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Illiquidity as risk factor in stocks

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Abstract

This paper analyses the effects of static and dynamic illiquidity risks of stocks in the period between 1995 and 2016. The methods employed are portfolio sorts and cross-sectional Fama-MacBeth regressions on firm characteristics. The illiquidity level premium seems persistent over time, but decreased in magnitude contemporaneously with lower market-wide illiquidity. Market-wide liquidity appears not to be a priced state variable, as exposure to market-wide liquidity is not compensated by a risk premium. The illiquidity level is not strongly related to this dynamic channel of illiquidity risk, as adding the dynamic risk factor to asset pricing models does not explain abnormal returns.

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1. Introduction

Liquidity of stocks is generally believed to be risky, meaning it`s realized outcome is unpredictable. However, it also shows commonality, meaning liquidity fluctuations are correlated. This holds for both individual stocks as the market as a whole (Chordia, Roll, & Subrahmanyam, 2000). Some stocks tend to realize low returns when the market is illiquid. An illiquid market can be seen as a low welfare state in which the marginal utility of investors is high according to asset pricing theory. For these stocks, a risk premium is likely to exist. Also, stocks with low average liquidity are not favored by investors as illiquidity broadly translates to high selling expenses. To compensate investors for holding these assets, a premium is likely to exist.

Illiquidity has a static channel where increases in illiquidity level are compensated with a higher return, to make up for higher expected trading costs. Illiquidity also has a dynamic channel, in which a stock`s lowest returns covariance with market illiquidity. These illiquidity channels have been investigated in older time periods, indicating a positive risk premium on both. To see if these documented results are robust and hold in the modern market, I empirically test the relation in a recent time sample. Therefore, my research question is: Is illiquidity in stocks a separate risk factor that requires compensation through a higher expected return?

The academic literature provides three papers with similar research questions regarding illiquidity as an aggregate risk factor. Amihud (2002) find a significant positve relation between illiquidity level and stock returns, motivating the higer returns a compensation for higher expected trading costs. The research by Pástor & Stambaugh (2003) shows that expected stock returns are cross-sectional related to the sensitivities of returns with fluctuations in market-wide liquidity. They find that stocks with high liquidity betas (high return sensitivities to liquidity) can produce abnormal returns, thus a positive alpha. On the other hand, Acharya and Pedersen (2005) state the exposure to market liquidity is only a small source of the total liquidity risk premium, as a different effect, the stocks`s liquidity covariance with market returns, is responsible for 80% of their found premium.

In this paper, I test if the illiquidity effects hold in the modern stock market. For the period between 1996 and 2016, I sort stocks in decile portfolios based on their illiquidity level and their exposure to a dynamic illiquidity risk factor. This risk factor is quantified as innovations of a first order autoregression on market-wide illiquidity. The portfolios are tested using the CAPM and the Fama-French 3- and 5-factor models. Subsequently, the risk factor is added to these models to see if the factor has explanatory power on returns. To check if the illiquidity effects hold controlling for firm specific characteristic, the Fama-MacBeth (1973) cross-sectional regressions are performed. For each month, returns are regressed on previous year firm characteristics, including the current ratio as indicator for firm liquidity. Regarding both the decile sort and the cross-sectional regressions, two subperiods are formed to check for time-varying effects.

I find persistence in compensation for stocks having a high illiquidity level, but the compensation decreases contemporaneously with market-wide illiquidity. No significant risk compensation is found for stocks realizing its lowest returns in times of market illiquidity, indicating market illiquidity is not a priced state variable. These findings are robust over time and controlling for firm characteristics.

Illiquid stocks tend to have a high exposure to the dynamic risk factor. Therefore, illiquid stocks are more likely to realize low returns in times of market illiquidity. However, the constructed risk factor has very low explanatory power on returns when added to the pricing models. Even more surprising, stocks sorted on the liquidity beta do not have aggregate portfolio liquidity betas parallel to the sort. This finding remains unexplained.

This paper confirms the previous findings by Amihud (2002) of increasing returns for increasing levels of illiquidity. His findings remain valid in times of low market-wide illiquidity. In addition, the relation holds controlling for extra variables, as the current ratio, the liquidity beta and earnings per share are considered in the cross-sectional Fama-French (1973) framework.

However, the paper contradicts findings by Pástor and Stambaugh (2003) who declare marketwide liquidity being a state variable important for pricing common stocks. In contrast to their findings, no significant postive risk premium is found for stocks more sensitive to aggregate liquidity. In the sort on historical liquidity betas no significant abnormal returns are found, considering the same asset pricing models. Likewise, in the cross-section only small non-significant effects are found of liquidity betas on returns. Therefore, this paper supports the claim by Acharya and Pedersen (2005) that the covariance of returns with market liquidity only explains a small fraction of the total liquidity risk premium.

2. Academic Literature

2.1 Defining liquidity

Liquidity is an ambiguous concept that cannot be observed directly, but generally refers to the traders` ability to trade a large quantity at low costs without causing price movement (Pástor & Stambaugh, 2003). In line with this definition, Halka and Huberman (2001) consider a market to be liquid if one can trade large quantities quickly after the desire to trade at a price that is near the stock price both before and after the trade takes place. They see liquidity as the speed and ease a stock can be traded, but acknowledge that this is not directly observable. Amihud and Mendeslon (1986) add to this that

Illiquidity works both ways. Both quickly (or in large quantity) buying and selling is expensive. Thus, it reflects the price impact of order flow, for a seller this means an incurred discount and for a buyer the payed premium.

Chordia, Roll, & Subrahmanyam (2000) distinguish two separate channels through which trading costs influence asset pricing. The first is the static channel, the influence of average trading costs. The second is the dynamic channel that influences risk, uncertainty on future liquidity. In this paper, the latter is taken in account as the stock`s returns sensitivities to innovations in market-wide illiquidity, given by a liquidity beta.

2.2 Liquidity measures

There are many proxies used to measure this unobservable stock liquidity in current literature. Halka and Huberman (2001) specify two quantities strongly related to liquidity: spread and depth. The spread refers to the difference between bid and ask prices of traded stocks. Depth refers to the number of units corresponding to those quoted bid and ask prices. Another used proxy is the stocks` turnover rate, the number of shares traded divided by the number of outstanding shares (Datar, Naik, & Radcliffe, 1998). However, the two most wide-known measures are constructed by the following researchers. The first is the liquidity measure by Pastor and Stambaugh (2003) who use the amount in which returns rebound upon high volume. They perform monthly auto-regressive regressions of excess market return per stock, scaled for growing dollar volume. The liquidity measure for each stock is given by ordinary least square estimate of the coefficient estimated for the contemporaneous return, multiplied with dollar volume. The measure by Amihud (2002) uses the ratio between absolute return to dollar trading volume. This method first calculates the each stock`s illiquidity individually on a daily frequency and then aggregates this to a yearly frequency by taking the average of all days. The market-wide illiquidity measure follows afterwards by taking the equally-weighted average of all individual stock per month. Because this last method estimates illiquidity instead of liquidity, it is referred to as an illiquidity measure.

2.3 Liquidity level

The static channel of liquidity is the direct result of a liquidity measurement method. It captures the level of liquidity at a certain moment in time, applicable for both individual stocks as the market as a whole. The reason liquidity is of such importance is that in efficient markets the trading costs following illiquidity should be related to expected returns. Amihud (2002) finds that the expected market returns in excess of the Treasury bill rate increase following increasing market illiquidity. He states that investors anticipate higher market illiquidity by pricing the stocks in a way that they receive a higher expected return. Therefore, the risk premium of the market includes a premium for liquidity, since stocks are not only riskier, but also less liquid than Treasury bills. Whereas Treasure bills can be traded in large amounts without impacting its price, for stocks the bid-ask spread is much higher, what causes price impact. The risk of making a price impact when trading stocks implies a risk on making costs.

Liquidity is not only believed to impact the total market excess returns, but also individual stocks. As shown in previous work, like Amihud and Mendelson (1986), the after-cost returns of trading is positively related cross-sectional to illiquidity of stocks because of expected trading costs. Stocks that are more illiquid on average are found to have higher expected returns to compensate for their higher risk of making costs when traded.

To see what the effect of illiquidity is on stocks Amihud (2002) regresses monthly stock returns on stock characteristics of the previous year in a cross-sectional model, following the Fama-MacBeth (1973) method. The main characteristics of interest is the stocks` relative level of illiquidity, with respect to market illiquidity. Included control variables are market beta, stock turnover, size, trading volume, stock volatility, dividend yield and cumulative past stock returns. He finds a consistent positive relation between stock returns and illiquidity, also checking for subperiods. This indicates a premium for holding illiquid stocks, as compensation for high expected trading costs.

2.4 Commonality of liquidity

Liquidity is believed to have common underlying determinants making transaction costs of individual stocks covariance positively over time. The importance of this commonality in illiquidity is that the associated trading costs might pose a source of non-diversifiable priced risk. The covariance of stocks towards the impact on underlying trading costs varies across individual securities and cannot be completely anticipated on (Chordia, Roll, & Subrahmanyam, 2000). The idea is that stocks that are sensitive to shocks of illiquidity, so the stocks with a higher impact of trading costs, require a higher expected return than similar assets that are not so sensitive. Evidence suggests fluctuations of various liquidity proxies are correlated across common stocks. Chordia, Roll & Subrahmanyam (2000) test this correlation by estimating a regression model of percentage changes in liquidity variables of individual stocks as a function of market averages. They find positive correlations for 85 percent of all stocks, strongly indicating commonality in liquidity. Their result holds when controlling for individual well-known determinants of liquidity as trading volume, volatility and price. Similar research by Halka and Huberman (2001) also provide evidence of commonality as their four liquidity proxies vary over time whilst having a cross-sectional common component. However, both papers do not identify the source driving this commonality in liquidity. They simply state it is there, not being caused by chance.

The issue then becomes whether systematic (market-wide) liquidity is priced in the stock market and whether a liquidity risk factor enters the stochastic discount factor as an additional state variable.

2.5 Liquidity beta

Standard asset pricing theory links cross-sectional differences in expected stock returns to returns` sensitivities to market-wide state variables that influence the investors` overall welfare. During unfavourable shifts in this welfare, investors have higher marginal utilities of wealth and are therefore more sensitive to the realized returns. Securities that tend to have their lowest returns realized during these states of low welfare therefore require additional compensation to offset these bad outcomes (Pástor & Stambaugh, 2003).

The importance of commonality in liquidity arises in the question whether liquidity is a priced state variable. If changes in aggregate liquidity are non-diversifiable, then investors should receive a premium for holding securities that have a negative covariance relative to aggregate illiquidity. The idea is that systematic shocks in liquidity affects the utility optimization behaviour of investors. Investors want to be compensated for holding stocks that are expected to have their lowest returns in illiquid states of the world. When these bad states occur, investors value every extra unit of return more highly. Higher demand for stocks that have positive returns in these bad states, lowers demand for stocks that do not. This lower demand translates to a lower stock price, which directly increases expected return. This increase in return is regarded an illiquidity premium, thus resulting from the negative covariance with illiquidity.

Brunnermeier & Pedersen (2007) take this relation a step further by considering leveraged investors, who can be forced to sell in low illiquidity states to pay off other unrelated positions. Leveraged investors are often limited by funding constrains, making them sell assets to reduce their positions when they risk hitting their capital constraint. These sell-offs occur during times of low liquidity for investors who hold assets with high sensitivities to market liquidity, making liquidation costlier. This causes a downward spiral of falling market liquidity, in which stock prices are more driven by funding constraints than changes in fundamentals. This contributes to a risk premium demanded for assets that have higher sensitivities to market liquidity. If this additional compensation would not exist, no investor would invest in such asset. Lower demand drops the price, thereby directly increasing expected return up to the point of the risk premium demanded.

Pástor and Stambaugh (2003) test if market-wide liquidity is an important state variable. They find evidence that expected stock returns are related to sensitivities of returns to fluctuations in aggregate liquidity in the cross-section. In their research they measure liquidity by assuming order flow causes greater return reversals in times of illiquidity. The stocks` individual liquidity is measured by the coefficient of the sign of previous day excess returns in a regression of excess stock return on market return and this sign effect. The monthly aggregate liquidity is subsequently measured as the equally weighted average of all individual liquidities. The paper does not take in account absolute levels of market liquidity, but instead focusses on innovations in liquidity. These innovations are measured by the fitted residual resulting from an autoregressive regression on changes in aggregate liquidity. The stocks` return sensitivities to market-wide liquidity are measured as the beta coefficient resulting from a regression of excess returns on the liquidity innovation and the Fama-French 3-factor model. These factors are the excess returns of the market portfolio and the size- and value effects, SMB and HML.

Subsequently, they perform a yearly sort on the predicted value of this beta for the individual stocks. The sort reveals that the expected return of the portfolios tend to increase with higher levels of the predicted liquidity beta. This result holds when controlling for the market portfolio, size, value and momentum effect. They also estimate the corresponding risk premium to quantify this pattern in returns. They do this using the generalized method of moments. They estimate a yearly premium of 7.56% when controlling for those 4 discussed traded factors.

Acharya & Pedersen (2005) dive deeper into the driving forces behind liquidity risk by specifying three different forms of liquidity risk. Using these inputs as extra beta`s, they estimate an illiquidity adjusted CAPM model. This model is similar to the original CAPM, but uses returns net of illiquidity costs. They do this by decomposing their so called `net beta`, where “net” refers to the subtraction of exogenous illiquidity costs. This beta takes in account the covariance between net stock returns and net market returns. The resulting identified risks are: (i) commonality of liquidity with the market, cov(Ri, Cm); (ii) the return sensitivity to the market liquidity, cov(Ci, Cm); and, (iii) the stock`s liquidity to market return (Ci, Rm). They find corresponding risk premiums of 0.08%, 0.16% and 0.82%, indicating that the most important source of risk accompanies stocks that tend to become illiquid when market returns are low. Thus, investors are willing to pay a premium to hold securities that are liquid during low market returns. This contradict the findings by Pástor & Stambaugh (2003), as the calculated premium for exposure to market-wide illiquidity is much smaller.

Acharya & Pedersen (2005) differ from Pastor & Stambaugh (2003) in the way they measure innovations in liquidity. First of all, they use Amihud`s liquidity measure to proxy a stock`s liquidity. They then also take the fitted residuals in an autoregression on aggregate liquidity, but do not take the first differences. Instead, they remove outliers and normalize liquidity to make it stationary. Furthermore, they estimate 25 portfolios instead of 10. Another difference is that Acharya and Pedersen also test portfolios sorted on size and book-to-market, as well as a sort on the liquidity measure.

The evidence provided above strongly indicates liquidity risk is priced in America`s biggest stock markets, as NYSE and AMEX data is used in the research discussed above. In the paper by Marcelo & Quirós (2006) a research is conducted for the Spanish stock market, to check whether the found effects hold in a different market. They also find a significant positive risk premium for liquidity in the Spanish market. They include their created illiquidity-mimicking factor in the CAPM and the 3-factor model by Fama and French. Next, the estimated alphas using time-series for each portfolio are compared before and after including the illiquidity risk factor. They compare these alphas based on each portfolios individual t-statistic and a joint Wald-test to check whether the alphas significantly differ from zero. Based on this, they conclude the illiquidity risk factor improves the asset pricing model. It is also mentioned that the models including the illiquidity factor improve substantially on their R-squared. This evidence suggests liquidity is a wide-spread effect, not limited to American stock markets, therefore supporting the importance of a liquidity premium in asset pricing.

3. Data and Summary Statistics

3.1 Data sources

I use data from the American stock markets NSYE and AMEX (or NYSE MKT) retrieved from the Center for Research in Security Prices (CRSP) database, thus excluding the NASDAQ index. Data for the periods January 1995 until December 2016 is used. The dataset is augmented with annual firm-specific balance sheet data from COMPUSTAT regarding the same periods. For the asset pricing models to be tested, I retrieve data from Kenneth French` website, as the database contains the relevant monthly risk factors and risk-free rate for the considered periods, constructed using CRSP data. The risk-free rate consists of the 1-month Treasury bill rate (from Ibbotson and Associates). To create an illiquidity measure I include daily stock data retrieved from CRSP. The reason the NASDAQ is not considered relates to this illiquidity measure, as it requires volume data on stock trades. Because trading on the Nasdaq is done mainly through market makers, the volume figures have a different meaning than the NYSE markets where trading is done directly by investors buying and selling (Amihud, 2002).

3.2 Illiquidity measure

Each stocks` monthly illiquidity is calculated using Amihud`s liquidity measure. Although this measure originally measures illiquidity on an annual basis, the method as used by Acharya & Pedersen (2005) is followed by applying a monthly frequency. Using this measure, stocks can be sorted in portfolios directly by its absolute value. In addition, when aggregating the measures, an illiquidity factor can be calculated.

The measure calculates the illiquidity of a stock, where stocks that are illiquid tend to have high price movement in response to little volume. The illiquidity is measured as:

$$(1) \qquad ILLIQ_t^i = \frac{1}{Days_t^i} \sum_{d=1}^{Days_t^i} \frac{|R_{td}^i|}{V_{td}^i}$$

where $|R_{td}^i|$ represents the absolute value of return and V_{td}^i the dollar value measured in millions per day *d*, for each stock *i* each month t. $Days_t^i$ stands for the number days included for each month per stock.

Subsequently, the estimated illiquidity measures are subjected to four criteria to increase the reliability of the estimation. Stock observations not satisfying the following criteria are removed from the sample: *(i)* The stocks have return and volume data of at least 15 days each month, and the stock must be listed in December of the previous year *(ii)* The yearly average stock price is greater than $5. *(iii)* The stock`s annual average market capitalization is available as measured by shares outstanding multiplied with stock price. *(iv)* The outliers of the measure its highest and lowest 1% tails of the distribution are removed, for stocks that already satisfy the first three criteria. The number of stocks that satisfy these conditions is on average 2364 each year, with a minimum and maximum respectively 2108 and 2633. The total remaining number of unique stocks in the whole dataset is 5257.

3.3 Summary statistics

3.3.1 Sorting criteria

The summary statistics of the determinants of the annual portfolio sorts are given in table 1. For the static channel this is the one year lagged average annual stock illiquidity. For the dynamic channel, this is the estimated liquidity beta. The liquidity beta results from a stocks` exposure to the illiquidity risk factor, augmented to the Fama-French 3-factor model (Fama & French, 1993).

It is seen that the distribution on absolute level of illiquidity is convincingly positive skewed. Given that the measure cannot be less than zero, and the maximum value is only 1.13, the greater amount of stocks are more liquid than the average liquidity. This is reflected in the reported positive skewness. Before winsorizing the data, the minimum value was around five times as small. On the contrary, the maximum value was with 107 much higher.

The liquidity betas appear normally distributed, as the mean value is almost in the middle of the minimum and maximum value and the skewness is close to zero. The maximum and minimum values are more extreme than for the illiquidity level. This is also reflected in the beta having a high standard deviation.

Sort	Mean	Standard dev.	Min	Max	Skew
Illiquidity level	0.04	0.10	0.00	1.13	4.22
Liquidity beta	-0.76	3.81	-14.07	12.08	-0.09

Table 1 *- Summary statistics of the portfolio sorting determinants. "Illiquidity level" corresponds to all stocks` absolute level as measured by Amihud`s illiquidity measure." Liquidity beta" indicates the coefficients of the augmented Fama-French 3-factor regression estimates on liquidity innovations, using 3 prior years.*

3.3.2 Market-wide illiquidity

Taking the average of all included stocks` scaled individual illiquidity measures results in the proxy for market–wide illiquidity. Figure 1 plots this series with a monthly frequency over the sample period. During the period 1996 till 2002 the market appears illiquid, for which certain events can be held responsible. During 1997, the Asian financial crisis took place, making world-wide impact. In 1998, liquidity was perceived dried up due to the collapse of LTCM, an enormous hedge fund, following up on the Russian debt crisis taking place. Between 2000 and 2002 the dot-com bubble collapsed, causing many listed companies to lose market value. At last, during this period the 9/11 attacks took place causing stock prices to decline.

After 2002, a negative trend can be observed, meaning the market is became more liquid towards recent time periods. A big exception in this trend is the global financial crisis, which started late 2007, what led to a wide-spread recession.

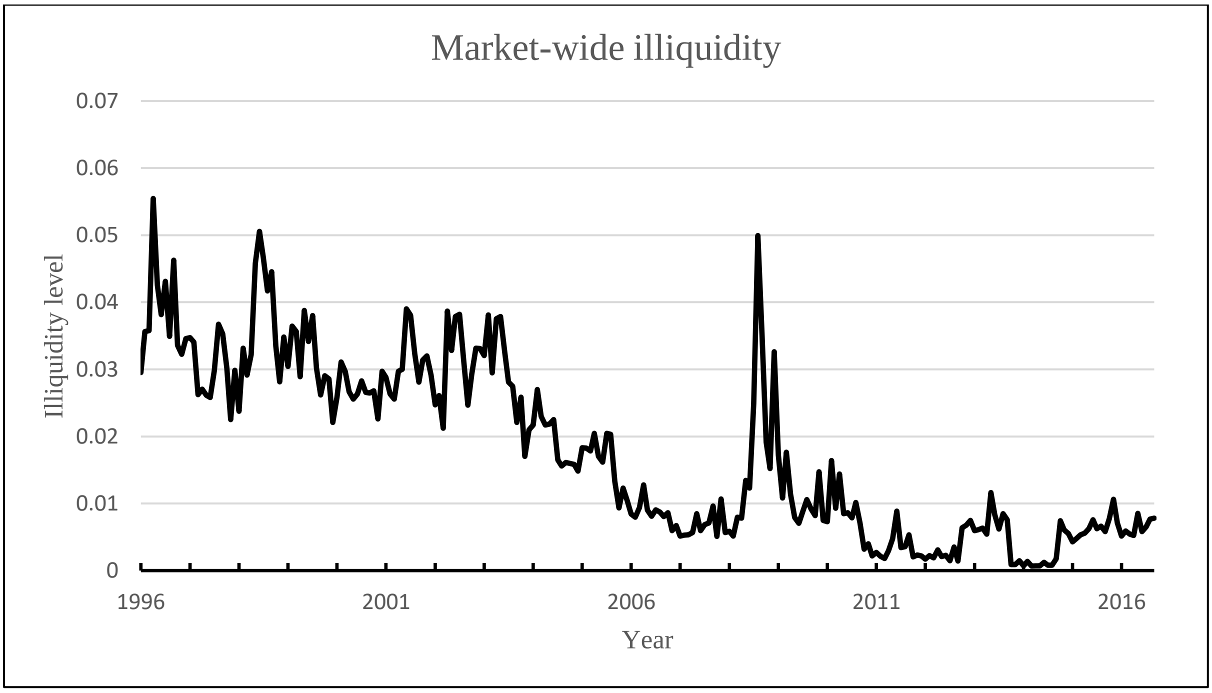

Figure 1 *– The aggregate illiquidity series. For every month, the market capitalization scaled average of Amihud`s illiquidity measure is taken for all NYSE and AMEX stocks that satisfy the Amihud criteria. Tick marks correspond to the start of a year.*

Furthermore, the aggregate time-series has a high autocorrelation (0.86), showing that market illiquidity moves predictably. This high autocorrelation is disturbing for the regression analysis, which is why the illiquidity innovations are formed. The first order autocorrelation is close to zero (-0.13), making the innovations in liquidity not predictable.

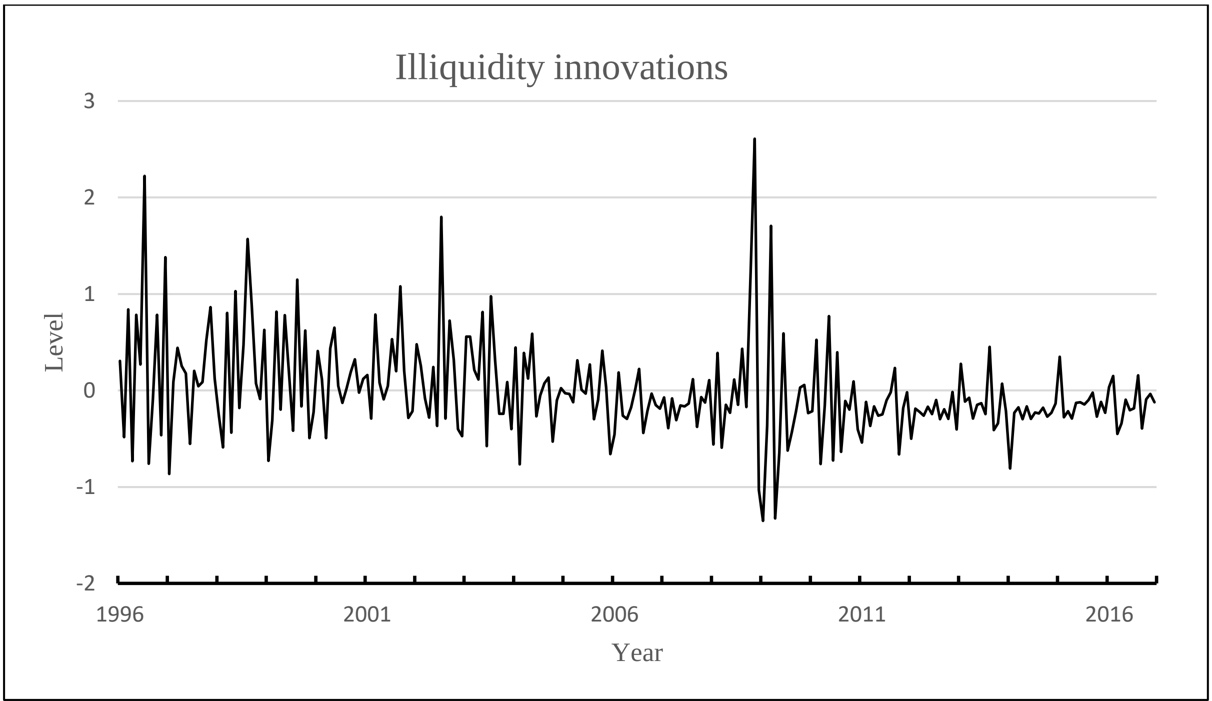

Figure 2 *– Illiquidity factor. The factor is a result of innovations from an first-order autoregression of the market-wide illiquidity series.*

In figure 2 the liquidity innovations are graphed. These innovations look stationary, and the Dickey-Fuller unit root test indeed strongly rejects a random walk (t-value: -17.8). Consistent with both the liquidity measures of Pástor & Stambaugh (2003) and Acharya & Pedersen (2005) the market shows high illiquidity innovations in the years 1996 until 2002. From 2002, the innovations gradually decrease as the market-wide becomes more liquid. During the crisis the innovations temporarily increase, consistent with the idea that this is an illiquid period. After 2012, the innovations reach consistently levels close to zero.

3.3.3 Risk factors

Table 2 reports summary statistics on the distribution of the market portfolio, the Fama-French 3- and 5-factors and the illiquidity innovation factor. As shown, the market has an average return of 0.60% per month, in excess of the risk free rate. But, these returns are offset by a high volatility. The illiquidity factor, after scaling, still takes low values as can be seen by its min and max values.

Factor	*Mean*	*Volatility*	*Min*	*Max*
MKT	0.60	4.50	-17.23	11.35
HML	0.26	3.21	-11.25	12.91
SMB3	0.20	3.46	-17.17	22.08
SMB5	0.24	3.27	-15.28	18.73
RMW	0.34	3.02	-19.11	13.52
CMA	0.29	2.19	-6.88	9.55
L	0.00	0.51	-1.35	2.61

Table 2 *- Factors` summary statistics. The market portfolio (MKT), the High-minus-Low (HML), both Small-minus-Big (SMB), the Robust-minus-Weak (RMW) and the (Conservative-minus-Aggressive) factor are retrieved from Kenneth-French`s data library. The liquidity sensitivities factor consists of the errors of a first-order autoregression on market illiquidity.*

The difference between the SMB factors resulting from the 3- and 5-factor models is shown to be small, as the main difference is only slightly more extreme values for the SMB3 factor. The HML and RMW factors have similar characteristics as the SMB factors. The CMA differs as its standard deviation and extreme values are smaller.

To see if the factors capture different variation in stock returns, the correlations between them is reported in table 3. In this table, it can be seen that the different factors of interest are in general not strongly correlated, indicating the factors capture different effects. The two newest Fama-French factors making the 5-factor model generate the highest correlations, with up to 0.64 between RMW and HML. The illiquidity factor (L) seems to be a standalone factor, adding possibly new information to the pricing models, as it correlates low with the other factors. The negative correlation of -0.27 with the excess market return confirms that recessions tend to be accompanied by low liquidity and therefore unexpected shocks.

Factor	*MKT*	*HML*	*SMB3*	*SMB5*	*RMW*	*CMA*	*L*
MKT	1						
HML	*-0.15*	1					
SMB3	*0.23*	-0.30	1				
SMB5	*0.21*	-0.13	0.98	1			
RMW	*-0.49*	0.45	-0.59	-0.50	1		
CMA	*-0.35*	0.64	-0.12	-0.02	0.30	1	
L	*-0.27*	0.03	-0.15	-0.17	0.12	0.19	1

Table 3 *– Correlation table for risk factors. The same factors as shown in table 2 are correlated against each other to see if they capture different variation.*

3.3.4 Fama-MacBeth variables

In table 4, the summary statistics of the annual characteristics are reported. These statistics are calculated on all the one year lagged value of the characteristics, as these values are the input for the Fama-MacBeth cross-sectional regressions. Illiquidity level is now transformed to relative levels. Because the mean of the relative illiquidity level is smaller than 1, more illiquid firms are dropped from the dataset due to missing values.

Characteristic	*Mean*	*Volatility*	*Min*	*Max*
Relative Illiq	0.39	0.95	0.03	11.13
Illiq beta	-0.66	4.13	-13.42	12.11
Mkt beta	1.00	0.82	-20.93	70.55
Ln size	7.88	1.56	2.64	12.90
BM	0.50	0.33	-3.98	4.52
EP	0.04	0.10	-7.51	1.19
CR	1.95	1.97	0.00	117.79

Table 4 *- Characteristics summary statistics. The annual characteristics used in the Fama-MacBeth cross-sectional regressions on stock returns are reported.*

Table 5 shows the variables are generally not closely correlated. The correlation between illiquidity level and liquidity beta is close to zero, but negative. A stronger negative correlation is expected if more illiquid firms have higher dynamic illiquidity risk. The correlation between current ratio and relative illiquidity is zero, meaning that liquidity on firm level does not seem to translate to liquidity in its stocks.

	Relative illiq	*Illiq beta*	*Mkt beta*	*Ln size*	*BM*	*EP*	*CR*
Relative illiq	1						
Illiq beta	*-0.04*	1					
Mkt beta	*0.01*	0.10	1				
Ln size	*0.09*	-0.03	0.01	1			
BM	*0.09*	-0.02	0.05	-0.30	1		
EP	*0.02*	0.02	-0.04	0.05	-0.02	1	
CR	*-0.00*	0.01	0.04	-0.20	0.05	-0.01	1

Table 5 *– Correlation table for individual stock characteristics. The correlations are reported for the annual variables. The stocks included are those satisfying Amihud`s criteria and not having missing values of any of the reported variables. The liquidity beta and market beta results from the augmented and normal Fama-French 3-factor model, using 3 year of prior data. Relative illiquidity results from the individual illiquidity level divided by market illiquidity. The market capitalization is transformed in natural logarithm, reported as Ln size. The book-to-market (BM), earnings per share per price (EP) and current ratio (CR) are balance sheet items.*

4. Methodology

4.1 Decile portfolios

Two portfolio sorts are performed to show potential cross-sectional dispersion in stocks` returns related to two different approaches of illiquidity risk, the static and dynamic channels. Both sorts are formed each year in January, making the holding period of the portfolios is one year. The formation is based on information available at that time. Therefore, the portfolio dispersion provides historically realistic investing strategies.

The first sort takes in account the absolute level of illiquidity, given by Amihud`s illiquidity measure. where stocks that are illiquid end up in the $10^{th}$ decile. The sort is rebalanced based on the stock`s average illiquidity over the previous year.

The second sort selects stocks based on their sensitivities to innovations of market-wide illiquidity, approximated by a liquidity beta. This beta is estimated using the liquidity augmented Fama-French 3-factor model. This sort uses the historical liquidity beta estimated using monthly observations from the prior 3 years as the criteria in which portfolio the stocks end up. This is in line with Pástor & Stambaugh (2003), who show that the historical liquidity beta is a good predictor of the ex-ante liquidity beta. The stocks with the highest negative return sensitivities to aggregate illiquidity end up in the 10^{th} decile. The liquidity betas in the higher deciles take a negative value since liquidity risk is defined as stocks having lower returns in times of positive illiquidity shocks. Recall that Amihud`s liquidity measure reports illiquidity levels, causing positive innovations measuring unexpected illiquidity. Therefore, the illiquidity risk corresponds to a negative return covariance to those innovations.

In addition, a 10-minus-1 portfolio is formed on both sorts. The construction follows deducting the returns of the first portfolio from the tenth portfolio. The idea behind doing this is mimicking a portfolio where the investor is not investing his own capital. By going long in stocks exposed to a high illiquidity effect and short in opposite stocks, the investor is only expected to receive a positive expected return if the risk is priced. Otherwise, an arbitrage position exists which is unlikely.

4.2 Illiquidity level sort

For the portfolio sort on the stocks illiquidity level, the stock`s yearly illiquidity is lagged by one year. To do so, first the annual illiquidity is computed as the simple average of the monthly measure:

$$(2) \qquad ILLIQ_y^i = \frac{1}{Months_y^i} \sum_{t=1}^{Months_y^i} ILLIQ_t^i$$

Before sorting the stocks in portfolios, the lowest and highest 1% of the tails in the distribution of lagged illiquidity level are removed.

4.3 Liquidity innovations

With the monthly measure per share, the aggregate market liquidity ($MILLIQ_t$) can be calculated. Of all stocks, the size-scaled weighted average is calculated using the following formula:

$$(3) \qquad MILLIQ_t = \frac{1}{N_t}\sum_{i=1}^{N_t}(m_{it}/M_t)\, ILLIQ_t^i$$

where N_t is the number of stocks in month *t*. $ILLIQ_t^i$ is the previous estimated illiquidity per stock each month. m_{it} is the market capitalization of stock *i* in month t. M_i is the sum of all included stocks` market capitalization. Market capitalization is defined as the number of stocks outstanding times the stock price. The frequency is yearly; the scaling factor remains equal for each stock throughout the year. By applying a scaling factor for market size, the market`s illiquidity is more affected by big firms than small firms.

Using the market-wide liquidity measure, the liquidity innovations can be estimated using a first-order autoregression. This regression is as follows:

$$(4) \qquad MILLIQ_t = \alpha + \beta\, MILLIQ_{t-1} + \varepsilon_t$$

where the error term, ε_t multiplied by a million, is the measure of the liquidity innovation in month *t*. Therefore, the liquidity innovation is defined as:

$$(5) \qquad L_t = 1{,}000{,}000\ \varepsilon_t$$

This arbitrary scaling is done to interpret the results more easily, as the magnitude is now close to those of the other risk factors. It does not alter results.

4.4 Liquidity beta sort

For the sort on return sensitivity to market illiquidity, the liquidity innovations are now added to the Fama-French 3-factor model to estimate the liquidity betas. The regarded stocks are those satisfying the Amihud criteria. Using 3 years of historical data, for each stock a beta is estimated for the last month of the previous year. The regressions take the following form:

$$(6) \qquad R_{it} = \alpha_i + \beta_i^{mkt} MKT_t + \beta_i^{smb} SMB3_t + \beta_i^{hml} HML_t + \beta_{iy}^{illiq} L_t + \varepsilon_{it}$$

where R_{it} is, for each stock *i*, the excess return over the risk free rate, per month *t.* This regression is performed on a window of 36 months. MKT_t represent the monthly value-weighted excess market returns. The other two factors, $SMB3_t$, HML_t, are payoffs originating form long-short spreads on portfolio sorts corresponding to market capitalization and book-to-market ratio. L_t is the added non-traded factor of liquidity. The betas resulting from the regressions are the stocks` sensitivities to these factors. The $\alpha_i$ captures each stock`s abnormal return, which is zero when the factors capture all cross-sectional variation. It is important to note that this risk factor measures illiquidity instead of liquidity. For that reason, high exposure to the dynamic risk factor means a high negative regression coefficient.

Before sorting the stocks based on the betas, the outliers are removed. This is done by removing the highest and lowest 1% in the tails of the distribution.

4.5 Asset pricing models

Now having formed decile portfolios, the effects of liquidity is further investigated using asset pricing models. If the illiquidity effects are priced, a systematic difference in abnormal returns is visible for models lacking an illiquidity risk factor. In addition to this, the point of interest is to see whether including illiquidity innovations improves the precision of asset pricing models. To check this, for both sets of sorted portfolios the alphas are computed regarding to the CAPM, Fama-French 3- and 5-factor model (2015). These regressions, in descending order, take the form of:

(7) $$R_{jt} = \alpha_j + \beta_j^{mkt} MKT_t + \varepsilon_{jt}$$

(8) $$R_{jt} = \alpha_j + \beta_j^{mkt} MKT_t + \beta_j^{smb} SMB3_t + \beta_j^{hml} HML_t + \varepsilon_{jt}$$

(9) $$R_{jt} = \alpha_j + \beta_j^{mkt} MKT_t + \beta_j^{smb} SMB5_t + \beta_j^{hml} HML_t + \beta_j^{rmw} RMW_t + \beta_j^{cma} CMA_t + \varepsilon_{jt}$$

Next, the illiquidity innovations are added to the models and the alphas are computed again. If adding the dynamic risk factor leads to being more equal to zero it adds value to the pricing models. Also, if the relation between static and dynamic risk can be investigated by adding the factor. A trend in the exposure with the factor for stocks sorted on illiquidity level contains information on a relation. The specification of the regressions is the same as (7), (8) and (9) but now with the added dynamic liquidity factor:

(10) $$R_{jt} = \alpha_j + \beta_j^{mkt} MKT_t + \beta_j^{illiq} L_t + \varepsilon_t^i$$

(11) $$R_{jt} = \alpha_j + \beta_j^{mkt} MKT_t + \beta_j^{smb} SMB3_t + \beta_j^{hml} HML_t + \beta_j^{illiq} L_t + \varepsilon_{jt}$$

(12) $$R_{jt} = \alpha_j + \beta_j^{mkt} MKT_t + \beta_j^{smb} SMB5_t + \beta_j^{hml} HML_t + \beta_j^{rmw} RMW_t + \beta_j^{cma} CMA_t + \beta_j^{illiq} L_t + \varepsilon_{jt}$$

4.6 GRS-test

To check if the liquidity innovations improve explaining cross-sectional variation in these models, the GRS-test (Gibbons, Ross, & Shanken, 1989) is used in addition of checking for the individual alphas` significance. This test checks if the intercepts of a set of linear time-series regressions are jointly equal to zero. The GRS-test on a finite sample is used, therefore it is assumed the models` errors are independently and identically distributed.

The GRS-test statistic is calculated as:

$$(13) \qquad z = \frac{T-n-1}{n}\left(1+\frac{\hat{\mathrm{E}}[r_t^m]^2}{\widehat{var}[r_t^m]}\right)^{-1}\boldsymbol{\hat{\alpha}}'\boldsymbol{\tilde{\Sigma}^{-1}}\boldsymbol{\hat{\alpha}} \sim F_{n,\ T-n-1}\ ,$$

where T is the number of periods and n is the number of portfolios tested. $\hat{\mathrm{E}}[r_t^m]^2$is the squared average excess return on the market, and $\widehat{var}[r_t^m]$ its corresponding variance. $\boldsymbol{\hat{\alpha}}'\boldsymbol{\tilde{\Sigma}^{-1}}\boldsymbol{\hat{\alpha}}$ is the variance-covariance matrix, estimated using the portfolios` estimated alphas ($\boldsymbol{\hat{\alpha}}$) and error terms` variance ($\boldsymbol{\Sigma}$). The corresponding P-value can be found as the z-statistic follows a F-distribution.

4.7 Fama-MacBeth regressions

To see what the average effect of the two illiquidity characteristics is on stock returns, Fama-MacBeth (1973) two-step regressions are performed in a similar way as done by Amihud (2002). Different from his approach are a new set of firm characteristics. These new variables include the earnings per share per price, liquidity beta and the current ratio.

For every month between 1998 and 2016, a cross-sectional regression of monthly stock returns on previous year annual stock characteristics is performed. This first step results in a coefficient each month, for every characteristic included. In the second step, the average of all these coefficients per characteristic is taken, calculating the average effect. Besides the illiquidity characteristics, other characteristics are considered to see if the illiquidity effects are robust and not a proxy for a different effect. For example, if all illiquid stock`s firms are small firms then the effect attributed to illiquidity can be caused by the small firms receiving higher returns due to the small firms effect. The regressions are also run without controlling for other characteristics to see how the effects change. To check for consistency over time, the regressions also run in two subperiods. The first subperiod is from 1998 until 2007, and the second from 2008 until 2016.

The illiquidity characteristics of the dynamic channel is the exact same liquidity beta used in sorting the stocks. However, for the static channel the yearly illiquidity level[1] is transformed to mean-adjusted values, following Amihud`s example to control for the time-varying levels of illiquidity. The static illiquidity characteristic is calculated by dividing the stock`s level by the market-wide level of illiquidity per year. The specification of this mean-adjusted illiquidity value is:

$$(14) \qquad MAILLIQ_y^i = \frac{(m_{it}/M_t)\ ILLIQ_y^i}{MILLIQ_y^i}$$

The firm specific control characteristics used in the cross-sectional regression are market beta, market capitalization (size), book-to-market ratio, earning per share to price ratio and current ratio. The required balance sheet data for book values, earnings per share and current assets and liabilities have an end of the year frequency. The annual shares outstanding are based on quarterly averages. At last, the characteristic size, book-to-market and earning per share ratio are based on yearly averages of monthly closing prices.

The current ratio is included as it is an important indicator of firm liquidity. The ratio is defined as current assets divided by current liabilities. If the ratio is low, the firm risks running out of cash while being obligated to fulfil liability payments, what can result in higher expenses. These expenses include higher financing costs through borrowing or otherwise selling assets quickly against lower prices (Eljelly, 2004).

To incorporate the market beta of each stock, it must be calculated first. The previous year characteristic is regarded as the market beta resulting from a regression in December of the prior year including 3 years of monthly observations. This is done for every stock using the Fama-French 3-factor model. The regression is the same as equation (6) estimating the liquidity betas, but excluding the illiquidity factor. For every stock in December of the years between 1997 and 2015 the regression is run on 36 months. The regressions take the following form:

$$(15) \qquad R_{it} = \alpha_i + \beta_i^{mkt} MKT_t + \beta_i^{smb} SMB3_t + \beta_i^{hml} HML_t + \varepsilon_{it}$$

Furthermore, stocks that do not have the data available on the analysed characteristics are removed. Although this might cause some bias in the dataset, this is needed to perform the regressions. After

[1] Although not specified, the yearly market illiquidity ($MILLIQ_y^i$) is the average of the monthly illiquidity levels ($MILLIQ_t$), of each year.

omitting missing data on stocks, the following cross-sectional regression is performed for all time periods for both sets:

$$(16) \qquad R_{it} = \alpha_t + \Theta_t C_{iy} + \Theta_t \not{C}_{iy} + \varepsilon_{it}$$

where R_{iy} is the return, of stock *i,* per year *y.* Θ_t is the effect each month of the previous year illiquidity characteristics. C_{iy} is the average of illiquidity level, whereas $\not{C}_{iy}$ is the estimated liquidity beta per stock. The average effect is subsequently calculated as the average of the estimated effects for each year.

To see if this estimated effect is robust, other annual (firm) characteristics are added to the regression model. This results in the following regression:

$$(17) \qquad R_{it} = \alpha_t + \Theta_t C_{iy} + \Theta_t \not{C}_{iy} + \boldsymbol{\Theta}`_t \boldsymbol{C}_{iy} + \varepsilon_{it}$$

where the added term $\boldsymbol{\Theta}`_t$ represents a vector of effects for each control characteristic captured in the vector $\boldsymbol{C}_{ty}$.

5. Results

5.1 Absolute Illiquidity sort

Every year the stocks are sorted in decile portfolios based on their previous year level of liquidity, measured as an average over the year based on Amihud`s illiquidity measure. Doing this allows to see whether cross-sectional differences exist between these portfolios. The sort is reported in table 7. The portfolios are rebalanced every year, thus have a holding period of one year. The periods included are 1996 to 2016, since the first year of the database did not have lagged values.

The first row in section A reports the post-ranking level of average illiquidity, which as it should, shows an upward trend. The realized level of illiquidity over the years shows the intended stock dispersion, as past illiquidity seems to be a good indicator for future illiquidity. If there was not an upward trend, the portfolios obviously do not capture the right illiquidity dispersion effects. Regarding this trend, it stands out that the 10th portfolio has a much higher increase of illiquidity compared to the 9th portfolio, as compared to the increase from the 8th to the 9th. The average illiquidity level only seems to move close to exponentially. This can be explained by the skewed distribution of the illiquidity level, where most stocks have small illiquidity values.

A different, very clear, relation is found looking at the average market capitalization of the portfolios. The first portfolio has an extremely high size, compared to the others. A clear monotonic downward trend of size is found with increasing levels of illiquidity. However, the cause of this is straightforward as the liquid portfolios include stocks from big companies, as those shares always tend to be more liquid. Given that the portfolios are constructed based on number of different shares, it is not a surprising pattern to see. For the book-to-market ratio, a same monotonic trend is seen, where liquid stocks are from firms with low book-to-market ratios. This is not surprising, as big companies (who have liquid stocks) tend to have low book-to-market values.

In the second row a slight trend of decreasing liquidity betas can be found. The reported betas are the equally-weighted average of the individual stocks realized liquidity beta per portfolio. It is ignored that not all included stocks have a beta, as a minimum of 3 years` data is required. The decreasing trend comes as expected, as it follows the finding by Acharya & Pedersen (2005) that illiquid stocks tend to have their lower returns during times of illiquidity. It is surprising that the 3rd decile shows a negative average, thereby standing out. Also, the decreasing trend on average liquidity betas seems not strong.

Another upward trend can be seen in average excess returns where, as expected, more illiquid stocks receive higher returns than liquid stocks. Expected in a sense that it is a relation previous literature found, but also because of the increasing monotonic trends in size and book-to-market averages. This indicates higher exposure relating to the size- and value effect, known to increase expected return. Illiquid stocks tend to belong to both small firms and firms with high book-to-market ratios, which are expected to pay higher returns as a compensation for higher risk.

To see if these higher returns are related to liquidity, and not to other exposures, the alphas resulting from the CAPM, 3- and 5-factor model are calculated. These alphas portrait abnormal returns not explained by the liquidity factor lacking models, which higher illiquid portfolios are expected to have. Indeed, in subsection B, an upward trend can be found in these alphas as well. This suggests illiquid stocks have higher returns due to being illiquid, and not because illiquidity proxies for high exposure to a different included risks factor. However, for the tenth portfolio a decrease in significance is found of abnormal returns when including more risk factors. For the 5-factor model the abnormal is not even significant on a 95% confidence level.

In subsection C, the coefficients with respect to the Fama-French 3-factor model, augmented with the liquidity factor, are reported for all portfolios. The liquidity betas become more negative in higher levels of average illiquidity. This indicates that illiquid stocks also tend to realize their lowest returns in times of high market-wide illiquidity. This result is in line with findings by Acharya & Pedersen (2005), who show a monotonic trend for portfolios sorted on illiquidity. The reason high exposure is captured by negative coefficients is due to the factor measuring sensitivity of returns to market illiquidity. When an unexpected illiquidity shock occurs, the factor negatively influences returns.

Regarding the market portfolio, a weak trend can be found in exposure to this risk factor. In increasing levels of illiquidity, the level of market exposure decreases. For the 10-minus-1 portfolio, the exposure is significant on a 99% level, therefore supporting the statement by Pástor & Stambaugh (2003) of decreasing market exposure following higher illiquidity.

In subsection D, the re-estimated alphas are given when adding the illiquidity innovations factor to the model. It is seen that the results are almost identical, what indicates that the factor does not capture the source causing dispersion effects following a sort on absolute illiquidity. The changes in alphas are tested using the GRS-test. This test checks whether the alphas are jointly equal to zero. By adding the liquidity factor the t-statistic increases for the three different models, as given in table 6. It appears the risk factor of dynamic liquidity as defined by innovations in market-wide illiquidity does not improve asset pricing models. The alphas are not getting closer to zero by adding the factor. This contradicts the findings by Marcelo and Quirós (2006) who conclude improvement in pricing when adding their liquidity risk factor.

Average illiquidity portfolios

Model:	*z-statistic*	*p-value*
CAPM	3.03	0.001***
CAPM Adjusted	3.25	0.001***
3-factor	3.02	0.001***
3-factor Adjusted	3.20	0.001***
5-factor	2.50	0.007***
5-factor Adjusted	2.64	0.005***

Table 6 *- The GRS-test is performed on the annual illiquidity level portfolio sort on all 6 models, testing the hypothesis of the alphas jointly being equal to zero. The asterisk marks correspond to: *** p<0.01, ** p<0.05, * p<0.1*

A check on robustness is performed by splitting the sample in two sub-periods, from 1996 until 2007 and 2008 until 2016. For both periods, the alphas of the three pricing models are calculated. Also reported are the averages of individual stocks` characteristics. These results are shown in table 8.

In the older subperiod of time, stronger illiquidity effects on returns are found. In this period, the alphas of the 9^{th}, 10^{th} and the 10-minus-1 portfolio show highly significant alphas resulting from the CAPM model. In the newer time sample, the 10^{th} portfolio realizes a positive alpha, but this is not significantly different from zero. The 10-minus-1 portfolio also shows an expected positive alpha, but it is only significant at the 90% certainty level. For both time periods the 10-minus-1 portfolios realize alphas significant on the 90% certainty level for the 3- and 5-factor models. This suggests the effect is present in both time periods. The most illiquid portfolio has the highest excess return, regardless the time sample.

The reason illiquidity level effect appears smaller in the newer period, as no significant alphas are found for the 9th and 10th portfolio, likely results from a decrease of market-wide illiquidity. After the latest financial crisis of the end of 2007, the market illiquidity remains low, as shown in figure 1. This is reflected by the portfolio illiquidity levels in the newer sample being lower than the older period. Low market illiquidity indicates low expected trading costs. If there is a smaller number of illiquid stocks available, it makes sense that the compensation in the form of abnormal returns is also smaller. However, the increasing trend of excess returns of more illiquid portfolios combined with the positive abnormal returns for the 10-minus-1 portfolios indicates persistence in the illiquidity level risk premium.

Furthermore, over time, the size and book-to-market trends are the same. The only clear difference is the decreasing trend of individual liquidity betas being weaker in the old sample. The clear decreasing trend found in the period of 2008 until 2016 indicates stocks having a high illiquidity level realize low returns in times of high market illiquidity.

In short, table 7 reports systematic differences in abnormal returns for stocks being sorted by their previous year average illiquidity level. The findings confirm the relation by Amihud (2002) of increasing abnormal returns in higher levels illiquidity. Although illiquid stocks tend to be more exposed to the dynamic channel of illiquidity risk, adding the dynamic risk factor of innovations in market-wide illiquidity to asset pricing models does not lead to better pricing models. The GRS-test determines the alphas to be significantly different form zero, and this result remains the same when adding the risk factor of liquidity. The results remain valid but smaller when the only the subperiod of 2007 until 2016 is considered. The risk premium for illiquid stocks was certainty available in periods before 2007, but appears to have decreased in magnitude. A logical reason for the decrease in compensation is the general decrease of market-wide illiquidity, where in the period between 2007 and 2016 illiquid stocks are hard to find. This prevents investors from receiving higher expected returns, as the expected trading costs are also low.

Table 7 Properties of Annual Portfolios Sorted on Previous Year Illiquidity level

Deciles:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(10-1)
						A. Averages					
Illiquidity level	0.000	0.001	0.002	0.003	0.005	0.010	0.018	0.033	0.069	0.226	
Liquidity beta	-0.51	-0.69	-0.73	-0.62	-0.82	-0.81	-0.87	-0.86	-1.03	-1.11	
Excess return	0.56	0.79	0.62	0.77	0.64	0.61	1.17	0.83	1.07	1.17	0.61
Size	43991	29415	6448	4384	3186	2544	1736	1003	757	680	
BM	0.41	0.47	0.50	0.55	0.56	0.57	0.60	0.62	0.64	0.71	
						B. Alphas					
CAPM α	0.02	0.17	-0.02	0.15	0.05	0.01	0.59***	0.32	0.51**	0.64***	0.62***
	(0.16)	(1.24)	(-0.11)	(0.89)	(0.34)	(0.07)	(3.31)	(1.54)	(2.29)	(2.80)	(2.74)
3-factor α	-0.01	0.08	-0.12	0.06	-0.04	-0.05	0.52***	0.20	0.41*	0.53**	0.54***
	(-0.07)	(0.64)	(-0.86)	(0.40)	(-0.29)	(-0.29)	(3.05)	(1.02)	(1.88)	(2.42)	(2.62)
5-factor α	-0.09	-0.03	-0.22	0.04	-0.08	-0.16	0.43**	0.09	0.25	0.43*	0.52**
	(-1.09)	(-0.24)	(-1.55)	(0.24)	(-0.51)	(-0.97)	(2.39)	(0.46)	(1.12)	(1.88)	(2.43)
						C. Coefficients					
MKT beta	0.95***	1.02***	1.03***	0.95***	0.92***	0.97***	0.88***	0.82***	0.89***	0.82***	-0.13***
	(49.87)	(36.00)	(31.95)	(26.18)	(26.85)	(26.13)	(22.21)	(17.55)	(17.69)	(16.08)	(-2.80)
SMB beta	-0.23***	-0.01	0.06	0.28***	0.13***	-0.00	0.22***	0.24***	0.15**	0.24***	0.47***
	(-9.36)	(-0.20)	(1.31)	(5.96)	(2.91)	(-0.08)	(4.15)	(3.86)	(2.29)	(3.60)	(7.61)
HML beta	0.13***	0.27***	0.30***	0.18***	0.25***	0.17***	0.12**	0.29***	0.26***	0.24***	0.11*
	(4.92)	(6.75)	(6.70)	(3.62)	(5.29)	(3.31)	(2.23)	(4.54)	(3.74)	(3.42)	(1.68)
Liquidity beta	-0.22	-0.63**	-0.46	-0.80**	-0.80***	-0.60*	-0.88**	-0.91**	-1.23***	-1.22***	-1.00**
	(-1.34)	(-2.57)	(-1.63)	(-2.57)	(-2.70)	(-1.88)	(-2.57)	(-2.27)	(-2.82)	(-2.76)	(-2.42)
						D. Alphas augmented models					
Aug. CAPM α	0.02	0.18	-0.01	0.17	0.07	0.02	0.60***	0.34	0.53**	0.66***	0.64***
	(0.17)	(1.33)	(-0.05)	(1.01)	(0.44)	(0.13)	(3.46)	(1.64)	(2.42)	(2.95)	(2.87)
Aug. 3 factor α	-0.00	0.09	-0.11	0.08	-0.03	-0.03	0.54***	0.22	0.43**	0.56**	0.56***
	(-0.01)	(0.75)	(-0.80)	(0.51)	(-0.18)	(-0.21)	(3.18)	(1.12)	(2.01)	(2.56)	(2.74)
Aug. 5 factor α	-0.09	-0.02	-0.21	0.05	-0.07	-0.15	0.44**	0.11	0.27	0.45**	0.54**
	(-1.05)	(-0.17)	(-1.51)	(0.31)	(-0.45)	(-0.92)	(2.49)	(0.52)	(1.21)	(1.99)	(2.52)

NOTE For every year between 1996 and 2016 eligible stocks are sorted in 10 portfolios based on their average level of liquidity in the previous year. Eligible stocks are common stocks traded on the NYSE and AMEX with an average yearly stock price of at least $5. Also, each year a minimum of 150 days on daily return and volume data is required. Shares lacking market capitalization data are also removed. Excess return is specified as monthly average returns over the sample period, exceeding the one-month Treasury bill rate. The market capitalization of the portfolios is given by "Size" and "BM" is the book-to-market ratio. The alphas are time-series regressions` constant of each portfolio`s excess returns on the CAPM, Fama-French 3-factor and Fama-French 5-factor models. The number of stocks used in this analysis vary per year between 1993 and 2360. The sensitivities of the portfolios to the market portfolio (MKT), the size factor (SMB), the value effect (HML) and to innovations to market-wide liquidity (Liquidity beta) are estimated using the Fama-French 3-factor model augmented with the liquidity factor.

*t-statistics in parentheses and *** $p<0.01$, ** $p<0.05$, * $p<0.1$*

Table 8 Properties of Annual Portfolios Sorted on Previous Year Illiquidity level

Deciles:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(10-1)
Subperiod 1996-2007											
A1. Averages											
Illiquidity level	0.000	0.001	0.002	0.005	0.008	0.015	0.026	0.047	0.098	0.272	
Liquidity beta	-0.20	-0.30	-0.24	-0.38	-0.41	-0.30	-0.39	-0.30	-0.56	-0.22	
Excess return	0.66	0.95	0.78	1.15	0.82	0.80	1.34	0.82	1.37	1.20	0.54
Size	29277	7789	4528	3499	2637	2068	1784	1066	714	618	
BM	0.36	0.43	0.48	0.53	0.52	0.53	0.56	0.60	0.63	0.70	
B1. Alphas											
CAPM α	0.18	0.45***	0.29	0.64***	0.35	0.30	0.83***	0.49	0.89***	0.82***	0.64**
	(1.31)	(2.81)	(1.61)	(2.75)	(1.60)	(1.35)	(3.25)	(1.61)	(3.17)	(2.94)	(2.11)
3-factor α	0.10	0.20	-0.01	0.48**	0.13	0.10	0.67***	0.24	0.49*	0.50**	0.40*
	(1.11)	(1.47)	(-0.05)	(2.26)	(0.64)	(0.46)	(2.70)	(0.80)	(1.97)	(1.99)	(1.72)
5-factor α	0.01	0.09	-0.07	0.45**	0.14	0.03	0.60**	0.13	0.38	0.44*	0.42*
	(0.16)	(0.66)	(-0.44)	(2.07)	(0.67)	(0.15)	(2.34)	(0.43)	(1.50)	(1.70)	(1.76)
Subperiod 2008-2016											
A1. Averages											
Illiquidity level	0.000	0.000	0.001	0.001	0.002	0.004	0.007	0.013	0.030	0.165	
Liquidity beta	-0.90	-1.16	-1.31	-0.91	-1.31	-1.43	-1.43	-1.54	-1.60	-2.08	
Excess return	0.48	0.58	0.41	0.27	0.40	0.37	0.95	0.84	0.68	1.11	0.63
Size	63393	57999	8980	5551	3910	3173	1673	921	814	761	
BM	0.48	0.51	0.54	0.57	0.60	0.62	0.65	0.65	0.65	0.74	
B2. Alphas											
CAPM α	-0.21	-0.23	-0.44*	-0.52**	-0.35*	-0.38	0.26	0.08	-0.00	0.38	0.59*
	(-1.49)	(-1.10)	(-1.96)	(-2.42)	(-1.77)	(-1.63)	(1.12)	(0.34)	(-0.01)	(1.04)	(1.72)
3-factor α	-0.20	-0.21	-0.43*	-0.51**	-0.36*	-0.38	0.25	0.07	-0.02	0.38	0.58*
	(-1.46)	(-1.04)	(-1.93)	(-2.36)	(-1.77)	(-1.62)	(1.07)	(0.32)	(-0.06)	(1.04)	(1.70)
5-factor α	-0.17	-0.17	-0.36	-0.50**	-0.32	-0.40	0.18	0.18	-0.03	0.47	0.64*
	(-1.17)	(-0.79)	(-1.59)	(-2.30)	(-1.54)	(-1.62)	(0.73)	(0.76)	(-0.08)	(1.22)	(1.77)

NOTE - Subperiods of sort on illiquidity level. For the periods 1996 until 2007 and 2008 until 2016, eligible stocks are sorted in 10 based on their average level of liquidity in the previous year. Eligible stocks are common stocks traded on the NYSE or AMEX with an average yearly stock price of at least $5. Also, each year a minimum of 150 days on daily return and volume data is required. Shares lacking market capitalization data are also removed. Excess return is specified as monthly average returns over the sample period, exceeding the one-month Treasury bill rate. The market capitalization of the portfolios is given by “Size” and “BM” is the book-to-market ratio. The alphas are time-series regressions` constant of each portfolio`s excess returns on the CAPM, Fama-French 3-factor and Fama-French 5-factor models.

*t-statistics in parentheses and *** p<0.01, ** p<0.05, * p<0.1*

5.2 Liquidity beta sort

In table 10, decile portfolios are formed in a similar way as table 6, but now categorized on the different sort. Instead of average illiquidity, all stocks are sorted based on the previous year liquidity beta. Stocks with the highest exposure to illiquidity risk are ranked in the top deciles. Because the risk factor consists of innovations based on measures on illiquidity instead of liquidity, this exposure means a negative regression coefficient. Again, the portfolios are subjected to annual rebalancing.

In subsection A, the average of each stocks` coefficient of the liquidity beta per portfolio is given regarding the augmented 3-factor model. In increasing portfolio deciles, this average beta should show a negative trend. If this is not the case, the previous year beta is not a good estimator of current year beta. Since the trend is monotonic negative, the portfolio sort portraits the stock dispersion as intended. The row “Hist. liq. beta” represents the historical liquidity beta. This is the average of individual liquidity betas used each beginning of the year to sort the stocks in the right portfolio. The closer these values are to the realized betas, the better the historical beta`s predictive power. The average difference appears small, indicating the historical beta is indeed a good predictor supporting the intended stock dispersion is achieved.

The average level of illiquidity appears fairly constant over the different portfolios. It is expected that more illiquid stocks are subjected to higher illiquidity risk, thus a trend of increasing average in higher deciles. This trend is somewhat visible, but appears very weak. The difference between the lowest and highest portfolio is small. This is a strange observation, given that when sorting on illiquidity level there appears to be a strict decreasing trend of individual liquidity betas. This finding is in line with the low negative correlation found between the level and beta of illiquidity. A liquidity beta is not a good proxy for a stock`s level of illiquidity.

Pastor and Stambaugh (2003) find significant alphas for stocks sorted on liquidity betas, for both the CAPM and the Fama-French 3-factor model. Here, the excess returns show an increasing trend. But, looking at subsection B, it is surprising to not find a single significant alpha. No systematic trend of abnormal returns is found when sorting on betas. This contradicts the finding of risk compensation for the dynamic channel of illiquidity risk.

In addition, Pástor and Stambaugh (2003) find a pattern of decreasing market betas in increasing levels of illiquidity. Table 10, however, shows an increasing trend. They also report a trend regarding size, where increasing portfolio liquidity betas have smaller size. Here, this relation is not found. The stocks in the second deciles have a substantial greater market capitalizations than the rest, but there is no further trend found.

In subsection C, a surprising result is found. When aggregating the individual returns to portfolio returns using value-weighted method, the decreasing monotonic trend of liquidity betas disappears. For an unknown reason, stocks have individual exposure to illiquidity innovations but not when grouped in a portfolio with similar stocks. To further investigate if this can be caused by the wrong stock dispersion, the realized average liquidity betas are computed per year for each portfolio. The results of these are graphically displayed in figure 3. For each year depicted by a colour, the dots on the far left correspond to the tenth portfolio, with the last dot on the right being the first portfolio. If the stocks are sorted correctly, the trend moves monotonic down from left to right, indicated with the arrow. For every year, the trend is close to monotonic. This relation is indicating good dispersion of stocks.

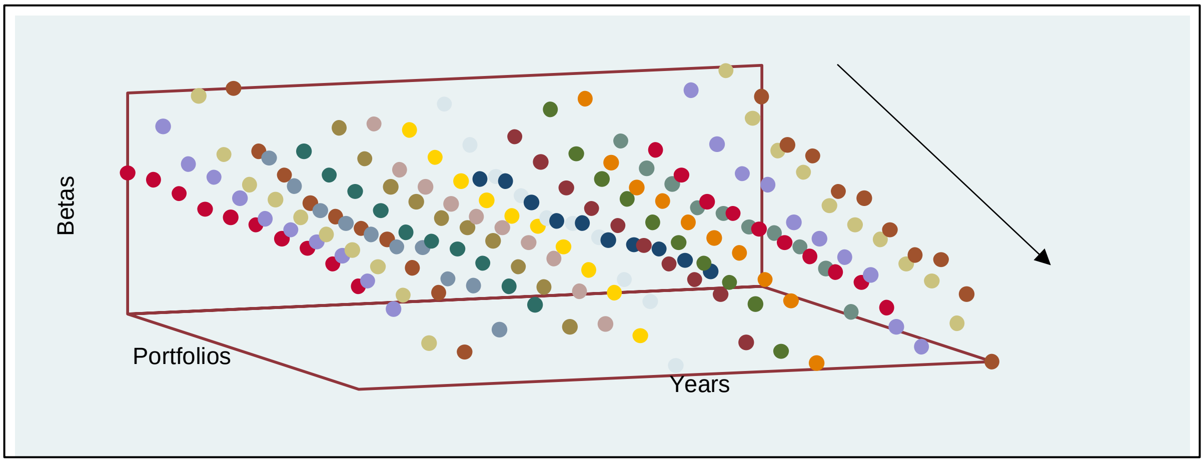

Figure 3 *– Stock dispersion. Per year, the realized average liquidity betas of the individual stocks are calculated for each portfolio. The colour depicts the corresponding year, where each year consists of 10 dots representing the decile portfolios. The years included, from left to right, are 1998 until 2016.*

The alphas of the augmented models in subsection D are almost identical as the one before adding the factor. The factor seems not to add new information to the pricing models. The GRS-test in table 9 again confirms the alphas remaining the same after adding the illiquidity factor.

Liquidity beta portfolios

Model:	*z-statistic*	*p-value*
CAPM	0.51	0.88
CAPM Adjusted	0.49	0.89
3-factor	0.52	0.79
3-factor Adjusted	0.50	0.80
5-factor	1.13	0.34
5-factor	1.11	0.35

Table 10 *- The GRS-test is performed on the annual illiquidity innovations sensitivity portfolio sort on all 6 models, testing the hypothesis of the alphas jointly being equal to zero. The asterisk marks correspond to: *** p<0.01, ** p<0.05, * p<0.1*

To check for robustness of the results over time, two subperiods are considered. In the appendix, table 12 shows the averages portfolios characteristic and alphas regarding the three asset pricing models. For the older period, the CAPM model reaches a weak significant (P<0.1) alpha for the tenth decile. For all pricing models, the 10-minus-1 portfolio returns are positive, although still not significant. This means there are no abnormal returns found for the older period. The opposite holds for the more recent period where insignificant negative abnormal returns are found. It appears the illiquidity effects of stronger in the period between 1998 and 2007. The unexplained switch of signs of the liquidity beta when aggregating the returns in portfolios is robust over time. The liquidity beta for the first decile corresponding to the augmented Fama-French 3-factor model is significantly negative for both periods, whereas a positive sign is expected.

Regarding table 8, it can be concluded that there appears no risk compensation for holding stocks that realize its lowest return during unexpected market-wide illiquidity shocks. In contrast to Pastor and Stambaugh (2003) no significant abnormal returns are not found for stocks having high exposure to the illiquidity innovations factor. The findings of this paper are more in line with Acharya and Pedersen (2005) who find only weak positive effects of this liquidity beta on returns. In table 8, the found illiquidity effects of dynamic risk are overall weak, but stronger in the period between 1998 and 2007. The findings indicate that high market-wide illiquidity is not a priced state variable within the scope of asset pricing theory. Furthermore, the dynamic risk factor does a poor job in explaining returns, as the alphas only become slightly closer to zero, tested jointly using the GRS-test.

Table 10 Properties of Annual Portfolios Sorted on Previous Year Sensitivity to Liquidity Innovations

Deciles:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(10-1)
						A. Averages					
Illiquidity level	0.026	0.023	0.025	0.029	0.036	0.034	0.035	0.034	0.030	0.031	
Liquidity beta	3.20	1.40	0.50	-0.15	-0.69	-1.08	-1.40	-2.08	-2.97	-4.95	
Hist. liq. beta	5.91	2.70	1.33	0.38	-0.41	-1.11	-1.88	-2.82	-4.25	-7.49	
Excess return	0.66	0.50	0.62	0.46	0.47	0.53	0.63	0.47	0.51	0.75	0.11
Size	5496	26254	7911	7618	6367	5898	6389	6965	8004	6570	
BM	0.57	0.55	0.56	0.53	0.54	0.54	0.52	0.54	0.54	0.58	
						B. Alphas					
CAPM α	0.16	0.07	0.16	0.04	0.06	0.06	0.18	0.01	-0.05	0.15	-0.02
	(0.93)	(0.41)	(1.36)	(0.27)	(0.34)	(0.38)	(1.25)	(0.05)	(-0.25)	(0.66)	(-0.06)
3-factor α	0.07	-0.01	0.13	-0.00	-0.02	0.00	0.16	-0.03	-0.08	0.14	0.08
	(0.44)	(-0.07)	(1.13)	(-0.02)	(-0.11)	(0.01)	(1.15)	(-0.24)	(-0.48)	(0.66)	(0.31)
5-factor α	0.02	-0.23	0.10	-0.13	-0.20	-0.13	0.01	-0.20	-0.15	0.08	0.05
	(0.14)	(-1.64)	(0.87)	(-0.91)	(-1.37)	(-0.94)	(0.09)	(-1.36)	(-0.89)	(0.34)	(0.21)
						C. Coefficients					
MKT beta	0.98***	0.88***	0.91***	0.87***	0.84***	0.93***	0.90***	0.97***	1.12***	1.18***	0.20***
	(27.76)	(25.83)	(34.44)	(27.66)	(24.10)	(29.30)	(28.74)	(28.69)	(28.64)	(23.28)	(3.49)
SMB beta	0.00	-0.10**	-0.04	-0.18***	-0.10**	-0.14***	-0.13***	-0.17***	-0.15***	-0.15**	-0.15**
	(0.05)	(-2.28)	(-1.03)	(-4.20)	(-2.12)	(-3.34)	(-3.13)	(-3.75)	(-2.90)	(-2.25)	(-2.03)
HML beta	0.34***	0.38***	0.14***	0.27***	0.34***	0.31***	0.16***	0.27***	0.22***	0.08	-0.26***
	(6.99)	(8.10)	(4.01)	(6.27)	(7.20)	(7.07)	(3.63)	(5.78)	(4.10)	(1.14)	(-3.33)
Liquidity beta	-1.36***	-0.25	-0.25	-0.50*	-0.58*	-0.67**	-0.63**	-0.16	-0.68*	-1.00**	0.37
	(-4.15)	(-0.80)	(-1.01)	(-1.71)	(-1.80)	(-2.26)	(-2.18)	(-0.50)	(-1.86)	(-2.11)	(0.70)
						D. Alphas augmented models					
Aug-CAPM α	0.14	0.07	0.16	0.03	0.05	0.05	0.17	0.01	-0.05	0.13	-0.01
	(0.85)	(0.38)	(1.33)	(0.22)	(0.29)	(0.33)	(1.20)	(0.03)	(-0.31)	(0.61)	(-0.03)
Aug-3 factor α	0.06	-0.01	0.13	-0.01	-0.02	-0.00	0.15	-0.04	-0.09	0.14	0.08
	(0.38)	(-0.09)	(1.11)	(-0.05)	(-0.14)	(-0.02)	(1.13)	(-0.24)	(-0.52)	(0.63)	(0.32)
Aug-5 factor α	0.00	-0.24*	0.10	-0.13	-0.21	-0.14	0.00	-0.20	-0.16	0.06	0.06
	(0.01)	(-1.67)	(0.83)	(-0.96)	(-1.43)	(-1.02)	(0.01)	(-1.37)	(-0.94)	(0.28)	(0.24)

NOTE.- For January of every year between 1998 and 2016 eligible stocks are sorted in 10 portfolios based on 36 prior months` time-series estimate of sensitivity to illiquidity innovations added to the Fama-French 3-factor model. Eligible stocks are common stocks traded on the NYSE or AMEX with an average yearly stock price of at least $5. Also, each year a minimum of 150 days on daily return and volume data is required. Shares lacking market capitalization data are also removed. Excess return is specified as monthly average returns over the sample period, exceeding the one-month Treasury bill rate. The market capitalization of the portfolios is given by "Size" and "BM" is the book-to-market ratio. The alphas are time-series regressions` constant of each portfolio`s excess returns on the CAPM, Fama-French 3-factor and Fama-French 5-factor models. The number of stocks used in this analysis vary per year between 1676 and 1942. The sensitivities of the portfolios to the market portfolio (MKT), the size factor (SMB), the value effect (HML) and to innovations to market-wide liquidity (Liquidity beta) are estimated using the Fama-French 3-factor model augmented with the liquidity factor.

*t-statistics in parentheses and *** p<0.01, ** p<0.05, * p<0.1*

5.3 Fama-MacBeth regressions

To estimate the effects of the relative illiquidity level and the liquidity beta on the cross-section of stock returns, the Fama-MacBeth (1973) regressions are performed, as done by Amihud (2002). This method regresses the monthly stock returns on previous year annual characteristics. These cross-sectional regressions are performed on both purely the illiquidity effects and the inclusion of control characteristics. The control characteristics are added to see if this causes the estimated effects to change, checking for robustness. The method generates estimates for 216 months, generating 228 sets of coefficients per model. In addition, two subperiods are formed to check for consistency over time. The period 1998 to 2007 consists of 120 months, with 108 months for the period 2008 to 2016. All stocks with missing data on characteristics are excluded, causing the average of stocks included each year to averages 922. The number of stocks used in the 3 models is the same.

Different from the earlier portfolio sorts, for each stock the illiquidity level is now taken as a fraction of market-wide illiquidity to control for time-varying effects of overall liquidity. This fraction considers the size scaled levels of illiquidity.

In table 10, for all months, the average coefficients are reported for 3 different models resulting from the Fama-MacBeth regressions. The average R-squared of all cross-sectional regressions is low, with only 0.06 for model 1. Reason for this low explained variation of the regression model can be explained by the input being individual stocks instead of portfolios. Individual stocks have idiosyncratic risk which is a source for unpredictable variation. The characteristics only provide broad tendencies that capture low variation on individual stock level.

In model 1, the relative illiquidity level is positive indicating higher returns for stocks that are on average less liquid. It is surprising that the effect is only weakly significant. This supports the expectation of a risk compensation for illiquidity, but also indicates the relation is not that strong. In model 3 the positive coefficient for illiquidity level remains the same in value when not controlling characteristics. This indicates the higher returns are attributed solely to the illiquidity level effect.

Regarding relative illiquidity, an interesting relation is found in the average coefficients when looking at the two subperiods. For all models, the coefficient becomes significant on a 95% certainty level in the period between 1998 and 2007, indicating a risk premium. For the other period, the coefficient becomes very small, even having a negative sign regarding model 1 and 3. The static illiquidity effects are found not to positively effect returns in the recent subperiod.

Table 11 Average Coefficients from Fama-MacBeth Cross-Sectional Regressions of Monthly Stock Returns on Previous Year Characteristics

	Model 1			*Model 2*			*Model 3*		
Variable	*All months*	*1998-2007*	*2008-2016*	*All months*	*1998-2007*	*2008-2016*	*All months*	*1998-2007*	*2008-2016*
Relative illiquidity level	0.06*	0.13**	-0.01	0.07**	0.14**	0.01	0.06	0.14**	-0.02
	(1.68)	(2.48)	(-0.11)	(2.04)	(2.61)	(0.20)	(1.37)	(2.48)	(-0.47)
Liquidity beta	-0.02	-0.02	-0.02	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01
	(-1.27)	(-0.93)	(-0.89)	(-0.84)	(-0.54)	(-0.66)	(-0.79)	(-0.55)	(-0.56)
Market beta	0.23	0.22	0.24						
	(1.43)	(1.13)	(0.93)						
Book-to-market	0.15	0.45*	-0.15						
	(0.99)	(1.91)	(-0.78)						
Ln size	-0.20***	-0.18***	-0.23***	-0.21***	-0.21***	-0.20***			
	(-4.20)	(-2.68)	(-3.36)	(-4.24)	(-3.01)	(-2.98)			
Earnings per share	-0.75	-0.98	-0.52						
	(-1.25)	(-1.25)	(-0.57)						
Current Ratio	-0.03	-0.00	-0.05**						
	(-1.16)	(-0.09)	(-2.25)						
Constant	2.50***	2.24***	2.75***	2.74***	2.83***	2.64***	1.16 ***	1.28***	1.01*
	(5.05)	(3.54)	(3.57)	(4.66)	(3.98)	(2.81)	(3.47)	(3.32)	(1.86)

NOTE – Average coefficients Fama-MacBeth regressions of different models. For every separate month a cross-sectional regression is done of monthly stock returns on previous year annual stock characteristics, where the average of the coefficients per month are presented in the table. In model 1, the effects of relative illiquidity level and liquidity beta are estimated while controlling for multiple other stock characteristics. Model 2 is different as it only controls for the stock characteristic of the natural logarithm of size. Model 3 regresses the illiquidity effects without controlling for any characteristic. Relative illiquidity level is estimated as The time period of the whole sample is 1998-2016, with cross-sectional averages calculated for this whole period and for two sub-periods. All models include the same observation, where stocks missing any variable are excluded.

*t-statistics in parentheses and *** p<0.01, ** p<0.05, * p<0.1*

In model 3, the liquidity beta shows a non-significant positive effect on returns. The negative average coefficient results in positive returns for stocks with high exposure to market liquidity, as these stocks have a negative liquidity beta. The effects are not strong as also in both model 1 and 2 the effect remains insignificant. Splitting up the periods does not affect the average coefficient of the liquidity beta.

As can be seen, the most influential characteristics on returns found in model 1 is the natural logarithm of size. Its significant negative sign indicates decreasing returns following higher market capitalization. This finding is in line with the size effect where stocks of small firms tend to have higher returns. In model 2, only size is used as a control variable for the regression estimates. This increases the coefficient for the relative illiquidity, indicating most illiquid firms are big firms in this sample, as controlling for lower returns by big firms the illiquidity effect increases. The contradicts the trend of decreasing size when illiquidity increases found in the portfolio sort. But, because most firms with missing data were illiquid.

As a check for robustness, the model 3 is ran without dropping any values missing control characteristics. This table is not reported, as it does not alter average effect of both illiquidity effects.

The proxy for a firm`s own liquidity, the current ratio, seems not to impact the illiquidity effects. Although not reported, a regression only including the current ratio as control characteristic does not change the illiquidity coefficients. However, the negative sign shown in the recent subsample of model 1 indicates a lower return for firms with an increasing ratio. This makes sense as firms with high current ratios are less likely to make costs to handle payments on liabilities, making them a saver investment. Therefore, a firm`s liquidity translates more towards lower returns in the form of a saver investment, then a proxy for a risk premium of the illiquidity of the firms` stocks.

The findings in model 1 for the period until 2007 are much in line with findings of Amihud (2002). For the overlapping characteristics used in the regression: market beta, size (in natural logarithm) and relative illiquidity, the estimated coefficients are similar. Amihud`s results only differ in higher coefficients and more significance. Because the time-span used by Amihud is 1964 to 1997, this can be a sign of a decreasing trend of liquidity effects.

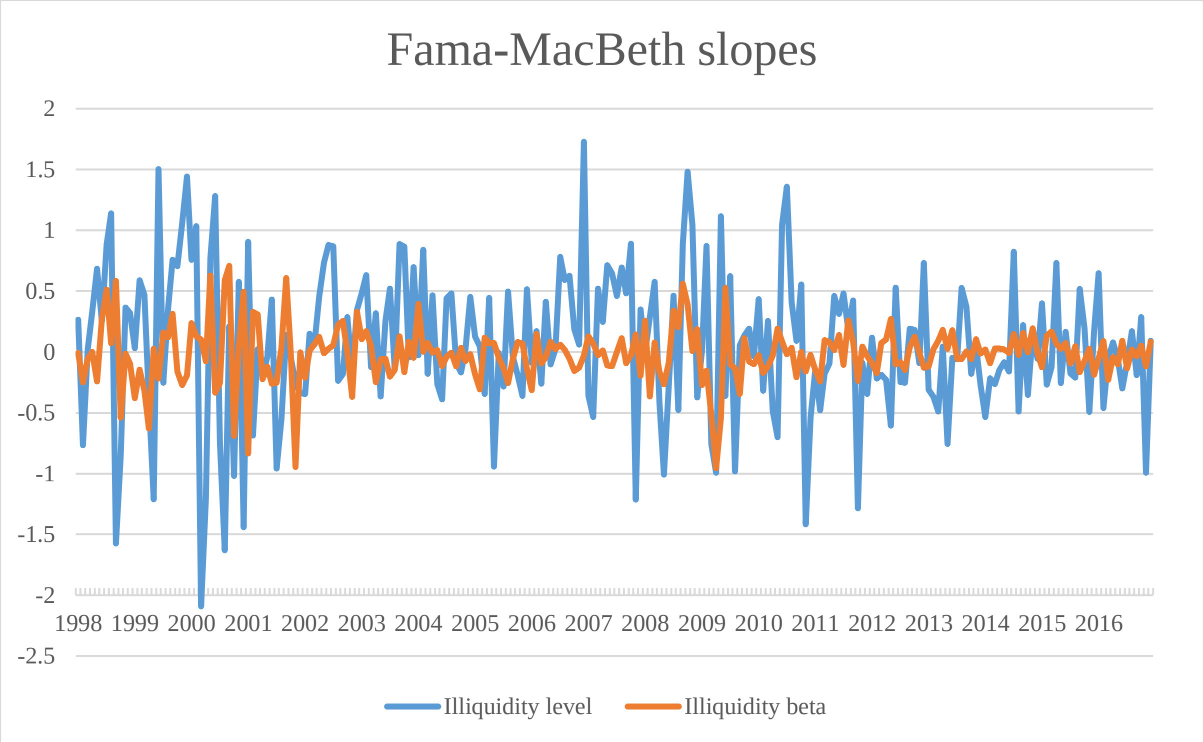

Figure 4 *– Fama-MacBeth regression coefficients. For each time between 1998 and 2016 a cross-sectional regression of monthly stock returns are performed on previous year characteristics. The resulting coefficients on relative illiquidity level and liquidity beta are found for each month in the figure, while controlling for the book-to-market ratio, current ratio, earnings per share and the natural logarithm of size. Tick marks correspond to each month.*

In figure 3, the coefficients of the two illiquidity effect coefficients are shown for each month in time. The correlation between the two coefficients over time is low, with 0.02. Both coefficients realize values closer to zero in the period after 2012. In total, the illiquidity level realizes a positive effect on returns for 53% of the included months, compared to 61% for the periods between 1998 and 2007. The liquidity beta has a positive effect on returns for 53% of all month, with 54% between 1998 and 2007. Again, a positive effect of the liquidity beta is given by a negative coefficient in figure 3.

The illiquidity effect is more present in older time periods and disappears towards more recent times. The effect of illiquidity level is robust controlling for firm characteristics, including a characteristic indicating a firm`s liquidity. The dynamic effect of liquidity risk is found to have a weak positive effect on stock returns. This is not consistent with Pástor and Stambaugh (2003) who report a significant premium for stock with exposure to market-liquidity.

6. Conclusion

In this paper, the static and dynamic channels of illiquidity in stocks traded on the NYSE and AMEX markets are analysed to determine whether stocks having exposure to these channels are compensated with higher returns. The static channel is referred to as the illiquidity level is defined by Amihud`s illiquidity measure. The dynamic channel of illiquidity risk is seen as stocks realizing their lowest return values during times of illiquidity. Exposure to market-wide liquidity is given by a liquidity beta, the coefficient resulting from a regression of the Fama-French 3-factor model augmented with innovations of a first order autoregression of market-wide illiquidity.

A return premium is found for stocks having a high illiquidity level, as compensation for high expected trading costs. The exposure of a stock`s returns to market-wide liquidity is found not to be the source of a risk premium. Market liquidity is therefore not regarded by investors as a priced state variable in which marginal utility of returns are higher.

These claims are based on portfolio sorts and Fama-MacBeth cross-sectional regressions. Sorting stocks on illiquidity level generates abnormal returns resulting from three asset pricing models, sorting on liquidity beta does not. For both channels however, stronger risk compensating effects are found in the period between 1998 and 2007 than between 2008 and 2016.

The Fama-MacBeth regressions confirm the time-varying effect of illiquidity level risk. Only the older subperiod shows higher returns for stocks having a higher than average illiquidity level. The average effect for the liquidity betas is found to be small but consistent over time. Both these findings are robust when controlling for firm specific characteristics.

The illiquidity level premium, being smaller in magnitude in the latter period, is likely explained by low market-illiquidity. The lack of a premium for stocks having a high illiquidity level seems logical as there are no illiquid stocks available.

At last, the dynamic illiquidity risk factor resulting from a first order regression on market-wide illiquidity is found to be weak in explaining returns. The alphas generated by the CAPM, Fama-French 3- and 5-factor models do not change when sorting stocks in decile portfolios both on their illiquidity level and their liquidity beta, as determined by the GRS-test.

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8. Appendix

(table 12 on the next page)

Table 12 Properties of Annual Portfolios Sorted on Previous Year Sensitivity to Illiquidity Innovations

Deciles:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(10-1)
Subperiod 1996-2007											
A1. Averages											
Illiquidity level	0.038	0.032	0.032	0.037	0.047	0.043	0.044	0.041	0.038	0.039	
Liquidity beta	3.35	1.61	0.75	0.15	-0.32	-0.48	-0.72	-1.57	-2.44	-4.40	
Hist. liq. beta	5.49	2.54	1.37	0.57	-0.03	-0.56	-1.20	-2.05	-3.36	-6.36	
Excess return	0.66	0.44	0.62	0.63	0.53	0.46	0.63	0.62	0.73	0.88	0.22
Size	4964	6069	7009	6243	4736	5442	5601	7235	8396	6307	
BM	0.53	0.53	0.53	0.51	0.53	0.51	0.50	0.52	0.51	0.52	
B1. Alphas											
CAPM α	0.37	0.22	0.35**	0.39*	0.32	0.21	0.37*	0.36	0.40	0.48*	0.11
	(1.48)	(0.82)	(2.17)	(1.69)	(1.21)	(0.96)	(1.80)	(1.61)	(1.64)	(1.81)	(0.34)
3-factor α	0.19	-0.05	0.28*	0.23	0.09	0.07	0.24	0.25	0.33	0.35	0.16
	(0.83)	(-0.24)	(1.76)	(1.24)	(0.38)	(0.37)	(1.32)	(1.31)	(1.47)	(1.41)	(0.50)
5-factor α	0.09	-0.25	0.28*	0.10	-0.05	-0.05	0.17	0.12	0.27	0.41	0.32
	(0.37)	(-1.24)	(1.72)	(0.51)	(-0.24)	(-0.25)	(0.92)	(0.64)	(1.16)	(1.59)	(0.98)
Subsample 2008-2016											
A1. Averages											
Illiquidity level	0.014	0.014	0.017	0.020	0.024	0.024	0.026	0.026	0.022	0.022	
Liquidity beta	3.04	1.18	0.22	-0.47	-1.08	-1.72	-2.14	-2.63	-3.54	-5.54	
Hist. liq. beta	6.37	2.87	1.28	0.17	-0.82	-1.70	-2.61	-3.66	-5.21	-8.71	
Excess return	0.66	0.56	0.61	0.29	0.41	0.60	0.62	0.32	0.28	0.62	-0.04
Size	6067	47867	8878	9091	8120	6386	7235	6676	7584	6851	
BM	0.61	0.58	0.58	0.54	0.56	0.57	0.54	0.57	0.58	0.65	
B2. Alphas											
CAPM α	-0.11	-0.15	-0.08	-0.39**	-0.30*	-0.18	-0.08	-0.46**	-0.60**	-0.27	-0.15
	(-0.50)	(-0.88)	(-0.48)	(-2.12)	(-1.86)	(-1.04)	(-0.42)	(-2.30)	(-2.48)	(-0.74)	(-0.38)
3-factor α	-0.11	-0.15	-0.07	-0.37**	-0.30*	-0.18	-0.08	-0.44**	-0.59**	-0.29	-0.18
	(-0.49)	(-0.87)	(-0.40)	(-2.04)	(-1.82)	(-1.00)	(-0.44)	(-2.24)	(-2.41)	(-0.82)	(-0.50)
5-factor α	-0.01	-0.15	-0.07	-0.34*	-0.28	-0.10	-0.12	-0.47**	-0.57**	-0.22	-0.21
	(-0.05)	(-0.80)	(-0.39)	(-1.81)	(-1.66)	(-0.53)	(-0.65)	(-2.26)	(-2.26)	(-0.61)	(-0.55)

NOTE - Subperiods of sort on illiquidity level. For the periods 1996 until 2007 and 2008 until 2016, eligible stocks are sorted in 10 based on their average level of liquidity in the previous year. Eligible stocks are common stocks traded on the NYSE or AMEX with an average yearly stock price of at least $5. Also, each year a minimum of 150 days on daily return and volume data is required. Shares lacking market capitalization data are also removed. Excess return is specified as monthly average returns over the sample period, exceeding the one-month Treasury bill rate. The market capitalization of the portfolios is given by "Size" and "BM" is the book-to-market ratio. The alphas are time-series regressions` constant of each portfolio`s excess returns on the CAPM, Fama-French 3-factor and Fama-French 5-factor models.

*t-statistics in parentheses and *** p<0.01, ** p<0.05, * p<0.1*