



**LUT School of Business and management**

**Bachelor's thesis**

**Financial management**

**Pricing liquidity risk in the Finnish stock market**

Likviditeettiriskin hinnoittelu Suomen osakemarkkinoilla

11.05.2019

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## ABSTRACT

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**School:** School of Business and Management  
**Degree programme:** Business Administration / Financial management  
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**Keywords:** liquidity, LCAPM, liquidity risk, systematic risk, Closing Percent Quoted Spread

Liquidity has been researched globally and locally increasingly in the 21st century. One of the innovations for this is liquidity-adjusted CAP-model (LCAPM). It has been found that local factors are determining considerable part of the liquidity premium and the differences between markets are significant. However, research in the Finnish stock market is limited and the results differ as the methodologies vary.

The aim of this research is to study the price of liquidity risk in the Finnish stock market and see how the methodology affects the results. The research period is from the beginning of 2002 till the end of 2018 and research data consists daily observations of 176 stocks. Liquidity is measured with Closing Percent Quoted Spread and the price of liquidity risk using unconditional LCAPM.

The results suggest that two of the three systematic components of liquidity risk are priced along with the expected illiquidity. This means that investors in the Finnish stock market want a premium for holding illiquid stocks and if their illiquidity co-moves with the market illiquidity and return. The size of the liquidity premium in Finland is on the same level with the emerging markets.

Compared to the prior studies in Finland it seems like the choice for illiquidity proxy is strongly driving the results. When it comes to the size of the liquidity premium, the use of whether the conditional or unconditional LCAPM is affecting greatly.

## TIIVISTELMÄ

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<b>Hakusanat:</b>	likviditeetti, LCAPM, likviditeettiriski, systemaattinen riski, Closing Percent Quoted Spread

Likviditeettiä on tutkittu globaalisti ja paikallisesti enemmissä määrin 2000-luvulla. Yksi innovaatio tätä varten on likviditeettimukautettu CAP-malli (LCAPM). Tutkimuksissa on huomattu, että paikalliset tekijät määräävät merkittävän osan likviditeettipreemiosta ja erot markkinoiden välillä ovat huomattavia. Tästä huolimatta aiheeseen liittyvä tutkimus Suomessa on rajallista ja tulokset vaihtelevat metodologian muuttuessa.

Tutkimuksen tavoitteena on tutkia likviditeettiriskin hinnoittelua Suomen osakemarkkinoilla ja tarkastella, kuinka metodologia vaikuttaa tuloksiin. Tutkimuksen aikaväli alkaa vuoden 2002 alusta päättyen vuoden 2018 loppuun ja aineisto koostuu päivittäisistä havainnoista 176:sta osakkeesta. Likviditeettiä mitataan *Closing Percent Quoted Spread* – luvulla ja riskiä tutkitaan ehdottomalla LCAP-mallilla.

Tuloksien mukaan kaksi kolmesta systemaattisesta likviditeettiriskin komponentista ovat hinnoiteltu odotetun epälikviditeetin lisäksi. Tämä tarkoittaa, että sijoittajat Suomen osakemarkkinoilla haluavat preemiota epälikvideistä osakkeista sekä näiden epälikviditeetin yhteisvaihtelusta markkinoiden epälikviditeetin ja tuoton kanssa. Likviditeettipreemion koko on samaa luokkaa kehittyvien maiden kanssa.

Verraten aikaisempiin tuloksiin Suomessa, epälikviditeetti-mittarin valinta näyttäisi vaikuttavan tuloksiin huomattavasti. Likviditeettipreemion koko riippuu taas merkittävästi siitä käytetäänkö ehdotonta vai ehdollista LCAP-mallia.

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## 1. INTRODUCTION

The basis of this study builds on the efficient market hypothesis. Fama (1970) introduced the theory, which states, that the prices in efficient market fully reflect all available information. The qualification of efficient market hypothesis can be broken down to three categories.

On weak-definition, winning the market using historical information shouldn't be possible, because the development of prices follows the unpredictable random walk, making technical analysis unavailing. In semi-strong terms, the prices should contain all the public information that contains in addition to historical information, all the current information (for example financial statement). The strong terms are fulfilled if even the inside information is included in the prices. (Fama, 1970)

Capital Asset Pricing Model (CAPM) is constituted on the evidence that the efficient market hypothesis is incorrect. The way investors gain excess returns with CAPM is by picking equities from the "efficient frontier" which minimizes the variance of returns and maximizes the expected returns at given risk level. However, the CAPM only considers market risk that includes the covariance of stock's and market's return. (Fama and French, 2004)

The investors can also gain excess returns by utilizing liquidity risk. This is because the expected illiquidity along with systematic liquidity risks correlate with expected excess returns. (Acharya and Pedersen, 2005) The fact that investors can gain an advantage in excess returns by using historical information of the stock's liquidity, conflicts with the weak terms of efficient market hypothesis, which is the grounds why liquidity should be studied.

## 1.1 What is liquidity?

From a perspective of a corporation it's important to understand how liquidity effects on its finance. For example, Wang & Simi (2015) investigate how corporate liquidity risk influences asset pricing models (therefore altering stock returns) when market's in recess. The paper shows how corporate finance and asset pricing are connected, concerning liquidity. Ahmed et al. (2019) divide liquidity literature in two distinct categories: corporate finance and asset pricing.

This research leaves the corporate viewpoint and focuses purely on asset pricing. The topic is interesting, not only because the expected liquidity and liquidity risks affect stock returns, but because the pricing of the liquidity risks depends on the market (Saad & Samet, 2015).

Definition of liquidity is not unambiguous, as the general understanding is that it's multi-dimensional. Kyle (1985) splits market liquidity to multiple distinct transaction costs which include the broadly used three dimensions: tightness, depth and resiliency.

Tightness explains the cost of turning over a position quickly. In an ideal world (where market is extremely tight) an investor could sell his position in desired price immediately. (Kyle, 1985) In reality, that is rarely possible, and the stockholder has to either wait or lower the selling price, therefore pay a price (either time or money) as an illiquidity cost.

Depth describes how large quantities market can take in without it affecting the price. (Kyle, 1985) In practice, the depth of the market manifests, for example, in a situation when selling in large quantities, causing the price to lower as all the bids in given price range are fulfilled, therefore turning out as an illiquidity cost.

Resiliency expresses the speed with the price moves back to an equilibrium from a bounce caused by an uninformative shock. (Kyle, 1985) In an optimal situation, the liquidity would cause the price to shift back to equilibrium immediately or the bounce caused by the news would be exactly right sized. In reality, these shocks affect the price a certain amount of time and tend to overreact, causing illiquidity costs as the investor can't liquidate his position in the equilibrium price.

Wyss (2004) starts measuring liquidity with four dimensions: trading time, depth, tightness and resiliency, with various liquidity measures. The trading time is defined as immediacy or as the time in an investor can sell his position at the current price.

However, Wyss (2004) found that liquidity cannot be fully explained by these four dimensions and introduced a bid-side and ask-side related liquidity as fifth and sixth dimension. Ask- and bid-side related liquidity are used to define market impact on both sides as they may function differently (Wyss, 2004). Sensoy (2019) also assumes and demonstrates that ask- and bid-sides are operating in different ways.

As it turns out, the liquidity is not an unambiguous concept indeed. Therefore, it's hard to capture all of its dimensions. After all, that is not the purpose of this research, but it's important to understand that the estimates on this field may alter because of that. The key elements that can cause these incoherencies are the different approaches in methodology, regarding which statistical and theoretical methods are used. Also, the proxies to indicate liquidity vary, which causes that they capture different dimensions of liquidity.

As stated above, the expected illiquidity affects stock's expected excess return and it is an unsystematic component of liquidity risk. Along with that, liquidity affects returns in a shape of three systematic liquidity risks, which are determined by the asset's and market's liquidity and return.

## 1.2 Systematic liquidity risks

*Commonality-in-liquidity* effect stems from a situation in which the asset's illiquidity increases along with the market illiquidity. It's caused by investors wanting a premium for holding a security with a risk of coming illiquid when market becomes illiquid. Chordia et al. (2000) were one of the firsts to document the co-movements of individual stock's and market's liquidity.

An intuition behind the *flight-to-liquidity* effect is, that the investors are willing to accept a lower returns on a security with high returns when market is illiquid. Pastor and Stambaugh (2003) found that the expected stock returns are related to the sensitivity of stock return to innovations in liquidity (sensitive stocks have higher expected returns) supporting this theory.

Third liquidity risk is called the *depressed wealth effect*. It's based on that the investors are prepared to acquire lower returns on a security that is liquid in times of a down market and vice versa. Acharya & Pedersen (2005) found this effect to be the most significant one of all the three risks in the US market (in time period from 1963 to 1999).

## 1.3 Global research

While introducing the liquidity-adjusted CAPM, which will be discussed in chapter 2, Acharya & Pedersen (2005) reported the total effect of liquidity risk to be 1.1% per year in the US market and combined with the expected liquidity, the overall effect to be 4.6% year. They also mentioned that their results differ with other similar researches and speculate that the differences are caused by different research methodologies, which is mentioned earlier as a sensitive element to cause diverse results.

Saad & Samet (2015) tested liquidity risks on 23 developed (which include Finland) and 60 emerging markets. They found that the liquidity risks are more greatly priced in emerging than



developed markets. Consistent with the results of Acharya & Pedersen (2005), they reported the most strongly priced liquidity risk to be liquidity's sensitivity to the market return (depressed wealth effect).

Another important finding of the study of Saad & Samet (2015) is, that the pricing is mostly determined by local factors in both categories. Findings of Lee (2011) are similar when it comes to the difference of the price of liquidity risk between developing and emerging. However, Lee (2011) found that the world price matters more than the local factors in countries where investors are global.

Persistent with earlier propositions, that the liquidity is multi-dimensional and pricing of the liquidity depends on the market, Vu et al. (2015) found in their study on the Australian market, that the pricing of illiquidity risk depends on the used proxies (which capture different dimensions of liquidity) and it differs from the other markets. A strong evidence for the later argument is, that they found a key stock-feature in the Australian market: firm size, controlling the results.

The empirical evidence around the world gives a reason to study the pricing of liquidity risk in Finland as it may vary greatly with other markets. It also shows us that conclusions shouldn't be made entirely based on one or few prior studies as the results can be strongly driven by the methodology, for example, use of different proxies or sorting portfolios based on different measures. Although, some hypotheses and baselines can be made by searching preceding literature, which is why the next chapter examines the earlier studies concerning the liquidity risk in the Finnish stock market.

#### 1.4 Prior research in the Finnish stock market

Vaihekoski (2009) studied whether the liquidity risk is priced in the Finnish stock market, using market and size portfolio data from 1987 to 2004 and measuring systematic liquidity risk with

value-weighted market-wide bid-ask spread. He found that the liquidity risk is negatively priced, supporting the flight to liquidity effect, which is caused by investors expecting a lower return on a stock that shows high returns when the market is illiquid.

Butt and Virk (2015) found that the price of illiquidity premium is substantially bigger in the Finnish stock market than in the US market. Butt (2015) described the Finnish market as rather illiquid while stating the reasons to use zero measure which doesn't apply that well to the US market because of its liquidity. Both of these studies support the findings of Vaihekoski (2009) by indicating that the flight to liquidity effect is priced. Butt (2015) also found that the other two: commonality in liquidity and depressed wealth effect, aren't significantly priced.

However, Ahmed et al. (2019) found that the expected illiquidity is priced and the exact opposite: commonality in liquidity and depressed wealth effect are the most significantly priced risks in the Finnish stock market, using data from January 1997 to July 2015. Alike with earlier results from global research section, they found that depressed wealth effect is the major factor in explaining the price of liquidity risk.

There can be various reasons why the results differ. For example, Ahmed et al. (2019) reported that the market situation, time period and methodology can be driving these differences and the time period of Vaihekoski (2009) and Ahmed et al. (2019) differs greatly.

This study utilizes the methods of both standpoints. For example, it uses same Closing Percent Quoted Spread (from now on referred as PQS) as Ahmed et al. (2019) (they also used adjusted ILLIQ-measure). A key difference in the studies is also the use of either unconditional or conditional LCAPM. The unconditional version assumes constant betas and the conditional considers trends and time variation. For instance, Butt and Virk (2015) used unconditional LCAPM like this study and Ahmed et al. (2019) used the conditional one. Factoring in these differences and combining the distinct methods of studying the liquidity risk, the Finnish stock market gives an interesting setting to study the subject.

## 1.5 Aim of the study

The earlier chapters gave several reasons to study the pricing of liquidity in Finland: the topic is not thoroughly searched, and the findings have great divergences. Also, the global research has pointed out that the pricing of liquidity risk differs depending on the market and the local factors are causing these differences, which is why studying the subject on individual area is important.

As mentioned above, the unconditional LCAPM is tested in the Finnish stock market by Vaihekoski (2009) and Butt & Virk (2015). The aim of the study is to test the unconditional LCAPM with a different proxy (PQS) and see if the results differ as the methodology changes.

1. *Is the expected illiquidity and aggregate systematic liquidity risk priced in the Finnish stock market?*
2. *Which components of the aggregate systematic liquidity risks are priced?*

## 1.6 Structure of the study

The study continues as follows: the second chapter focuses on theoretical and methodological matters in the study, creating an abstract foundation in which the empirical parts build on. The third chapter describes and prepares the data (for example, which stocks are included). The fourth chapter is the empirical part that focuses on answering the research questions by running statistical methods on the data. The fifth and final chapter concludes the study.

## 2. THEORETICAL FRAMEWORK AND METHODOLOGY

Acharya & Pedersen (2005) suggested the unconditional liquidity-adjusted CAPM, which states that the required excess return ( $E_t(r_t^i - r^f)$ ) is equal to the expected relative illiquidity cost ( $E_t(c_t^i)$ ) plus four betas times the risk premium  $\lambda$ . (Eq. 1)

$$E_t(r_t^i - r^f) = E_t(c_t^i) + \lambda\beta^{1i} + \lambda\beta^{2i} - \lambda\beta^{3i} - \lambda\beta^{4i} \quad (1)$$

Symbols  $r_t^i$ , and  $c_t^i$  refer to the return (r) and illiquidity cost (c) of security (i) in time t.  $r^f$  refers to risk-free rate of return.

Even though the expected level of illiquidity isn't defined as a risk, it affects the expected excess return as stated in the equation 1. Amihud & Mendelson (1986) proposed a theory of said correlation and proved it empirically. So overall there are four liquidity-oriented factors to affect excess return: the level of liquidity and three components ( $\beta_2$ ,  $\beta_3$  and  $\beta_4$ ) of systematic liquidity risk.

The first beta is defined as a market risk just like in the standard CAPM. It's caused by the co-movement of the stock's and market's return (Eq. 2). The idea behind the market risk is, that the asset becomes riskier the stronger it interacts with the market return. The rest of the betas are caused by the three types of liquidity risk. Term c refers to innovations in illiquidity (explained in chapter 4.3) in equations 2-5.

$$\beta^{1i} = \frac{cov(r_t^i, r_t^M)}{var(r_t^M - c_t^M)} \quad (2)$$

The first liquidity beta ( $\beta_2$ ) is referring to the commonality-in-liquidity effect which is caused by the co-movement of stock's and market's innovations in illiquidity. Equation 3 defines it mathematically:

$$\beta^{2i} = \frac{cov(c_t^i, c_t^M)}{var(r_t^M - c_t^M)} \quad (3)$$

The second liquidity beta ( $\beta_3$ ) considers the flight-to-liquidity effect which originates from the covariance of stock's return and market's innovations in illiquidity. Because the investors are willing to accept a lower return on a security with high return when market is illiquid, the beta affects required returns negatively. (Eq. 4)

$$\beta^{3i} = \frac{cov(r_t^i, c_t^M)}{var(r_t^M - c_t^M)} \quad (4)$$

The third liquidity beta ( $\beta_4$ ) stems from the depressed wealth effect that is caused by the covariation of stock's innovations in illiquidity and market's return. It also affects required returns negatively because the investors are prepared to acquire lower returns on a security that is liquid in times of a down market. (Eq. 5)

$$\beta^{4i} = \frac{cov(c_t^i, r_t^M)}{var(r_t^M - c_t^M)} \quad (5)$$

In addition to these theory-based risks, this study implements the aggregate of them, describing the systematic liquidity risk (Eq.6). It's also to avoid a potential multi-collinearity problem caused by including all risks in same regression (Lee, 2011). Also, the aggregate systematic risk can be presented combining all four betas (Eq.7).

$$\beta^{5i} = \beta^{2i} - \beta^{3i} - \beta^{4i} \quad (6)$$

$$\beta^{6i} = \beta^{1i} + \beta^{2i} - \beta^{3i} - \beta^{4i} \quad (7)$$

Along with market and liquidity risks, Lee (2011) controls the regressions along with other variables, such as book-to-market and market capitalization. Butt (2015) and Vu et al. (2015) also add momentum to these variables. This study uses book-to-market and size to control over the other variables that have an impact on stock returns to stabilize the model.

With all that is stated above, there can be made seven different specifications of the LCAPM by using control variables and measuring each of the betas separately ( $\beta_1$  is allowed in all equations except equation 14, because it doesn't correlate with the liquidity betas) to see how they affect excess returns. (Equations 9-15)

$$E_t(r_t^i - r^f) = \alpha + \kappa E_t(c_t^i) + \lambda \beta^{1i} + \varphi_1 BM_t + \varphi_2 Size_t + \mu_t^i \quad (9)$$

$$E_t(r_t^i - r^f) = \alpha + \kappa E_t(c_t^i) + \lambda \beta^{1i} + \lambda \beta^{2i} + \varphi_1 BM_t + \varphi_2 Size_t + \mu_t^i \quad (10)$$

$$E_t(r_t^i - r^f) = \alpha + \kappa E_t(c_t^i) + \lambda \beta^{1i} + \lambda \beta^{3i} + \varphi_1 BM_t + \varphi_2 Size_t + \mu_t^i \quad (11)$$

$$E_t(r_t^i - r^f) = \alpha + \kappa E_t(c_t^i) + \lambda \beta^{1i} + \lambda \beta^{4i} + \varphi_1 BM_t + \varphi_2 Size_t + \mu_t^i \quad (12)$$

$$E_t(r_t^i - r^f) = \alpha + \kappa E_t(c_t^i) + \lambda \beta^{1i} + \lambda \beta^{5i} + \varphi_1 BM_t + \varphi_2 Size_t + \mu_t^i \quad (13)$$

$$E_t(r_t^i - r^f) = \alpha + \kappa E_t(c_t^i) + \lambda \beta^{6i} + \varphi_1 BM_t + \varphi_2 Size_t + \mu_t^i \quad (14)$$

$$E_t(r_t^i - r^f) = \alpha + \kappa E_t(c_t^i) + \lambda \beta^{1i} + \lambda \beta^{2i} + \lambda \beta^{3i} + \lambda \beta^{4i} + \varphi_1 BM_t + \varphi_2 Size_t + \mu_t^i \quad (15)$$

All of the equations are formed based on Acharya and Pedersen (2005), Vu et al. (2015) and Ahmed et al. (2019). Acharya and Pedersen (2005) defined  $\kappa$  as a scale term for the level of

illiquidity  $E_t(c_t^i)$  to adjust the variation of estimation and holding period, but this study follows the methods of other papers and lets it be a free parameter. In the spirit of Vu et al. (2015),  $\varphi_1$  and  $\varphi_2$  are defined as coefficients for the book-to-market ratio (BM) and the natural logarithm of market capitalization (Size) in month t.  $\alpha$  is the constant and  $\mu_t^i$  is the residual (error term) in each regression.

Equation 14 which defines the aggregate systematic risk ( $\beta^{6i}$ ) is important, because Acharya and Pedersen (2005) set a restriction that each beta's risk premium ( $\lambda$ ) should be the same. (Eq. 16) Therefore, the premium for aggregate systematic risk ( $\lambda$ ) and  $\kappa$ -parameter of expected illiquidity in this regression define the values that are later used to calculate the prices of expected illiquidity and each liquidity risk.

$$\lambda_1 = \lambda_2 = -\lambda_3 = -\lambda_4 \quad (16)$$

## 2.1 Proxy selection

The first chapter highlighted how important factor proxies are, because each of the proxies capture the multi-dimensional liquidity differently. The use of different proxies for measuring illiquidity is quite diverse. Butt (2015) uses zero measure which fits better in the Finnish than the US market, because the Finnish market is rather illiquid. Fong et al. (2017) studied the proxies and their ability to capture the level of illiquidity. They found PQS to be, by far, the best monthly percent-cost proxy.

Because this research is limited, only one proxy will be used to get the best estimation of the price of liquidity risk. PQS could be considered the best proxy if the selection is restricted to only one measure. PQS was proposed by Chung and Zhang (2014) who found it to be good approximation (low-frequency measure) of the bid-ask spread from intraday data. It's defined in equation 17:

$$\text{Closing Percent Quoted Spread}_t^i = \frac{1}{\text{Days}_t^i} \sum_{d=1}^{\text{Days}_t^i} \frac{\text{Ask}_{td}^i - \text{Bid}_{td}^i}{(\text{Ask}_{td}^i + \text{Bid}_{td}^i)/2} \quad (17)$$

where  $\text{Days}_t^i$  is data available for a security  $i$  in month  $t$ ,  $\text{Ask}_{td}^i$  is the closing offer price and  $\text{Bid}_{td}^i$  is closing bid price of security  $i$  on day  $d$  in month  $t$ .

Even though the PQS-measure is the best proxy to capture its designated dimension of liquidity, the use of only one proxy is a major restriction of this study. Hirvonen (2016) argued that PQS captures the tightness dimension well because it measures direct trading costs, but because it doesn't consider the trading volume at all, it can't capture the depth and resiliency. Those dimensions are important especially when trading in large volumes (Hirvonen, 2016). Therefore, the findings of this study are most suitable for the small investors, whose trading volumes aren't that sizeable.

## 2.2 Portfolio development

Following the steps of Acharya and Pedersen (2005) in the use of unconditional LCPAM, the betas are based on each stock's returns and innovations in illiquidity along with the market equivalents. The use of innovations in illiquidity is because illiquidity is persistent, so calculating betas with just monthly illiquidity measures would cause problems with autocorrelation.

There is a custom to assign betas to each individual stock by forming portfolios and appointing the portfolio beta to each stock within the portfolio, to avoid high level of noise in the estimates. This study utilizes the practice of Acharya & Pedersen (2005) and Vu et al. (2015) by forming portfolios based on illiquidity that is the focus of this study, and additionally on standard deviation of illiquidity ( $\sigma$ ), size and book-to-market ratios for robustness.



The portfolios are sorted by historical information from the previous year to avoid look-ahead bias. The benefit of dividing portfolios based on past information is to dodge any bias that would be caused by using information that wouldn't be available in the beginning of the year.

Quintile illiquidity portfolios are formed based on the stock's average illiquidity,  $\sigma$  (illiquidity), size and BM-values, therefore ending up with four sets of five quintile portfolios. The use of quintile portfolios is to secure there's enough stocks in each portfolio considering that there aren't too many stocks trading in Finland (Ahmed et al. 2019). After that, equally weighted returns and illiquidity are calculated for each portfolio in given year and the betas are computed based on those measures. (Acharya & Pedersen 2005 and Ahmed et al. 2019)

### 3. DATA DESCRIPTION

The data is gathered from Thomson Reuters Datastream from time period of 1.1.2002 to 31.12.2018. The idea behind the research was to define the price of liquidity risk in 21<sup>st</sup> century in Finland but the time period is delayed, avoiding any confusion in prices that could be caused by Finland transferring from Finnish markka to euro. The data consists daily prices, closing bid and ask prices along with book-to-market values and market capitalizations. Lagged to a value of previous month's 10-year Finnish government bond yield (yearly rate converted to monthly values) are used as risk-free return.

Before the elimination of unfit stocks, the sample was 176 stocks. Following the procedures of Ahmed et al. (2019), Lee (2011) and Acharya and Pedersen (2005) the penny stocks aren't deducted but the stocks are required to have at least 100 trading days over the research period. After the filtering, there are 146 stocks left. The data consists both active and dead companies in order to avoid survivorship bias.

## 4. EMPIRICAL PART

The empirical part starts by calculating the required measures to compute illiquidity betas, which are PQS and monthly returns along with their market wide counterparts. The PQS-measure is calculated as described in equation 16 and following Ahmed et al. (2019) the stock is required to have at least 10 trading days (valid bid and ask prices) in a month to obtain a PQS value for that month. The monthly stock returns are calculated as a difference between the first and last price divided by the starting price in the month. The prices have been adjusted for dividends or other corporate actions.

Table 1. *The monthly returns, PQS-measures and their characteristics.*

	<b>Returns</b>	<b>PQS</b>
Observations	29 782	23 121
Mean (%)	0.394	2.355
Standard deviation (%)	9.546	4.4
Median (%)	0	1.18
Lowest value (%)	-67.54	0
Highest value (%)	252.73	115.95

As illustrated in Table 1, the total observations for monthly returns is 29 782 and for PQS-measures 23 121. The mean values are 0.39 and 2.4 percent, whereas median values are 0 and 1.2 percent. The standard deviation for mean value is 9.5 percent for returns and 4.4 percent for PQS-measures. The highest and lowest value for returns is 253% and -68%, for PQS-measures they are 1.2 and 0 percent.

Following the steps of Acharya and Pedersen (2005), Saad and Samet (2015) and Ahmed et al. (2019) the market return and illiquidity are calculated as an equally weighted mean of return

and illiquidity of all the stocks that are being traded. The market return is calculated using the 29 782 monthly returns and market illiquidity by applying the 23 121 PQS values using the same equal weight. Because a criterion for PQS-measures was to have at least 10 trading days in a month, calculating the market return based on only the previously mentioned 23 121 observations would favour liquid stocks. So even though some of the monthly return values aren't used when calculating betas, because the PQS-values are missing, they are used to define market return, so it will be closer to reality.

#### 4.1 Creating the portfolios

In addition to market portfolio, stocks are sorted to quintile portfolios based on their illiquidity, illiquidity variation, market capitalization and book-to-market ratio. The stocks are required to have valid observations in size and BM-values to be included.

Illiquidity sorted portfolios are created by calculating the previous year's average illiquidity and sorting stocks to 5 quintiles in the beginning of each year based on that measure. Similarly, illiquidity-variation ( $\sigma$ ) portfolios are generated by sorting stocks based on the standard deviation of illiquidity in the previous year. The values of preceding year are also used when sorting book-to-market portfolios, but size portfolios are arranged by the market capitalization in the beginning of the year. (Acharya and Pedersen, 2005)

This study doesn't include transaction cost and because the sorting window is only one year, the trading costs, which are generated from swapping stocks annually from quintile to other, might consume a portion of the illiquidity premium. The benefit of the short sorting window is, that the portfolios are more correctly divided than in longer sorting window. This is because the stock that has been labelled as illiquid might as well be highly liquid after few years. Therefore, the illiquidity portfolios are more homogenous when sorting with long time period, but because the trading isn't needed as often as with a one-year window, trading costs won't consume so much of the profits.

Now having 4 sets of 5 quintile portfolios, monthly returns and illiquities are calculated for each portfolio. Contrary to Acharya & Pedersen (2005), who calculated them as both value and equally-weighted, but presented only value-based results, returns and illiquities are calculated as equally-weighted averages.

Equally-weighted mean values are used, because in this sample the stock prices aren't restricted (data consists penny stocks as well) for the reason that the sample would otherwise be too small. If value-based measures were used, there is a risk that large stocks would drive results. Acharya and Pedersen (2005) advocate the use of equally-weighted return and illiquidity on the grounds that a stock sample is only a small component of all wealth which overrepresents large and liquid equities. Essentially, calculating equal-weighted averages compensate some of this error by giving more weight to smaller equities.

Table 2 presents the properties of illiquidity sorted quintiles. The characteristics of the rest of the portfolios are not reported as the main focus is the illiquidity sorted portfolios. The sorting is successfully done as the illiquidity measure rises from 0.22 percent in the first quintile to 6.11 percent in the last quintile. Returns rise from 0.58 to 1.18 percent from first to last portfolio, but in between the rising is not linear.

Size seems to follow illiquidity as the most liquid portfolio (1) has the biggest market capitalization in almost 19 million euros and the size decreases constantly to 45 thousand euros in the most illiquid (5) portfolio. Book-to-market ratios don't seem to follow illiquidity, based on values presented in Table 2.

The difference of 0.6 percent in returns between the most illiquid and most liquid portfolio confirms that there is an illiquidity premium. It is also noteworthy, that their standard deviation is almost the same, so the risk isn't differing greatly. Annualized, this premium is 7.44% which is a lot, especially considering that the risk isn't altering.

Table 2. *Descriptive statistics of monthly values of illiquidity sorted portfolios as mean values.*  $\sigma$ -terms refer to standard deviation of returns and illiquidity. Size is reported in thousands of euros.

Quintile	1	2	3	4	5
Returns (%)	0.58	0.49	0.46	0.41	1.18
$\sigma$ (r%)	5.27	5.12	5	4.55	5.4
Illiquidity(PQS%)	0.22	0.71	1.35	2.35	6.11
$\sigma$ (c%)	0.16	0.34	0.6	0.94	3.09
Size (k€)	18 700	588	177	89	45
BM	2.34	2.29	2.43	2.56	2.11

#### 4.2 Innovations in illiquidity

As mentioned earlier in theoretical part, illiquidity is persistent, and because of that illiquidity has to be measured as innovations in it. Similar to Acharya and Pedersen (2005), Vu et. al. (2015) and Ahmed et al. (2019) innovations in illiquidity (on portfolio level which includes the market portfolio) are calculated with autoregressive model (AR (2)). (Equation 18)

$$c_t^p = a_0 + a_1 c_{t-1}^p + a_2 c_{t-2}^p + u_t^p \quad (18)$$

where c refers to illiquidity (measured with PQS), t to given month and p to particular portfolio. The hypothesis of persistent illiquidity is confirmed in the regressions, for example, AR (2) regressions on the market portfolio have R<sup>2</sup>-ratio of 93 percent.

In equations 2-5, where betas are calculated, term  $c$  refers to innovations in illiquidity. The residual  $u$  is appointed to each portfolio as innovations in illiquidity that is stationary and not autocorrelated. The same AR(2) filtering is done for individual stock illiquidity and the residuals are used later in the regressions as the expected illiquidity ( $E(c)$ ) because the illiquidity that is measured with PQS is not stationary.

Acharya and Pedersen (2005) also calculated innovations in market returns with AR(2) model but using plenty of other control variables. This study uses the methods of other studies (for example, Vu et al. 2015) by using only simple market returns under this term.

Stationarity is tested with Augmented Dickey-Fuller test finding unit roots using maximum lags (12) for each of the innovations in illiquidity and return series. Null hypothesis that all panels contain unit roots is strongly (at 1% level) rejected for every series, except for innovations in illiquidity in  $\sigma$  (illiquidity) sorted portfolios. After adding one more lag to the filtering, also this series is stationary with p-value of 0.02.

#### 4.3 Pricing the liquidity risk

Theoretical part reported that the risk premium of each systematic risk ( $\lambda$ ) and the price of expected liquidity is defined by the regression of equation 14. Following the steps of Acharya & Pedersen (2005) and Ahmed et al. (2019) the risk affecting returns is defined as a difference between each beta in the most illiquid and liquid portfolio. As the focus of this study is to estimate the liquidity risk, only the values of each liquidity risk ( $\beta_2$ ,  $\beta_3$  and  $\beta_4$ ) are reported.

Table 3 presents illiquidity betas for each quintile in illiquidity sorted portfolios and a difference between the most illiquid and liquid portfolio. The signs of each beta in every portfolio is as expected: commonality-in-liquidity ( $\beta_2$ ) with a positive sign and flight-to-liquidity ( $\beta_3$ ) and depressed wealth effect ( $\beta_4$ ) with a negative one.

Absolute values of  $\beta_2$  and  $\beta_4$  are rising as the portfolio illiquidity rise (first quintile is the most liquid and fifth quintile the most illiquid) from 0.0007 and 0.0023 to 0.0148 and 0.0558 creating differences of 0.0141 and 0.0535. The biggest risk stems from the depressed wealth effect.

Table 3. *Illiquidity betas of illiquidity sorted portfolios from the whole time period. Difference refers to a distinction between the most illiquid (5) and most liquid (1) portfolio.*

Portfolio	$\beta_2$	$\beta_3$	$\beta_4$
1	0.0007	-0.0473	-0.0023
2	0.0023	-0.0504	-0.0159
3	0.0033	-0.0495	-0.0278
4	0.0054	-0.043	-0.0417
5	0.0148	-0.0442	-0.0558
Difference	0.0141	0.0031	-0.0535

Contrary to theoretical and earlier empirical evidence,  $\beta_3$  values act inversely with a positive difference. Also,  $\beta_3$ - values are rather big compared to other portfolios, for example, in the second quintile  $\beta_3$  has a value of -0.0504 while other to betas are 0.0023 and -0.0159. Yet, because the values don't have a great divergence between portfolios, the difference of  $\beta_3$  is the smallest of all three betas (0.0031). Deduced from the positive difference, the flight-to-liquidity effect is not priced in the Finnish stock market.

Now that the risks are defined, the next part is to estimate the risk premium ( $\lambda$ ) from regression on equation 14. Because of the panel data, a proper estimation method needs to be defined. Breusch and Pagan test for random effects reports that there are no random effects. Also, Hausman-test retells that random effects estimations are incorrect. (Both tests are ran on equation 15 that includes all betas) F-tests on all regressions on equations 9-15 compute that there are fixed effects on 1% risk level. Therefore, the estimation method is fixed effects model.

Table 4 reports the fixed effects panel-data regressions on equations 9 to 15 (first regression refers to equation 9 et cetera). In line with the expectations, the expected liquidity ( $E(c)$ ) is priced ( $\kappa$ ) on 1% risk level in every regression. The constant ( $\alpha$ ) is insignificant in 4 of the 7 regressions and rather small (-0.097 to 0.012), which improves the fit of the model. The book-to-market ratio and size are significant in every regression and their coefficients remain roughly the same: BM-ratio has a constant coefficient and size component varies from 0.018 to 0.022. This implicates that both of them affect excess returns, but they don't follow liquidity that well, at least for the BM-ratio component which persists on the value -0.001.

Contrary to earlier evidence, the  $\beta_1$  coefficient is negative in the regressions (insignificant in regression 3). Acharya and Pedersen (2005) had similar problems in the regressions that included illiquidity betas and noted that it may imply that liquidity risk matters over the market risk. Troublesome estimation is in the first regression, where only  $\beta_1$  coefficient is computed and it is still negative and significant. It has to be considered, that the beta values are computed based on sorting by liquidity, therefore it may cause this effect in the results.



Table 4. Regressions on the equations 9-15, first column refers to equation 9 et cetera. Each regression is ran on individual stocks and their previous month's values: innovations in illiquidity ( $E(c)$ ), BM and size, along with 4 betas that are defined depending on the portfolio the stock is in the current year (Betas 2-4 reported in Table 3). The values in table represent premiums (lambdas) associated with each beta along with corresponding alpha and coefficients of BM and Size factors. Markings \*, \*\* and \*\*\* denote that the coefficients are statistically significant on 10, 5 and 1% level of significance outside of confidence interval. Values in parentheses represent t-statistics.

	1	2	3	4	5	6	7
<b><math>\alpha</math></b>	-0.011 (-0.5)	-0.037 (-1.57)	0.011 (0.45)	-0.092*** (-3.64)	-0.091*** (-3.64)	-0.02 (-0.84)	-0.097*** (-2.99)
<b>E(c)</b>	0.282*** (7.28)	0.27*** (6.68)	0.275*** (6.99)	0.286*** (7.08)	0.281*** (6.97)	0.304*** (7.54)	0.274*** (6.74)
<b><math>\beta_1</math></b>	-0.081*** (-9.34)	-0.125*** (-12.22)	-0.02 (-0.84)	-0.077*** (-8.8)	-0.107*** (-11.49)		-0.275*** (-6.54)
<b><math>\beta_2</math></b>		2.05*** (8.42)					2.986*** (4.49)
<b><math>\beta_3</math></b>			2.2*** (2.74)				-4.716*** (-4.01)
<b><math>\beta_4</math></b>				-0.722*** (-7.86)			-0.017 (-0.07)
<b><math>\beta_5</math></b>					0.596*** (8.33)		
<b><math>\beta_6</math></b>						-0.068*** (-8.14)	
<b>BM</b>	-0.001*** (-6.00)	-0.001*** (-6.14)	-0.001*** (-5.99)	-0.001*** (-6.08)	-0.001*** (-6.11)	-0.001*** (-6.02)	-0.001*** (-6.2)
<b>Size</b>	0.018*** (14.01)	0.023*** (16.28)	0.019*** (14.24)	0.022*** (16.15)	0.023*** (16.3)	0.019*** (14.02)	0.022*** (15.92)

Beta 2-6 coefficients are all significant in their individual regressions. The coefficient of  $\beta_2$  has a relatively high value (2.05) while  $\beta_4$ 's is -0.722 which is also noticed in the last regression where  $\beta_2$  coefficient is 2.986 and significant but  $\beta_4$  coefficient is not significant and only -0.017. It can be deduced, that commonality-in-liquidity risk is highly priced with a great lambda, but the risk isn't that significant (defined in Table 3).  $\beta_3$  coefficient is acting oddly as it was noticed from Table 3, where a conclusion that flight-to-liquidity effect is not priced was drawn. The coefficient is 2.2 in regression 3 and -4.716 in regression 7 and statistically significant in both cases.

The aggregate liquidity risk's ( $\beta_5$ ) coefficient occurs positive (0.596) as it should, but the aggregate systematic risk ( $\beta_6$ ) component is negative -0.068. Based on earlier observations the negatively priced market risk is causing the overall risk to be negative. Also,  $\beta_3$  coefficient is acting strangely alone (positive in regression 3), arguably because it isn't priced, and as shown in equation 7, it is subtracted in the calculation of the aggregate risks. This can also cause incorrect sign on  $\beta_6$ . Because the lambda of  $\beta_5$  is positive, but the  $\beta_6$  coefficient is negative, the relatively high  $\beta_1$  values (compared to other betas) with their negative components turn the aggregate systematic risk negative. Therefore, to calculate the prices of liquidity risks, the lambda is defined as absolute value of  $\beta_6$  coefficient (0.068).

Now that the liquidity risks are defined along with the risk premium ( $\lambda$ ), the price of liquidity risk can be defined ( $\beta_2$  and  $\beta_4$ ,  $\beta_3$  is not priced). The annual premium for commonality-in-liquidity effect is  $12 \cdot (0.0141 \cdot 0.068) = 1,15\%$  and for the depressed wealth effect  $12 \cdot (0,0535 \cdot (-0,068)) = 4.37\%$ . The aggregate annual liquidity risk premium is therefore 5.52 percent.

Compared to earlier studies, for example, to Ahmed et al. (2019) who reported an annual premium of 1.9% and 1.13% for PQS and Adjusted Illiquidity-measure, the premium of this study is enormous. On the other hand, the greatest premium is caused by the depressed wealth effect, similarly to Ahmed et al. (2019). Also, Acharya and Pedersen (2005) and Saad & Samet (2015) found depressed wealth effect premium to be considerably highest of all three

liquidity risks, but the total price for liquidity risk was only 1.1% (US) and 0.73% (for developed markets which include Finland).

However, Ahmed et al (2019) and Saad & Samet (2015) used the conditional model which considers time variation. There've also been signals that the Finnish market is much more illiquid than the US market. Therefore, the results of Lee (2011) who used the unconditional model are a better comparison. Lees (2011) illiquidity premium for emerging markets is 5.58% which is amazingly close to the 5.52% of this study. This implies the same observation that Ahmed et al. (2019) did; the Finnish market is more comparable to the emerging markets when it comes to liquidity.

Chapter 4.2 considered in advance, that the premium might be higher in estimations than in reality, because the sorting window is short and transaction costs could be significant because trades must be executed more often to sort the portfolios accordingly. Also, the methodology differs from Ahmed et al. (2019) as they sorted portfolios based on three pre-ranking betas and this study used preceding illiquidity as sorting criteria. Compared to Acharya and Pedersen (2005) the methodology differs, as they ran the regressions on portfolio level, but this study uses individual stocks as the subject.

Acharya and Pedersen (2005) priced the expected illiquidity with the value of  $\kappa$  from regression 6 and the difference in illiquidity ( $E(c)$ ) between the most illiquid and liquid portfolio. Their method gives an annual price of 21.66 percent for expected illiquidity which is inaccurately high. This is arguably caused by using individual stock's innovations in illiquidity as  $E(c)$  in the regressions but PQS-measure to define the difference between the portfolios. Therefore, the price of expected illiquidity cannot be used but it can be deduced that it is significantly priced in the Finnish stock market.

#### 4.4 Robustness tests

This chapter focuses on studying how unconditional LCAPM fits for portfolios sorted on different criteria. Similar to Acharya and Pedersen (2005) these sorting principles are illiquidity variation ( $\sigma$ ), BM-ratio and size. The process remains exactly the same as described earlier for the illiquidity sorted portfolios, the only difference is the sorting criteria.

Table 5 introduces the regressions in which the betas are defined by  $\sigma$  (illiquidity) sorted portfolios. The sorting criteria could be expressed as how sensitive the stock's illiquidity is to alter, ergo, how risky the stock is when it comes to liquidity. It was noticed in Table 2, that the standard deviation of illiquidity is rising along with liquidity, so the portfolios might not differ substantially from illiquidity sorting.

As expected, the results aren't differing greatly, but some deviation can be found:  $\beta_2$  and  $\beta_4$  coefficients are correctly priced with values 0.841 and -0.213 which both are smaller than in Table 4, but the latter is not statistically significant. The systematic risk ( $\beta_6$ ) component with absolute value of 0.09 is somewhat higher. The coefficients of expected illiquidity, BM-ratio and size also last in the approximately same values: 0.265 to 0.302, -0.001 and 0.018 to 0.021.

The market risk ( $\beta_1$ ) coefficients are still negative and their absolute values are just a little bit smaller (-0.046 to -0.097). The  $\beta_3$  component remains positive (1.64) in regression 3 and regression 7 (0.62) opposed to Table 4, indicating that the flight-to-liquidity is not priced. Also, the aggregate liquidity risk ( $\beta_5$ ) coefficient is positive with a value of 0.344 which is about half of the value reported in Table 4. Because the price of liquidity risk diminishes, but the aggregate systematic risk is larger, it can be concluded that market risk is driving the risk to be negative which was supposed earlier.

Table 5. Regressions on the equations 9-15, first column refers to equation 9 et cetera. Each regression is ran on individual stocks and their previous month's values: innovations in illiquidity ( $E(c)$ ), BM and size, along with 4 betas that are defined depending on the portfolio the stock is in the current year (portfolio sorting based on  $\sigma$  (illiquidity)). The values in table represent premiums (lambdas) associated with each beta along with corresponding alpha and coefficients of BM and Size factors. Markings \*, \*\* and \*\*\* denote that the coefficients are statistically significant on 10, 5 and 1% level of significance outside of confidence interval. Values in parentheses represent t-statistics.

	1	2	3	4	5	6	7
<b><math>\alpha</math></b>	-0.005 (-0.23)	-0.022 (-0.9)	0.016 (0.65)	-0.032 (-0.95)	-0.059* (-1.78)	0.005 (0.22)	-0.021 (-0.57)
<b><math>E(c)</math></b>	0.274*** (7.02)	0.299*** (7.22)	0.265*** (6.76)	0.318*** (7.71)	0.315*** (7.63)	0.316*** (7.66)	0.3*** (7.21)
<b><math>\beta_1</math></b>	-0.088*** (-9.9)	-0.096*** (-10.11)	-0.046** (-2.43)	-0.069*** (-3.67)	-0.07*** (-5.96)		-0.072** (-2.29)
<b><math>\beta_2</math></b>		0.841*** (3.42)					0.683** (2.17)
<b><math>\beta_3</math></b>			1.64*** (2.59)				0.62 (0.72)
<b><math>\beta_4</math></b>				-0.213 (-1.12)			-0.081 (-0.42)
<b><math>\beta_5</math></b>					0.344** (2.35)		
<b><math>\beta_6</math></b>						-0.09*** (-9.35)	
<b>BM</b>	-0.001*** (-6.07)	-0.001*** (-5.97)	-0.001*** (-6.11)	-0.001*** (-6.1)	-0.001*** (-6.07)	-0.001*** (-6.08)	-0.001*** (-6)
<b>Size</b>	0.018*** (13.86)	0.02*** (14.34)	0.018*** (14.09)	0.019*** (13.95)	0.02*** (14.1)	0.019*** (13.78)	0.02*** (14.34)

The same conclusions could be conducted for the  $\sigma$  (illiquidity) and liquidity sorted portfolios: the expected illiquidity and commonality-in-liquidity are priced along with the aggregate risks ( $\beta_5$  and  $\beta_6$ ). Also, the book-to-market ratio and size are affecting returns but aren't alternating much when measuring different liquidity risks. However, the price of depressed wealth effect is not significant. The differences could be caused by using AR(3) filtering instead of AR(2).

Table 6 presents the regressions ran on stocks that have book-to-market ratio sorted portfolio betas assigned to them. It was noticed earlier, that the BM-ratio coefficients didn't vary in different liquidity risk estimations in earlier tables so it might not track LCAPM so well. Similar remark was made by Acharya and Pedersen (2005), who reported that LCAPM performs poorly on BM-by-size portfolios.

This can be seen in Table 6, where  $\beta_2$  coefficient is negative (-0.906),  $\beta_3$  component (-0.528) is insignificant and  $\beta_4$  lambda is positive (0.203). Also, the negative coefficient (-0.217) of  $\beta_5$  demonstrates, that LCAPM doesn't fit on the book-to-market ratio – sorted portfolios. The aggregate systematic risk ( $\beta_6$ ) remains negative with value of -0.048. This is caused by the negative component of  $\beta_5$  and the negative price (in regressions 1 to 5) of market risk ( $\beta_1$ ) which varies from -0.032 to -0.085. However, the market risk is positively priced in regression 7, but the other coefficients, especially the ones of  $\beta_2$  and  $\beta_3$ , are fluctuating greatly, as their values are -8.427 and 6.42.

The price of expected illiquidity lasts on the same level as in the other tables as it varies from 0.271 to 0.294. Also, the coefficients of BM-ratio (-0.001) and size (0.017-0.021) are remaining the same. This is because these variables are coming from individual stocks, so they aren't changing as opposed to betas.

Table 6. Regressions on the equations 9-15, first column refers to equation 9 et cetera. Each regression is ran on individual stocks and their previous month's values: innovations in illiquidity ( $E(c)$ ), BM and size, along with 4 betas that are defined depending on the portfolio the stock is in the current year (portfolio sorting based on book-to-market ratio). The values in table represent premiums (lambdas) associated with each beta along with corresponding alpha and coefficients of BM and Size factors. Markings \*, \*\* and \*\*\* denote that the coefficients are statistically significant on 10, 5 and 1% level of significance outside of confidence interval. Values in parentheses represent t-statistics.

	1	2	3	4	5	6	7
<b><math>\alpha</math></b>	-0.039* (-1.69)	-0.083*** (-3.48)	-0.027 (-1.1)	-0.062** (-2.52)	-0.067*** (-2.79)	-0.073*** (-3.04)	-0.312*** (-5.42)
<b><math>E(c)</math></b>	0.271*** (6.92)	0.28*** (6.81)	0.273** (6.97)	0.278*** (6.77)	0.279*** (6.79)	0.275*** (6.7)	0.294*** (7.13)
<b><math>\beta_1</math></b>	-0.055*** (-6.7)	-0.032*** (-2.99)	-0.085*** (-3.79)	-0.049*** (-5.95)	-0.033*** (-3.2)		0.471*** (4.45)
<b><math>\beta_2</math></b>		-0.906*** (-2.69)					-8.427*** (-4.65)
<b><math>\beta_3</math></b>			-0.528 (-1.42)				6.42*** (4.75)
<b><math>\beta_4</math></b>				0.203** (2.37)			-0.569** (-1.98)
<b><math>\beta_5</math></b>					-0.217*** (-2.65)		
<b><math>\beta_6</math></b>						-0.048*** (-6.19)	
<b>BM</b>	-0.001*** (-5.83)	-0.001*** (-5.92)	-0.001*** (-5.9)	-0.001*** (-5.91)	-0.001*** (-5.92)	-0.001*** (-5.83)	-0.001*** (-5.78)
<b>Size</b>	0.017*** (13.43)	0.2*** (14.6)	0.017*** (13)	0.02*** (14.55)	0.02*** (14.57)	0.02*** (14.92)	0.021*** (15.25)

In Table 7, that introduces the regressions in which the betas are determined by size-sorted portfolios, all the betas from 2 to 6 have expected signs in their regressions. The market risk  $\beta_1$  is still negative, but the  $\beta_2$  coefficient (0.944) is positively priced as well as the  $\beta_3$ - and  $\beta_4$ -equivalents negatively (-0.163 and -0.148).

Both the aggregate liquidity risk ( $\beta_5$ ) and the aggregate systematic risk ( $\beta_6$ ) are positively priced with values 0.115 and 0.004. The  $\beta_6$  coefficient is relatively small which is caused arguably by the negative component of the market risk. The reported values of  $\beta_1$  are the lowest compared to the other three tables and because of this, the positively priced aggregate liquidity risk turns  $\beta_6$  coefficient to be positive too. In regression 7, the betas are escalating aggressively, for example, the  $\beta_2$  component has value of 26.92.

Even though, it seems like size-sorted portfolio betas fit in the LCAPM, none of the betas in any regression is significant. This means that these results have no economic value. As noticed in the other tables, the individual stock variables' coefficients remain on the same level.



Table 7. Regressions on the equations 9-15, first column refers to equation 9 et cetera. Each regression is ran on individual stocks and their previous month's values: innovations in illiquidity ( $E(c)$ ), BM and size, along with 4 betas that are defined depending on the portfolio the stock is in the current year (portfolio sorting based on size). The values in table represent premiums (lambdas) associated with each beta along with corresponding alpha and coefficients of BM and Size factors. Markings \*, \*\* and \*\*\* denote that the coefficients are statistically significant on 10, 5 and 1% level of significance outside of confidence interval. Values in parentheses represent t-statistics.

	1	2	3	4	5	6	7
<b><math>\alpha</math></b>	-0.095*** (-2.69)	-0.136*** (-3.48)	-0.094*** (-2.64)	-0.136*** (-3.44)	-0.132*** (-3.41)	-0.126*** (-3.27)	-0.061 (-0.97)
<b><math>E(c)</math></b>	0.246*** (6.3)	0.281*** (7.1)	0.246*** (6.3)	0.281*** (7.1)	0.281*** (7.1)	0.279*** (7.04)	0.285*** (7.18)
<b><math>\beta_1</math></b>	-0.029 (-1.09)	-0.008 (-0.27)	-0.037 (-1)	-0.006 (-0.22)	-0.012 (-0.44)		-0.192 (-1.46)
<b><math>\beta_2</math></b>		0.941 (1.51)					26.92 (1.61)
<b><math>\beta_3</math></b>			-0.163 (-0.31)				-2.69 (-1.38)
<b><math>\beta_4</math></b>				-0.148 (-1.4)			4.438 (1.56)
<b><math>\beta_5</math></b>					0.115 (1.32)		
<b><math>\beta_6</math></b>						0.004 (0.15)	
<b>BM</b>	-0.001*** (-5.83)	-0.001*** (-5.77)	-0.001*** (-5.83)	-0.001*** (-5.77)	-0.001*** (-5.77)	-0.001*** (-5.76)	-0.001*** (-5.7)
<b>Size</b>	0.019*** (14.78)	0.021*** (12.83)	0.019*** (14.74)	0.021*** (12.86)	0.021*** (12.94)	0.019*** (14.83)	0.021*** (12.92)

## 5. CONCLUSION

Using the unconditional liquidity-adjusted CAPM (LCAPM), this study investigated the pricing of expected illiquidity and liquidity risk in the Finnish stock market in time period from January 2002 to December 2018, using Closing Percent Quoted Spread (PQS) as a proxy for illiquidity. The liquidity risk can be presented as its three systematic components: commonality-in-liquidity ( $\beta_2$ ), flight-to-liquidity ( $\beta_3$ ) and depressed wealth effect ( $\beta_4$ ).

Both the expected illiquidity and liquidity risk are priced. However, it was found that flight-to-liquidity is not priced, contrary to the findings of Butt (2015), Butt and Virk (2015) and Vaihekoski (2009), who also studied the liquidity risk in Finland. This implies that the choice for proxy is strongly driving the results. The investors in the Finnish stock market want a premium for holding a stock that is illiquid, and if its illiquidity co-moves with the market illiquidity and return (commonality-in-liquidity and depressed wealth effect).

Similar to the study of Ahmed et al. (2019) and global studies, the depressed wealth effect has the highest risk premium in the Finnish stock market. The annual risk premium for the aggregate liquidity risk is 5.52 percent. Comparing to the prior studies, this implies that the price of liquidity risk in the Finnish market is on the same level with emerging markets. Also, the choice between the conditional and unconditional LCAPM is affecting the size of liquidity premium greatly.

The notable shortcomings of this study are excluding the trading costs and time variation of liquidity. Also, the PQS-measure captures merely the direct trading costs, therefore excluding depth and resiliency, so the estimates apply only when trading with small quantities. An estimation problem, that has been identified earlier, was also noticed in the robustness tests. The unconditional LCAPM doesn't explain the entire investment universe in the Finnish stock market, as the model fit poorly on stocks which had their betas assigned from differently sorted portfolios.

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