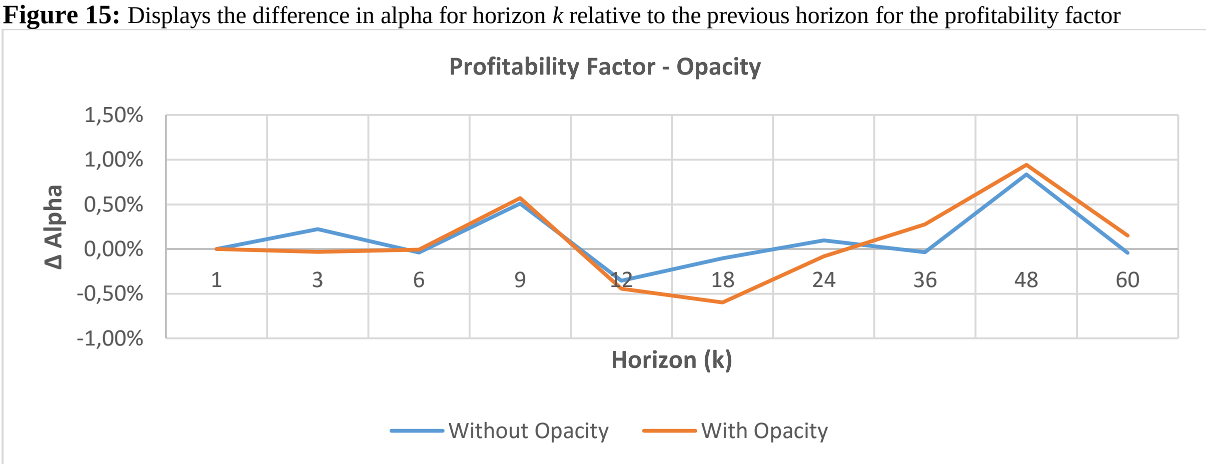
Figure 14: Displays the difference in alpha for horizon *k* relative to the previous horizon for the momentum factor



4.4.5 *Profitability Factor*

Figure 15 shows that for some horizons opacity can perform as an explanatory variable in explaining the dispersion of how the profitability factor is priced. The difference in alphas is namely closer to zero for the 3, 6, and 24 months horizons, when opacity is included in the regression. However, the difference in alphas for most horizons can be better explained with regressions wherein opacity is not included. So, the dispersion in the pricing of the profitability factor at various horizons can be better explained by opacity relative to the other factors. However, the regressions without including opacity generally still perform better. When looking at statistical evidence in Table 9, it can be observed that there is indeed more evidence that opacity can explain the dispersion in how the profitability factor is priced. The 3, 6, 9, 12, 24, and 48 months horizons have z-statistics closer to zero for regression that include opacity.

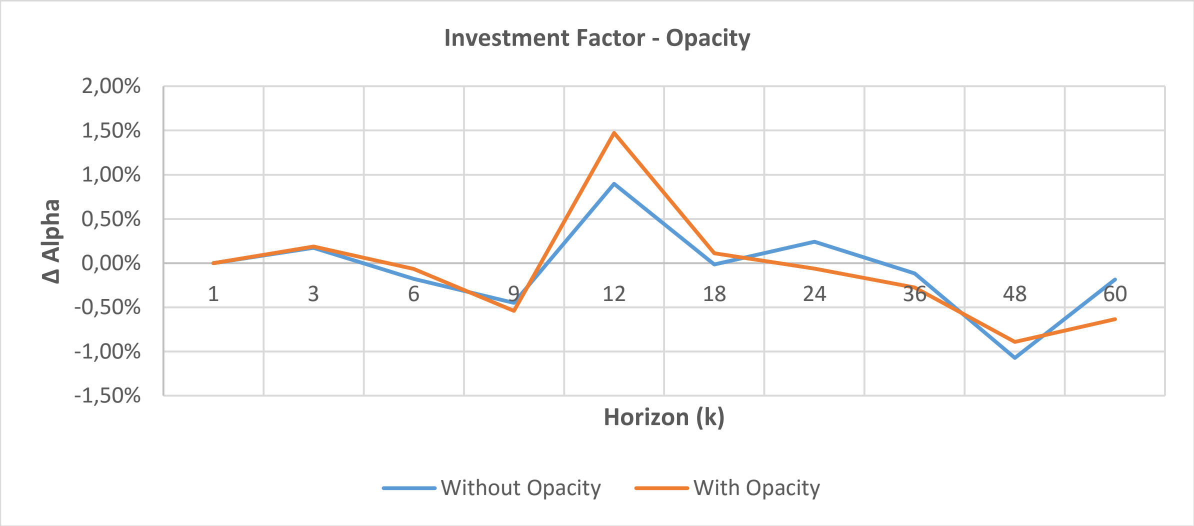
Figure 15: Displays the difference in alpha for horizon *k* relative to the previous horizon for the profitability factor



4.4.6 *Investment Factor*

Figure 16 shows that for the investment factor the alphas for some horizons are closer to zero when incorporating opacity in the regression (e.g. 6, 24, and 48 months horizons). But as concluded for the profitability factor, the dispersion in the pricing of various horizons for the investment factor can be generally better explained by the regression wherein opacity is not included. Statistically, there is also more evidence that opacity can explain the dispersion in how the investment factor is priced. Table 9 shows that at the 3, 6, 9, 24, and 48 months horizons the z-statistics are closer to zero when including opacity as a control variable. Despite there being more evidence that opacity can explain the dispersion of how the investment factor is priced, this evidence is not overwhelming.

Figure 16: Displays the difference in alpha for horizon *k* relative to the previous horizon for the investment factor



CHAPTER 5: Conclusion

5.1 Conclusion

Recent literature on investment horizons recognizes dispersion in the pricing of systematic risk factors at various horizons. This study investigates whether there is indeed dispersion in how six systematic risk (i.e. the market, size, value, momentum, profitability and investment) factors are priced over various horizons, through examining data from the Chinese stock market. In other the words, this study tries to test whether a systematic risk factor is priced at one horizon, where it is not priced at another horizon.

Firstly, this study documents excess returns for the six systematic risk factors at various horizons. The excess returns fluctuate across horizons for all systematic risk factors, which shows that there is dispersion in how the systematic risk factors are priced at various horizons. The excess returns for the market and value factor are significant and negative for generally all horizons. However, the excess returns are lowest at the intermediate-term horizons, proved by the 12 months horizon that generates the lowest excess return out of all horizons for both the market and value factor. The profitability factor has only significant excess returns over the 18, 24, and 36 months horizons, and is therefore just priced at the relative intermediate-term horizons. The size and the momentum factor display significant alphas across all horizons, those systematic risk factors are therefore priced at every horizon examined. The investment factor has significant excess returns only for horizons longer than 12 months. The investment factor seems to be priced over relatively longer horizons.

In addition, this study also reports alphas for the systematic risk factors at various horizons. The alpha denotes risk-adjusted excess returns relative to a particular asset pricing model or other benchmark. In this study the benchmark is the Fama-French five-factor model + momentum. This study reports alpha, because nowadays investors do not just try to reap the highest possible excess return, but also look to outperform a predetermined benchmark. Also the alphas tend to fluctuate across horizons for all systematic risk factors, which again shows that there is dispersion in how systematic risk factors are priced at various horizons. The most significant alphas for the market and value factor can be find at the longer-term horizons. For the market factor the 36, 48, and 60 months horizons are significant and positive, and for the value factor horizons longer than 12 months are significant and positive. However, for both the market and the value factor there are a few significant alphas over relatively shorter horizons as well (i.e. the 3 months horizon for the market factor, and the 1 and 9 months horizon for the value factor). The size factor does capture a positive significant alpha at the 1 month horizon and a negative significant alpha at the 36 months horizon. The momentum factor is positively priced at short-term horizons, implied by positive and significant alphas at the 1 and 3 months horizons. However, when moving across longer horizons the 12 and 48 months horizons capture significant negative alphas. The profitability factor has positive alphas at all horizons examined. And lastly, the investment factor displays negative alphas at short-term horizons (i.e. 1, 3, 6, and 9 months horizons) and long-term horizons (i.e. 48 and 60 months horizons).

Table 11 provides a summarization of the results for the excess returns and the alphas. Where the ‘’+’’ and ‘’-‘’ signs display whether the significant excess returns and alphas are positive or negative.

The results concerning the excess returns and alphas have a few implications for investors in the real world that want to invest in China. Both short-term and long-term horizon investors that aim to generate significant excess returns should invest in stocks with a high exposure to the size factor and/or the momentum factor. For both the size and momentum factor all horizons are priced positively and are therefore profitable. Additionally, long-term horizon investors that aim to obtain positive excess returns, can safely invest in stocks with a high exposure to the investment factor, because excess returns are positive and significant for horizons longer than 12 months. Investors should not buy stocks with exposure to the remaining systematic risk (i.e. market, value, profitability) factors that are, either not priced, or negatively priced. Investors that try to generate alpha relative to the Fama-French 5–factor model + momentum, should invest in stock with a high exposure to the market factor if they have investment horizons of, either 3, 36, 48, or 60 months. Short-term horizon investors that want to reap alphas should invest in stocks with high exposure to the size factor (positively priced at the 1 month horizon) or the momentum factor (positively priced at the 1, and 3 months horizons). Long-term horizon investors that want to obtain alpha should invest in stocks with a high exposure to the value factor, while alphas are positive and significant for horizons longer than 12 months. An investor also gathers alpha when buying stocks with high exposure to the profitability factor, irrelevant of the horizon.

Table 7: This table provides an overview of all significant excess returns and alphas found. When a cell is empty it means that the excess return or alpha appeared not to be significant at a 1% significance level. When a ‘’+’’ is displayed it means that the excess return or alpha is positive and significant at a 1% significance level, and when a ‘’-‘’ is displayed it means that the excess return or alpha is negative and significant at a 1% significance level. Again, the alphas are relative to the Fama-French 5-factor model + momentum.

Overview Results

Horizon	**Market Factor**		**Size Factor**		**Value Factor**		**Momentum Factor**		**Profitability Factor**		**Investment Factor**	
(k)	***ER***	***α***	***ER***	***α***	***ER***	***α***	***ER***	***α***	***ER***	***α***	***ER***	***α***
1			+	+		-	+	+		+		-
3	-	+	+		-		+	+		+		-
6	-		+		-		+			+		-
9	-		+		-	-	+			+		-
12	-		+		-		+	-		+		
18	-		+		-	+	+		-	+	+	
24	-		+		-	+	+		-	+	+	
36	-	+	+	-	-	+	+		-	+	+	
48	-	+	+		-	+	+	-		+	+	-
60		+	+		-	+	+			+	+	-

This study did also try explain the dispersion in how horizons were priced over various horizons by introducing two control variables: illiquidity and opacity. Both graphical and statistical evidence did not support the view that the two control variables were able to explain the dispersion in how systematic risk factors are priced over various horizons.

Theoretically, this study shows that there is a possibility of making profits by investing in stocks that are exposed to certain systematic risk factors at certain horizons. However, in practice, it might be a bit more complicated to get money out of the Chinese stock market. First of all, China has a stock market that is underdeveloped and unstable. Therefore, it can be that the profitable nature of certain systematic risk factors at certain investment horizons are profitable over the used sample period in this study, but appear to unprofitable in the future. Secondly, the government in China is still heavily involved in the Chinese stock market. For example, the government restricts investors in China from short-selling, which limits the opportunities of making high returns in the Chinese stock market. And lastly, it might be difficult to evaluate systematic risks and make proper portfolio management decisions in an opaque market like the Chinese stock market, because of the lack of longer track records in Chinese stocks.

5.2 Limitations

This study tries to explain the dispersion in systematic risk factors with including opacity as a control variable. As explained before, both the momentum factor and opacity do arise because of an under reaction to new information. Intuitively, it is expected that when these two variables are in the same regression they tend to interfere, and have a high level of multicollinearity. However, this study finds that the two variables are not correlated, and therefore opacity remains in the regression as a control variable.

Secondly, this study is performed in China, which has relatively young stock markets. For example, the Shenzhen and the Shanghai stock markets only reopened in 1990. Because of that, the Chinese stock markets are dominated by relatively small firms. Comparably, Western stock markets (e.g. NYSE) are more mature and are represented by both relatively small and big firms. Therefore, it could be that, due to the domination of relatively small firms, the size effect is not that pronounced in the Chinese stock markets. However, this study reports significant and positive excess returns for all horizons, therefore the size effect is discernible in this study.

Also, this study looks at systematic risk neglecting business specific risk. Business specific risk is the type of risk that comes with company or business industry you invest in. For example, the risk that a firm defaults or the firm skipping a dividend pay-out that was expected. This kinds of risks cannot be measured by beta. However, these kind of risks can be reduced through diversification.

Finally, this study does also neglect transaction costs and taxes, which will have an impact on substantially decreasing excess returns. This is especially true for short-term horizon investors that trade more frequently and therefore have higher transaction costs.

5.3 Future research

The quest why systematic risk factors are priced differently across various horizons is still ongoing. When considering that in this study just two out of many control variables are tested to explain the dispersion in the pricing of systematic risk factor across horizons, there are much more control variables that can be tested by academics to explain this dispersion. Alternatively, academics can also try to find different proxies for illiquidity or opacity that are better able to explain the dispersion in the pricing of systematic risk factors across horizons.

Furthermore, this study just focuses on how certain individual systematic risk factors are priced. It might be interesting for future research to combine certain systematic risk factors and see how they are priced across different horizons.

Another possible extension to this study is incorporating transaction costs and taxes in calculating the excess returns of a long portfolio over a short portfolio. For example, incorporating transaction costs can lead to new insights, because a distinction is made in transaction costs for short-term investors, which are generally higher, and transaction costs for long-term investors, which are generally lower.

To conclude, the topic of short- and long-term risk in stock markets' is a relatively new field in the academic literature. There remains still a lot of room for additional research which could lead to new interesting insights regarding this topic.

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APPENDIX A

Appendix A tends to explain the variables used in this study, by respectively denoting the variable code, the name of the variable, the definition of the variable, and the source of where the variable is collected (in italic).

AT – Assets: This item represents the total assets/liabilities of a company at a point in time
Source: WRDS Compustat Global

COGS – Cost of Goods Sold: This item represents all costs directly allocated by the company to production, such as material, labour and overhead.
Source: WRDS Compustat Global

CSHOI – Common Shares Outstanding: This issue-level item represents the net number of common/ordinary shares outstanding as of the company's fiscal year-end.
Source: WRDS Compustat Global

P – Price: This item represents the official closing monthly price adjusted for dividends, stock splits and many other changes to make every price comparable over time.
Source: Datastream

PPEGT – Property, Plant and Equipment: This item represents the cost and/or valuation of tangible fixed assets used in the production of revenue.
Source: WRDS Compustat Global

RECT – Receivables: This item represents an asset designation applicable to all debts, unsettled transactions or other monetary obligations owed to a company by its debtors or customers.
Source: WRDS Compustat Global

REFT – Revenue: This item represents Sales/Turnover (Net) plus Operating Revenues.
Source: WRDS Compustat Global

SALE – Sales/Turnover: This item represents gross sales (the amount of actual billings to customers for regular sales completed during the period) reduced by cash discounts, trade discounts, and returned sales and allowances for which credit is given to customers, for each operating segment.
Source: WRDS Compustat Global

TEQ – Stockholders Equity: This item represents the common equity, preferred equity and nonredeemable non-controlling interest of a company.
Source: WRDS Compustat Global

TXDITC – Deferred Taxes and Investment Tax Credit: This item represents the accumulated tax deferrals due to timing differences between the reporting of revenues and expenses for financial statements and tax forms and investment tax credit.
Source: WRDS Compustat Global

XINT – Interest and Related Expense: This item represents the periodic expense to the company of securing short- and long-term debt. Where possible, this item is collected as a gross figure (for example, if interest expense is reported net by the company, interest income and/or interest capitalized will be added back to arrive at a gross figure).
Source: WRDS Compustat Global

XSGA – Selling, General and Administrative Expense: This item represents the sum of all direct and indirect selling expenses and all general and administrative expenses of a company.
Source: WRDS Compustat Global

VO – Turnover by Volume: This item represents the monthly turnover by volume, measured in Chinese Yuan.
Source: Datastream

ATTACHMENT

Table 8: A z-test is performed to test whether there is a significant difference in the change of alpha spreads for horizon *k* relative to horizon *k-1*. For example, the coefficient of horizon *k=3* is the z-statistic based on the difference in alpha spreads between the 3 months and the 1 month horizon. Both the z-statistics for differences in the alpha spread for regressions without illiquidity (1) and with illiquidity (2) are given. A lower z-statistic shows that there is less dispersion in one horizon relative to the previous horizon. The formula of the z-test is given as: $z = (\alpha_2 - \alpha_1)/\sqrt{\sigma_1^2/n_1 + \sigma_2^2/n_2}$. The sample period is June 1995 – December 2015.

Z-Statistics for Regressions With and Without Illiquidity

Horizon	β_k^{MKT}		β_k^{SMB}		β_k^{HML}		β_k^{UMD}		β_k^{RMW}		β_k^{CMA}	
(k)	**(1)**	**(2)**	**(1)**	**(2)**	**(1)**	**(2)**	**(1)**	**(2)**	**(1)**	**(2)**	**(1)**	**(2)**
1	2.31	6.14	-3.80	-3.06	0.87	3.85	-4.88	-5.43	0.63	0.60	0.53	-0.08
3	-3.28	-2.08	-0.45	-2.19	-0.37	-1.35	-2.36	-2.57	-0.12	-0.43	-0.51	0.47
6	1.16	0.57	-0.43	-0.76	-0.91	-1.01	0.26	-1.46	1.38	-0.32	-1.29	-0.33
9	-0.21	0.53	0.67	0.10	1.15	3.48	-1.84	-2.67	-0.99	1.14	2.57	-0.74
12	1.34	1.10	-1.70	-0.89	3.08	3.57	1.49	2.72	-0.30	0.46	-0.04	-1.19
18	-0.38	-2.02	-0.44	0.46	1.14	-0.10	-0.53	0.48	0.24	0.97	0.67	1.06
24	3.46	3.15	-1.99	-3.14	1.66	0.86	0.29	3.57	-0.10	0.26	-0.30	-0.21
36	-2.42	-1.96	3.60	5.07	-1.88	-2.14	-0.69	-0.21	2.59	1.61	-2.97	-5.63
48	0.39	-1.30	0.50	0.89	0.80	0.68	1.81	2.68	-0.14	0.88	-0.58	0.65

Table 9: A z-test is performed to test whether there is a significant difference in the change of alpha spreads for horizon *k* relative to horizon *k-1*. For example, the coefficient of horizon *k=3* is the z-statistic based on the difference in alpha spreads between the 3 months and the 1 month horizon. Both the z-statistics for differences in the alpha spread for regressions without opacity (1) and with opacity (2) are given. A lower z-statistic shows that there is less dispersion in one horizon relative to the previous horizon. The formula of the z-test is given as: $z = (\alpha_2 - \alpha_1)/\sqrt{\sigma_1^2/n_1 + \sigma_2^2/n_2}$. The sample period is June 1995 – December 2015.

Z-Statistics for Regressions With and Without Opacity

Horizon	β_k^{MKT}		β_k^{SMB}		β_k^{HML}		β_k^{UMD}		β_k^{RMW}		β_k^{CMA}	
(k)	**(1)**	**(2)**	**(1)**	**(2)**	**(1)**	**(2)**	**(1)**	**(2)**	**(1)**	**(2)**	**(1)**	**(2)**
1	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
3	2.31	1.80	-3.80	-3.21	0.87	1.17	-4.88	-5.10	0.63	-0.07	0.53	0.43
6	-3.28	-3.45	-0.45	-0.21	-0.37	0.04	-2.36	-3.02	-0.12	-0.01	-0.51	-0.13
9	1.16	0.74	-0.43	-1.11	-0.91	-0.71	0.26	0.95	1.38	1.14	-1.29	-1.13
12	-0.21	-0.17	0.67	0.56	1.15	0.31	-1.84	-1.89	-0.99	-0.92	2.57	3.08
18	1.34	1.28	-1.70	-1.85	3.08	2.64	1.49	1.27	-0.30	-1.29	-0.04	0.23
24	-0.38	-0.91	-0.44	-0.83	1.14	1.28	-0.53	-0.63	0.24	-0.15	0.67	-0.12
36	3.46	3.78	-1.99	-2.12	1.66	2.25	0.29	-0.44	-0.10	0.55	-0.30	-0.50
48	-2.42	-1.79	3.60	3.86	-1.88	-2.48	-0.69	0.39	2.59	2.19	-2.97	-1.77
60	0.39	-1.34	0.50	0.49	0.80	1.27	1.81	1.74	-0.14	0.37	-0.58	-1.41

Table 10: This table reports the level of illiquidity for the top decile (i.e. decile with 10% stocks that have the highest exposure to a particular risk factor) and the bottom decile (i.e. decile with 10% stocks that have the lowest exposure to a particular risk factor). Illiquidity is measured by the Amihud illiquidity measure.

Overview Illiquidity Levels at Different Horizons

Horizon	β_k^{MKT}		β_k^{SMB}		β_k^{HML}		β_k^{UMD}		β_k^{RMW}		β_k^{CMA}	
(k)	***D1***	***D10***	***D1***	***D10***	***D1***	***D10***	***D1***	***D10***	***D1***	***D10***	***D1***	***D10***
1	0.4840	0.4427	0.4669	0.4049	0.4316	0.4285	0.5036	0.4142	0.4067	0.5516	0.5283	0.3890
3	0.5155	0.4626	0.4438	0.4767	0.4690	0.4499	0.4984	0.4330	0.4343	0.5202	0.4578	0.4170
6	0.4691	0.5094	0.4268	0.5222	0.4859	0.4487	0.4978	0.4474	0.4383	0.4756	0.4686	0.3986
9	0.4839	0.4840	0.4293	0.5231	0.4600	0.4470	0.5195	0.4443	0.4188	0.4503	0.4246	0.4354
12	0.5279	0.5099	0.4177	0.5223	0.4559	0.4344	0.5065	0.4436	0.4099	0.4616	0.4278	0.4387
18	0.5502	0.4710	0.4180	0.4672	0.4652	0.4344	0.4702	0.4499	0.4271	0.4809	0.4398	0.4506
24	0.5428	0.4454	0.4248	0.4740	0.4662	0.4391	0.4578	0.4529	0.4114	0.4629	0.4317	0.4450
36	0.4850	0.5198	0.4280	0.4575	0.4469	0.4886	0.4888	0.4167	0.4573	0.4268	0.4412	0.4658
48	0.4818	0.5097	0.4463	0.4600	0.4726	0.4573	0.5242	0.4118	0.4631	0.4467	0.4454	0.4830
60	0.5013	0.4711	0.4447	0.4866	0.5061	0.4362	0.5083	0.4297	0.4615	0.4570	0.4306	0.4852

Table 11: This table reports the level of opacity for the top decile (i.e. decile with 10% stocks that have the highest exposure to a particular risk factor) and the bottom decile (i.e. decile with 10% stocks that have the lowest exposure to a particular risk factor). Opacity is measured by the variance in discretionary accruals.

Overview Opacity Levels at Different Horizons

Horizon	$\boldsymbol{\beta_k^{MKT}}$		$\boldsymbol{\beta_k^{SMB}}$		$\boldsymbol{\beta_k^{HML}}$		$\boldsymbol{\beta_k^{UMD}}$		$\boldsymbol{\beta_k^{RMW}}$		$\boldsymbol{\beta_k^{CMA}}$	
(k)	***D1***	***D10***	***D1***	***D10***	***D1***	***D10***	***D1***	***D10***	***D1***	***D10***	***D1***	***D10***
1	0.0078	0.0061	0.0063	0.0105	0.0076	0.0075	0.0088	0.0067	0.0090	0.0058	0.0060	0.0084
3	0.0062	0.0088	0.0065	0.0101	0.0072	0.0084	0.0097	0.0068	0.0086	0.0065	0.0062	0.0086
6	0.0062	0.0081	0.0076	0.0077	0.0072	0.0083	0.0089	0.0068	0.0092	0.0070	0.0068	0.0083
9	0.0065	0.0074	0.0077	0.0068	0.0070	0.0080	0.0090	0.0063	0.0086	0.0067	0.0069	0.0083
12	0.0063	0.0075	0.0077	0.0071	0.0073	0.0072	0.0091	0.0062	0.0083	0.0066	0.0067	0.0085
18	0.0069	0.0073	0.0076	0.0068	0.0069	0.0078	0.0085	0.0066	0.0077	0.0077	0.0065	0.0083
24	0.0068	0.0074	0.0082	0.0064	0.0072	0.0079	0.0084	0.0066	0.0076	0.0069	0.0064	0.0090
36	0.0062	0.0077	0.0087	0.0057	0.0060	0.0085	0.0080	0.0064	0.0083	0.0061	0.0068	0.0076
48	0.0059	0.0077	0.0080	0.0053	0.0060	0.0083	0.0081	0.0063	0.0077	0.0064	0.0074	0.0074
60	0.0063	0.0080	0.0076	0.0064	0.0070	0.0079	0.0074	0.0072	0.0073	0.0074	0.0074	0.0079