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Liquidity Risk in the Finnish Stock Market

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Tutkimuksessa tarkastellaan likviditeettiriskin hinnoittelua sekä sen vaikutusta osakkeiden tuottoihin Suomen osakemarkkinoilla. Lisäksi tutkimuksessa selvitetään, onko likviditeettiriskissä havaittavissa trendiä. Kolmantena tutkimuksen kohteena on valittujen likviditeetin mittareiden mahdolliset erot tuloksissa. Tutkimusaineisto koostuu kaikista Suomen osakemarkkinoilla listatuista osakkeista aikavälillä 1/1997–7/2015 pois lukien sijoitusrahastot. Likviditeettiriskin vaikutusta osakkeiden tuottoihin tutkitaan estimoimalla ehdollinen versio Acharya ja Pedersenin (2005) likviditeetti-CAPM-mallista (LCAPM). Tutkimuksessa käytetään kahta uutta likviditeetin mittaria, *PQS* ja *AdjILLIQ*, mikä mahdollistaa tulosten vertailun näiden välillä. Ehdolliset, ajassa muuttuvat likviditeettiriskit estimoidaan käyttäen usean muuttujan DCC-GARCH-mallia, kun taas likviditeettiriskin hinnoittelua tutkitaan hyödyntämällä kiinteiden vaikutusten paneeliregressiota. Empiiriset tulokset osoittavat, että sijoittajat ovat valmiita maksamaan preemion suojautuakseen varallisuusshokkeja vastaan sekä sitä vastaan, että heillä on likvidi osake silloin, kun markkinat yleisesti ovat epälikvidit. Sijoittajat eivät kuitenkaan ole halukkaita maksamaan preemiota osakkeista, joiden tuotot olisivat korkeammat silloin, kun markkinat yleisesti ovat epälikvidit. Annualisoidut likviditeettipreemiot Suomen osakemarkkinoilla ovat 1.77% *PQS*-likviditeettimittaria käyttäen ja vastaavasti 1.04% *AdjILLIQ*-mittarilla. Tutkimus myös osoittaa, että Suomen osakemarkkinoilla likviditeettiriskeissä ei ole laskevaa trendiä ja sijoittajien tulisikin huomioida likviditeettiriski portfolioidensa hajauttamisessa.

ABSTRACT

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This study explores the pricing of liquidity risk and its effect on stock returns in the Finnish stock market. In addition to that, it investigates whether there is a trend in liquidity risk. Finally, it analyzes whether the two chosen liquidity measures provide different results. The data consists of all the common shares listed in the Finnish stock market during the period of 1/1997–7/2015. To examine whether liquidity risk affects stock returns in the Finnish stock market, this study utilizes a conditional version of liquidity-adjusted capital asset pricing model (LCAPM) by Acharya and Pedersen (2005). Two recently proposed illiquidity measures – *PQS* and *AdjILLIQ* – are used in the empirical estimation to see whether there are differences in the results between the measures. The time-varying conditional liquidity risks are estimated by using a multivariate DCC-GARCH model, while the pricing of the liquidity risk is conducted by applying fixed effect panel regression. The results imply that investors in the Finnish stock market are willing to pay a premium to hedge from wealth shocks and having liquid assets during the declined market liquidity. However, investors are not willing to pay a premium for stocks with higher returns during illiquid markets. The total annualized illiquidity premiums found in the Finnish stock market are 1.77% and 1.04%, based on the *PQS* and *AdjILLIQ* measures, respectively. The study also shows that liquidity risk does not exhibit decreasing trend, and investors should consider liquidity risk in their portfolio diversification in the Finnish stock market.

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Jani Hirvonen

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LIST OF ABBREVIATIONS

AdjILLIQ – Modified Amihud Illiquidity Measure

AMEX – American Stock Exchange

ARCH – Autoregressive Conditional Heteroscedasticity

ASX – Australian Stock Exchange

CAPM – (Traditional) Capital Asset Pricing Model

DCC – Dynamic Conditional Correlation

EGARCH – Exponential Generalized Autoregressive Conditional Heteroscedasticity

GARCH – Generalized Autoregressive Conditional Heteroscedasticity

GMM – Generalized Method of Moments

ILLIQ – Amihud (2002) Illiquidity Measure

LCAPM – Liquidity-Adjusted Capital Asset Pricing Model

LSE – London Stock Exchange

NASDAQ – National Association of Securities Dealer Automated Quotation

NYSE – New York Stock Exchange

OLS – Ordinary Least Squares

PES – Percent Effective Spread

PQS – Closing Percent Quoted Spread

TAQ – The Trade and Quote Database of NYSE

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1 INTRODUCTION

Liquidity is an elusive and multidimensional concept that plays a key role in asset pricing and financial market as it facilitates better risk sharing and improves trading efficiency. However, there is no single and clear definition of liquidity; by using the definition of Kyle (1985), liquidity can be characterized by its somewhat overlapping attributes of tightness, depth, and resiliency. According to Kyle (1985, 1316) tightness refers to the cost of transaction, such as the bid-ask spread, while in a deep market there are a sufficient amount of pending orders on both the bid and the ask side, precluding a larger order from significantly moving the price. Resiliency refers to how long it takes stock prices to recover back to equilibrium from a random, uninformative shock (Kyle 1985, 1316).

The studies related to liquidity can be roughly divided to those which concentrate on liquidity and corporate finance, and those which concentrate on liquidity and asset pricing. While the studies related to corporate finance are interested, for instance, in how liquidity can affect the cost of capital and capital structure theories, the asset pricing side is more interested in the premium associated with the liquidity of a stock. (Holden et al. 2013, 319; 342). This study focuses on the latter and positions itself to explore liquidity and asset pricing in the Finnish stock market.

The previously presented characteristics tend to be exhibited in liquid markets, and well-functioning markets are definitely in the interest of market participants. Investors may avoid trading illiquid stocks since it affects the returns of their stocks due to higher buying and selling costs associated with illiquid stocks. Regulators are also interested in liquidity, because the more liquid the market, the less volatile it often is. Regarding these participants in the market it can be easily seen that liquidity has a tremendous role for the functionality of a security market; investors want to trade at lower costs, and regulators appreciate less volatile markets since they attract more investors with their lower level of uncertainty. (Harris 2003, 394) Being in the interest of investors, regulators, exchanges and other market participants, it is no wonder why liquidity has been an intriguing topic among the researchers.

The papers investigating asset pricing with liquidity dimension have mainly focused either on liquidity level or a single liquidity risk factor. Prior studies focused on the microstructure of liquidity and found that expected returns increase with the level of illiquidity (e.g. Amihud and Mendelson, 1986; Eleswarabu, 1997; Amihud, 2002). Later, studies focused on market-wide components of liquidity, and literature has found three dimensions associated with systematic liquidity risks that are commonality in liquidity (e.g. Chordia et al., 2000; Hasbrouck and Seppi, 2001; Huberman and Halka, 2001), flight to liquidity (e.g. Pastor and Stambaugh, 2003; Korajczyk and Sadka, 2008; Kim and Lee 2014), and depressed wealth effect (Acharya and Pedersen, 2005). Liquidity level and these three liquidity risks were first time theoretically modelled by Acharya and Pedersen (2005), when they proposed the liquidity-adjusted capital asset pricing model (LCAPM), a comprehensive asset pricing model combining the level of liquidity and the three systematic liquidity risks.

Economically speaking, commonality in liquidity represents a non-diversifiable risk that emerges from a situation where a stock becomes illiquid when the market overall is illiquid, and investors want compensation for bearing that risk. Flight to liquidity is seen to stem from a situation where investor tries to change position in illiquid asset into more liquid assets which cause investors see those asset as uncertain and assets' implied values decline and, thus, having negative effect on stock returns. Depressed wealth effect ensues from a situation where a selling investor tries to liquidate a position in illiquid assets but is unable to do that which causes wealth problems for the investor, and hence having a negative effect on stock returns. (Acharya and Pedersen 2005, 382–383)

Liquidity risk and its pricing implications have been extensively studied in the US market and other larger markets. However, the US market can be seen as the most liquid market in the world (Bekaert et al., 2007), which implies that it may not be the best for empirical testing of the illiquidity effect. Finland appears to be an appropriate market for this purpose since it is relatively illiquid, as depicted by Butt and Virk (2015, 682). Even though research has been conducted with regards to the Finnish stock market, more research is needed. Swan and Westerholm's (2002) findings imply that a lower level of liquidity means higher returns. However, recent studies by Butt (2015) and Butt and Virk (2015) tested the four liquidity risks and found that flight to liquidity is the most significant and dominating dimension of liquidity risk in the Finnish stock market. The first one reports that the asset specific illiquidity, commonality in liquidity and depressed wealth effect remain not appropriate dimensions in the Finnish stock market, while the later support the notion that flight to liquidity is priced but also reports that the level of illiquidity is positively related to stock returns. Both of these studies also support the findings of Vaihekoski (2009) that flight to liquidity is negatively priced in the Finnish stock market.

However, the study of Butt (2015) used only one measure of liquidity that is zero return suggested by Lesmond et al. (1999), which is highly questionable since liquidity is multidimensional phenomenon. Additionally, the study did not account for time-variation in liquidity. These shortcomings are partially fulfilled by Butt and Virk (2015) when using Amihud’s (2002) illiquidity measure along with zero measure. They also tested time variation by deducting the time period which is illiquid according to Amihud’s measure. However, they assumed constant betas over time as they estimated an unconditional version of the LCAPM. In addition, they did not observe the time variation in illiquidity risk. Hence, this study aims to fill this gap by estimating a conditional version of the LCAPM with newly proposed illiquidity proxies. Furthermore, the conditional specification of the LCAPM allows for the investigation of trends in illiquidity risks that have been previously studied in the US market (Hasgströmer et al., 2013) and globally (Saad and Samet, 2015) but never before in the Finnish stock market.

The purpose of this study is to examine relationship between stock excess returns and liquidity risk and a possible time trend in liquidity risk in the Finnish stock market. Thus, this study will contribute to the literature in several ways. First, to the knowledge of the author this is the first study that incorporates two recently developed low-frequency liquidity proxies that have shown high correlation with their high-frequency counterparts in the Finnish stock market. Second, this study estimates a conditional version of the LCAPM for the first time in the Finnish stock market. Third, this paper enriches the previous findings in the Finnish stock market by exploring whether different dimensions of liquidity risk can be incorporated in the Finnish stock market or whether these new measures produce similar results with the previous findings. Finally, the conditional specification of the LCAPM allows for investigation of linear trends in liquidity risks in the Finnish stock market.

To estimate a conditional version of the LCAPM, this study utilizes the dynamic conditional correlation generalized heteroscedasticity (DCC-GARCH) model by Engle (2002) to estimate conditional illiquidity risks. The conditional illiquidity risks are estimated at portfolio level and to increase the power of the test the portfolio loadings are assigned to individual stocks. Then individual stocks are used as test assets in the LCAPM specifications, when estimating the price of the illiquidity risk by applying fixed effect panel regression. The data analyzed in this study covers all the common stocks that have been listed in the Finnish stock market during the period of 1/1997–7/2015, including dead and de-listed stocks. The time period was selected on the basis of ensuring a sufficient amount of observations while keeping in mind the extent of a Master's thesis. The research questions of this study are as follows:

> *1. Are liquidity risks priced in the Finnish stock market? More precisely, is the asset specific level of illiquidity priced in the Finnish stock market and are systematic co-movements in liquidity priced in the Finnish stock market?*
>
> *2. Is there a decreasing trend in liquidity risk?*
>
> *3. Does the choice of illiquidity measure affect the relationship between liquidity risk and stock returns?*

The first research question allows for the investigation whether investors are compensated for bearing the liquidity risk during declined market returns or liquidity. This attempts to shed light on whether investors should consider other systematic risks besides the traditional market risk in the Finnish stock market. The second question can be seen to complement the first research question by investigating time-series dimension of liquidity risk. The third question stems from the fact that liquidity is a multi-dimensional phenomenon and different measures could capture different dimensions.

By studying the research questions, it is possible to expand the understanding of liquidity risk in the Finnish stock market. However, there are some limitations that should be considered.

First, the number of stocks listed in the Finnish stock market sets restrictions for the stock selection process. It is a common practice to deduct penny stocks from the sample, but due to the limited number of stocks listed in the Finnish stock market this process could not be followed in this study and penny stocks are included. Another limitation of this study is that stock market liquidity is an immense topic and all its attributes cannot be covered by using only two measures. The focus of this study is to test the suitability of these two illiquidity measures in asset pricing context in the Finnish stock market; hence it does not examine the capability of these measures to capture true transaction costs. This study thus relies on the previous studies' results of these measures being suitable illiquidity proxies. Furthermore, this study focuses only on the small Finnish stock market and hence the results cannot be applied to bigger stock markets. Nevertheless, the methodology chosen in this study might be suitable for other small markets.

The rest of the paper is organized as follows. Next section gives a detailed description of the theoretical framework of the study and presents the research hypotheses. Third section introduces the data and depicts the chosen methodology in detail. Fourth section shows the estimation results and discusses statistical significance of the results, while the fifth section pays attention to the economic significance of the results. Finally, the last section summarizes and concludes the main findings of this paper.

2 THEORETICAL FRAMEWORK

2.1 What is Liquidity?

As liquidity is a broad and elusive concept, it can be difficult to give it a precise and commonly accepted definition. There is, however, a consensus that liquidity plays a key role in asset pricing and financial markets, as it facilitates better risk sharing and improves trading efficiency. Hence, liquidity is a concern of many market participants, including institutional and individual investors, regulators, and exchanges.

Liquidity can be examined by concerning the modern theory of market microstructure: since it formulates the trading process as an interaction between liquidity suppliers and liquidity demanders, liquidity has a vital role in the securities market. Hence, a simple definition for the market liquidity can be considered as the ability to trade a considerable quantity of a security at a low cost in a short time, so that the liquidity suppliers offer to buy a particular security at a bid price or sell it at an ask price, and then liquidity demanders agree to buy the security at the ask price or sell it at the bid price. (Holden et al. 2013, 266) Additionally, Foucault et al. (2003, 4) demonstrate that investors are concerned about liquidity since it affects the returns of their stocks due to higher buying and selling costs associated with illiquid stocks. Harris (2003, 394) argues that regulators are also interested in liquidity because the more liquid markets are often less volatile. Regarding these participants in the market, it can be easily seen that liquidity has a tremendous role in the functionality of a security market; investors want to trade at lower costs and regulators appreciate less volatile markets since they attract more investors with lower level of uncertainty.

Amihud and Mendelson (1991, 56–57) suggested that there are four distinct components in defining the costs associated with illiquidity that are bid-ask spread, market impact cost, delay and search costs, and direct transaction costs. By using the more generalized definitions, liquidity can be defined to refer to any other cost incurred when trading an asset, such as the time it takes to execute a transaction (Lippman and McCall 1986), the ability to trade large volumes (Datar et al., 1998**)** and the price impact (Amihud 2002). Thus, liquidity encompasses transactional properties of the market from its tightness, depth and resiliency as suggested by Kyle (1985). Tightness refers to the cost of transaction, such as the bid-ask spread, while in a deep market there are a sufficient amount of pending orders on both the bid and the ask side, precluding a larger order from significantly moving the price. Resiliency refers to the speed with which prices recover back to equilibrium from a random, uninformative shocks. In conclusion, liquidity proxies used in the literature can be classified into these three categories. However, these categories are somewhat overlapping, and empirical definitions span from direct trading costs (tightness), measured by bid-ask spread (quoted or effective), to indirect trading costs (depth and resiliency), measured by price impact as expressed in Lesmond (2005).

As indicated, the three mainly used attributes of liquidity (tightness, depth and resiliency) are represented by direct and indirect trading costs, and measured by bid-ask spread and price impact, respectively. The execution costs aroused from a round-trip (initially buying at the offer and subsequently selling at the bid) are the bid-ask spread, while market impact is defined as the additional costs, over and above the spread, that a trader may face to have a large order execute quickly. Due to market impact, the effective spread is wider on average for a large order than a small order. (Schwartz and Francioni 2004, 66)

2.2 Measuring Liquidity

As described, liquidity can be considered a multi-dimensional concept, which makes it more difficult to measure. Thus, there is no single measure of liquidity that can capture all the elements of it. The choice of the measures to incorporate into the analysis can be made on the based on the characteristics of the market or on the dimension of liquidity to measure, for instance.

There have been proposed an extensive number of liquidity measures, that can be divided into two classes. The first class calculates the trading cost directly from high-frequency transactional data, and the other uses low-frequency data to calculate measures. Thus, besides the characteristics of a market, one major concern is the availability and quality of the market data. Therefore, some liquidity proxies may need high frequency data (i.e. transaction data), while some of the proxies can be derived by using low-frequency data. On the one hand, using the high-frequency data could obviously give more accurate estimates for the proxies, and hence more accurate models (Hasbrouck, 2009). On the other hand, the transaction data may not be available for long periods, and even for the US market it is only available since 1983, and for many countries the transaction data is not available at all (Goyenko et al. 2009).

Many of the liquidity proxies used in the literature are employed them on daily or monthly data. Consequently, this has aroused conflicting views of which measure is better and whether these proxies truly capture the transaction costs. Furthermore, one can always question whether the measures really are related to investor experience. Nevertheless, high-frequency data could be more expensive compared to low-frequency data, which may advocate the use of the latter, and drive researchers and practitioners to use low-frequency measures.

Even though, generally, the liquidity measures are proposed using low-frequency data due to the lack of long time-series, using the high-frequency data admittedly allows for gauging the finer estimates of liquidity. High-frequency liquidity measures are calculated by using the intraday date, and can be categorized into percent-cost and cost-per-volume proxies. (Kang and Zhang 2014, 51) The categories also can be seen to represent the two dimensions that represent the direct and indirect costs associated with the three attributes (tightness, depth, and resiliency) described in the section 2.1 While the percent-cost proxies apprehend trading costs as a percentage of the price or a percent bid-ask spread, the cost-per-volume proxies capture the price impact.

As previously described high-frequency liquidity measures might be more accurate to capture the elusive concept of liquidity. However, acquiring high-frequency data can be expensive and cumbersome so it may be more efficient to use low-frequency measures of liquidity. (Fong et al. 2014, 2) There have been conducted several studies concerning whether low-frequency liquidity proxies can capture the liquidity properly. According to Hasbrouck (2009) and Goyenko et al. (2009) low-frequency measures can be effectively used to capture liquidity in the US market, while Fong et al. (2014) and Kang and Zhang (2014) report that there is high correlation between low-frequency and high-frequency liquidity measures globally and in emerging markets, respectively.

In this study one low-frequency proxy is chosen for price impact and one for spread. The selection of the measures is based mainly on the studies of Fong et al. (2014) and Kang and Zhang (2014). In the two following sub-chapters, discussion about price impact measures and spread measures are presented, and the selected measures utilized in this research are depicted in detail.

2.2.1 Price Impact

For the cost-per-volume high-frequency measure, one widely used benchmark is a measure that is sometimes referred as *Five-minute price impact*, which measures the derivative of the cost arising from demand for a certain amount of liquidity over five minutes, that may differ substantially from the same amount of immediate liquidity (e.g. Goyenko et al., 2009 and Hasbrouck, 2009). This measure can be constructed by calculating the price impact, λ (*Lambda*), which is the slope of the price function (Hasbrouck, 2009). Goyenko et al. (2009) tested a set of low-frequency liquidity proxies against a bunch of spread and price impact benchmarks of liquidity in the US market in 1993–2005, and reported that the price impact is difficult to capture with low-frequency measures. They used three different benchmarks for price impact, namely *Static Price Impact*, *Lambda* and *5-Minute Price Impact*, and concluded that Amihud’s (2002) illiquidity measure can capture two of the three benchmarks while none of the price impact proxies could capture *Static Price Impact*. Amihud’s (2002) illiquidity measure was also found to performing well on a global level in a comparative study of Fong et al. (2014), when analyzing thirteen price impact proxies related to *Lambda*. Subsequently, *Lambda* is used as a high-frequency benchmark in this study to choose low-frequency measure for illiquidity.

Amihud (2002) illiquidity measure is a low-frequency proxy for price impact, and is probably the most widely used measure in finance literature that has advantage of being easy to calculate and interpret. Amihud (2002) characterizes the illiquidity of a stock as follows:

$$ILLIQ_t^i = \frac{1}{Days_t^i} \sum_{d=1}^{Days_t^i} \frac{\left|R_{t,d}^i\right|}{Vol_{t,d}^i} \tag{1}$$

In equation (1), $R_{t,d}^{i}$ is the return on day *d* in month *t*, $Vol_{t,d}^{i}$ is the euro trading volume (in thousands) on day *d* in month *t*, $Days_{t}^{i}$ is the number of days for which data is available for a given stock *i* in month *t*. Hence, as can be derived from the equation 1, Amihud defines the stock illiquidity as the average ratio of absolute daily stock returns to daily trading volume in a month (multiplied by 10^6) (Amihud 2002, 37). As described in Amihud (2002), illiquidity can be interpreted as the average daily association between a volume unit and the price change. Additionally, Amihud (2002) mentions that another economic interpretation is related to consensus belief about new information among investors. The stock price changes without trading if traders agree about the implication of news, but disagreement causes trading volume to increase. In addition to ease of calculation and interpretation, one advantage of *ILLIQ* comes from the fact that it captures price impact, which is more significant for large volumes of trades, and hence for investors who are trading large volumes, namely institutional investors. However, the *ILLIQ* measure suffers from the drawback that it requires stocks to have non-zero trading days in most of the time in a particular month to be valid; otherwise it becomes undefined (Amihud, 2002). Hence, for smaller and less traded markets like emerging markets and Finland, the *ILLIQ* measure may remain undefined for a significant period of time.

In fact, a comparative study of different low-frequency proxies by Fong et al. (2014) reveals that Amihud's (2002) *ILLIQ* measure is not performing well in the Finnish stock market, finding only a correlation of 0.238 with the high-frequency benchmark *Lambda*. To overcome the drawbacks of the *ILLIQ* measure, Kang and Zhang (2014) propose a new measure, *AdjILLIQ*, which is a modified version of Amihud's *ILLIQ* measure and can be interpreted to be non-trading-day adjusted *ILLIQ* measure. Specifically, the measure is a combination Amihud and *ZeroVol* illiquidity measures.

Kang and Zhang (2014) define *ZeroVol* measure simply as a proportion of zero-volume days in a month:

$$ZeroVol = \frac{\text{Number of days with zero volume in a month}}{\text{Total number of trading days in a month}} \tag{2}$$

The *ZeroVol* can be considered to be a sibling of the *ZeroReturn* measure, which is the proportion of zero return days in a month, as proposed by Lesmond et al. (1999). The economic intuition of *ZeroReturn* measure is that informed traders only trade if the gain from their private information is greater than the offset by transaction costs. In other words, the value of the information signal should exceed the cost of trading, or otherwise marginal investors will diminish trading or not trade at all which leads to a zero return. Consequently, the measure can be interpreted so that the higher the proportion of zero-return (zero-volume) days, the higher the illiquidity is.

As the non-trading days are more common in markets smaller than the US or other large markets, the suitability of *AdjILLIQ* can be substantial in emerging markets and markets with low or zero trading volume in notable days in a month, as proved by Kang and Zhang (2014). They specify the *AdjILLIQ* as log transformation of the original Amihud *ILLIQ* measure multiplied by the sum of one and the proportion of non-trading days in a particular month (*ZeroVol*), as depicted below:

$$AdjILLIQ_t = \left[\ln\left(\frac{1}{Days_t^i} \sum_{d=1}^{Days_{i,t}} \frac{\left|R_{t,d}^i\right|}{Vol_{t,d}^i} \right) \right] \times \left(1 + ZeroVol_t^i\right) \tag{3}$$

In the formula $Days_{i,t}$ is non-zero trading volume days for stock *i* in month *t,* $\left|R_{td}^i\right|$ is the absolute value of the return on stock *i* on day *d* in month *t,* and Vol_{td}^i , is the euro trading volume (in thousands) on day *d* in month *t*. $ZeroVol_t^i$ is the proportion of zero-volume of days of stock *i* within month *t*. *Ln* refers to natural logarithm, which is taken over the *ILLIQ* measure to take into account extreme large values. Like the original *ILLIQ* measure, the higher value implies lower liquidity. Adjusting a widely used price impact measure for zero-volume trading days, the *AdjILLIQ* measure has many advantages. First, due to adjustment, it is suitable for markets with low turnover rates as well as for markets with high turnover rates. Kang and Zhang (2014) find that this measure proves to be better in market that are characterized as having inactive trading and low stock turnover, and performs well in actively-traded market as well. This results are definitely interesting concerning this research. As pointed out by Butt (2015, 205;207), the Finnish stock market has more than twice the number of zero returns compared to the US market, and despite the fact that it is a developed market, it resembles more emerging markets with regards to zero return illiquidity measure. This fact is the main reason to choose *AdjILLIQ* as one measure of illiquidity. Furthermore, the Finnish market is characterized as thin trading, which supports the use of the *AdjILLIQ* illiquidity measure (Vaihekoski 2009, 1552). Additionally, the calculation only needs daily return and volume data (Kang and Zhang, 2014).

2.2.2 Spread

Effective spread is one widely used high-frequency benchmark for spread, which means the difference between the price at which a market maker buys or sells a security and price at which the dealer later sells or buy it. In other words, effective spread can be seen as the true transaction costs associated with each trade, since it is actual difference between the bid and ask, adjusted for any price movements. (Goyenko et al. 2009, 154–155) Because the effective spread can be seen to depict better the true costs associated with each trade, in this research *Percent Effective Spread* (*PES)*, that is the same as effective spread but it is in a relative form, will be used as high-frequency benchmark for the selection of low-frequency proxy for spread. Compared to quoted spread, effective spread can be seen as either price improvement or price deterioration. If effective spread is higher than quoted spread, the price adjustment has worsened the price. Similarly, if effective spread is lower than quoted, the price adjustment has been favorable for the investor.

Percent effective spread cannot be measured directly by obtaining low-frequency, such as daily data. One popular proxy for spread is *"Zeros"* from Lesmond et al. (1999), that have been used in global level (Lee, 2011; Kim and Lee, 2014; Saad and Samet, 2015) and in the Finnish stock market (Butt, 2015; Butt and Virk, 2015). This measure has the advantage of its easiness to estimate, as it only requires daily return data (Lesmond et al. 1999, 1137). However, in their study Fong et al. (2014) researched nine percent-cost proxies for spread in multiple exchanges around the world, and their results showed (Fong et al. 2014, 43–45) that *"Zeros"* is not performing well capturing the spread with regards to percent effective spread in the Finnish stock market. Chung and Zhang (2014) proposed a new liquidity measure, Closing Percent

Quoted Spread (from here on referred to as *PQS*), and reported it to be superior to other percent cost proxies, having a high correlation with percent effective spread, percent quoted spread, and percent realized spread. Fong et al. (2014) studied also how well this measure is capturing percent effective spread in the Finnish stock market. Their results suggest that it has the highest cross-sectional and time-series correlation, as well as the lowest root mean squared error (Fong et al. 2014, 43–45). Hence, in this study the *PQS* measure of illiquidity is used as a proxy for percent effective spread.

Chung and Zhang (2014, 97) define *PQS* as:

$$PQS_t^i = \frac{1}{Days_t^i} \sum_{d=1}^{Days_t^i} \frac{Ask_{td}^i - Bid_{td}^i}{(Ask_{td}^i + Bid_{td}^i)/2} \tag{4}$$

As illustrated in equation 4, the measure accounts for bid-ask spread where Ask_{td}^i is the closing offer price of stock *i* on day *d* in month *t*, Bid_{td}^i is the closing bid price of stock *i* on day *d* in month *t*, $Days_t^i$ is the number of days for which data is available for a given stock *i* in month *t*. Thus, in *PQS* the bid-ask spread is divided by mean of Ask_{td}^i and Bid_{td}^i. As *PQS* is comprising of bid-ask spreads, it does not have limitations for the size of the trades, and is hence a more suitable measure for small trades. The advantage of *PQS* measure is its straightforwardness in calculations and its easy, intuitive interpretation. Additionally, it is an effective low-frequency measure but also has top results for estimating high-frequency measures.

2.2.3 Comparison of the Measures

The proxies for illiquidity utilized in this study are chosen to capture both price impact and spread in order to see whether they provide different results. Their high-frequency counterparts are *Lambda* and *Percent Effective Spread* for price impact and spread, respectively. Since the proxies are designed to capture either the price impact or spread, the economic meaningfulness of the results may differ between the measures. Figure 1 draws and summarizes the main relations between dimensions that measures capture and the interest groups with different trading volumes. As *PQS* is designed to capture the percent effective spread, it can be seen measuring direct trading costs and hence capturing the dimension of market tightness. Subsequently, as *PQS* is a percent-cost proxy and does not account for trading volume, it may be more in the interest of small individual investors. *AdjILLIQ* is a proxy for price impact, and in turn attempts to capture monthly price response of one thousand euros trading volume and do while not measuring direct cost of a trade. Thus, it can be considered to be more related to depth and resiliency. Furthermore, as it accounts for large trading volumes, it can be thought to be more in the interest of institutional investors who may execute larger transactions.

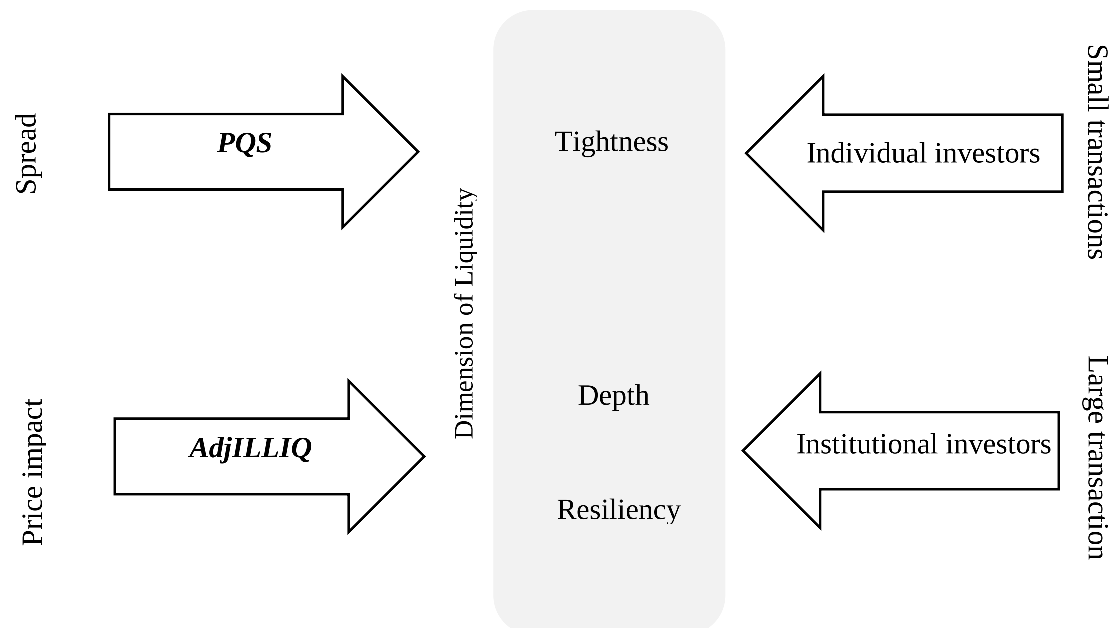

Figure 1. Summary of the illiquidity measures

Concerning the suitability of the measures with respect to the liquidity-adjusted capital asset pricing model (LCAPM) of Acharya and Pedersen (2005), *PQS* can be seen to be more appropriate. This is due to model specification that requires illiquidity to be measuring the cost of selling (see detailed LCAPM specifications in section 2.4). Nevertheless, *AdjILLIQ* can be seen to measure the indirect cost of selling with higher value implying higher costs associated with selling, and hence it could also be investigated under the LCAPM framework.

Besides these two illiquidity measures, there are a lot of others that could be incorporated in the study, and good papers for the US market and global markets are provided by Goyenko et al. (2009) and Fong et al. (2014), respectively, to determine which measure(s) to include in one's study. However, this paper utilizes only two of them, *PQS* and *AdjILLIQ*, because the scope of the study is not to analyze the correlation between low-frequency measures and their corresponding high-frequency benchmarks, but to test the asset pricing implication of the two measures that captures different dimensions of liquidity.

2.3 Previous Studies on Liquidity Risk

An extensive number of studies have been conducted regarding the liquidity and asset pricing, and the topic has aroused vast interest in recent years. As mentioned previously, four dimensions of liquidity risks have been indicated in the literature. First of those dimensions can be considered to be asset specific: that is, the level of illiquidity. The other three dimensions belong to systematic liquidity, and arise from the covariance between stock illiquidity and market illiquidity, covariance between stock return and market illiquidity, and covariance between stock illiquidity and market return. Those three covariance risks in the literature of finance referred to as commonality in liquidity, flight to liquidity, and depressed wealth effect.

2.3.1 The Level of Liquidity

The studies concerning the relationship between the level of illiquidity and assets' return are extensive for the US market. One of the first empirical testings of the relationship between expected returns and the level of liquidity was carried out by Amihud and Mendelson (1986), who proposed a theory in which expected stock returns are increasing with the illiquidity. They tested this theory by examining the effect of securities' bid-ask spreads, as a measure of illiquidity, on their returns in the New York Stock Exchange (NYSE) in the period of 1961–1980. The findings suggested that the returns increase with the level of illiquidity, supporting their proposed theory. Amihud and Mendelson (1986) suggested that investors with longer holding periods are holding stocks with higher spreads, implying a clientele effect which causes the positive relation between returns and increasing spread.[1] Amihud and Mendelson (1986) not

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[1] Clientele effect implies to different types of investors who are attracted to a particular kind of security which effects on the price of a security, if circumstances, for instance liquidity, change. One paper presenting the idea of clientele effect is provided by Miller and Modigliani (1961).

only provided the groundwork for explaining relationship between illiquidity and expected stock illiquidity, but they also seemed to explain some of the criticism towards the traditional capital asset pricing model (CAPM). For instance, Mehra and Prescott (1985) argued that the traditional model with frictionless market cannot explain the equity premium, and concluded that the premium is most likely explained through some model with a friction. In this sense, the Amihud-Mendelson (1986) theory seemed providing economically meaningful and significant reasoning to explain equity premium. However, Eleswarabu and Reinganum (1993) questioned these results by arguing that there might be monthly seasonality in the Amihud-Mendelson (1986) model. This criticism can be considered to stem from a broader discussion, since many studies showed that traditional CAPM beta is only priced in January (e.g. Keim, 1983). Therefore, Eleswarabu and Reinganum (1993) tested the Amihud-Mendelson (1986) model in NYSE by extending time-period under analysis up till 1990. Their results showed that the liquidity premium associated with the bid-ask spread is significant only during January, and the premium for non-January months cannot be distinguished from zero. Nevertheless, Eleswarabu (1997) found support for the Amihud-Mendelson (1986) model using NASDAQ data for the period of 1973–1990, and reported that expected returns are increasing with the higher spreads. These results differ from the previous studies by Eleswarabu and Reinganum (1993), and Eleswarabu (1997) pointed out that the differences could be possibly explained by the ability of the quoted spread to capture actual trading costs being better in NASDAQ than in NYSE.

While the prior studies of the relationship between liquidity level and expected returns focused on bid-ask spread as proxy for illiquidity, some researchers argued that the quoted bid-ask spread could be a noisy proxy. For instance, Lee (1993) showed that some large trades can occur outside the bid-ask spread, while some small trades occur inside it. In their study, Brennan and Subrahmanyam (1996) focused on the variable cost of trade (trade-size dependent), that tried to address the adverse selection problem caused by privately informed trader that can be captured by price impact as theoretically modelled by Kyle (1985). They reported that price impact, measuring the level of illiquidity, has positive effect on stock returns in NYSE and American Stock Exchange. Additionally, Amihud (2002) proposed a new price impact measure and estimated relationship between expected stock returns and expected illiquidity over time and across them. The study, exploring stocks traded in the NYSE in the years 1963–1997, found a positive relationship between expected illiquidity and expected stock returns, supporting the previous evidence.

Regarding markets other than the US market, Chan and Faff (2005) found strong support for the relationship between illiquidity level and stock returns when studying Australian Stock Exchange (ASX) for the period from 1990 to 1998. They estimated annual premium between illiquid and liquid stocks as high as 20 percent. However, they remarked that economic interpretation of this premium should be done with caution. In any case, Chan and Faff (2005) showed the significance and the need for studying markets other than the US market, as the illiquidity may play a more substantial role in them due to thinner trading. Later, Chen et al. (2010) studied Tokyo Stock Exchange (TSE) and reported a strongly significant positive relationship between the expected stock returns and the level of illiquidity in the period of 1975–2004. Additionally**,** Lam and Tam (2011) found a positive relation between expected returns and the illiquidity level when conducting a research on the Hong Kong stock market by using nine proxies for the illiquidity level. However, Eun and Huang (2007) found that the level of illiquidity is not associated with higher returns in the Chinese stock market, suggesting that Chinese investors, who are characterized as short-term traders, are willing to pay premium for more liquid stocks. This is consistent with the findings of Amihud and Mendelson (1986) that illiquid stocks are held by long-term investors. Additionally, Nguyen and Lo (2013) documented evidence from the New Zealand stock market, concluding that the less liquid stocks exhibit significantly lower returns than stock with more liquidity, which is inconsistent with the Amihud-Mendelson (1986) theory.

Concerning the Finnish stock market, Swan and Westerholm (2002) investigated the illiquidity-return relationship over the period of 1993–1998, and reported a strong evidence of negative long-run relationship between excess returns and the level of liquidity. Their results were in line with those of Amihud and Mendelson (1986), and implied that long-term investors could benefit from this liquidity premium by applying a buy and hold strategy. However, with more recent data, covering the time period of 1994–2009, Butt (2015) showed that the level of illiquidity is not related to stock returns in the Finnish stock market. Nevertheless, Butt and Virk (2015) reported a positive relationship between the level of illiquidity and expected stock returns, when examining illiquidity effect and illiquidity risks in the Finnish stock market for the same period as Butt (2015).

2.3.2 Commonality in Liquidity

Investors holding stocks that become illiquid when the market illiquidity is high want to get compensated for holding those stocks, which, in turn, means higher premium, as stated in Cochrane's (2001) wealth effect theory. In the literature of finance, this phenomenon is usually referred to as commonality in liquidity, and its existence has been widely recognized. Commonality in liquidity was studied and documented for the first time by Chordia et al. (2000**)** within the US market. They argued that commonality in liquidity could represent a source of non-diversifiable priced risk, which may affect asset prices if investors demand higher expected return from stocks with higher sensitivity to market-wide liquidity shocks. By investigating the intra-day data with 1,169 stocks on 254 trading days of NYSE data for the year 1992, they pointed out that liquidity is more than just an attribute of a single asset, as individual measures of liquidity co-move with each other: in other words, they found that commonality in liquidity is an important characteristic of liquidity. These results were supported by Huberman and Halka (2001), who reported there to be a common component of liquidity when investigating 240 stocks traded in the NYSE in 1996. However, when studying 30 stocks in Dow Jones Industrial Average, obtained from the NYSE's TAQ database, Hasbrouck and Seppi (2001) could not find conclusive evidence of such common component.

Concerning markets other than the US markets, commonality in liquidity has been recognized elsewhere as well. When examining the Australian Stock Exchange (ASX), Fabre and Frino (2004) found evidence of commonality in liquidity. Later Vu et al. (2015) reported that commonality in liquidity is priced, and the most significant dimensions of the three systematic liquidity risks in the ASX. In addition to this, by applying asymptotic principal component analysis (PCA), Foran et al. (2015) captured commonality in liquidity in the London Stock Exchange (LSE) and reported that commonality in liquidity is positively priced in the cross-section of stock returns. There seems to be a consensus about the existence of common component of liquidity, and some studies have even proposed that there might exists a global component of commonality in liquidity. Brockman et al. (2009) studied whether commonality in liquidity is solely a local phenomenon or whether it has a global component. With their large set of data from 46 exchanges across 38 countries, they reported that commonality in liquidity is significant for most of the markets under investigation. The findings were interesting and produced supporting evidence that firm-level illiquidity cannot be understood in isolation, but it is determined partly by exchange, industry, regional and global commonality component. However, Brockman et al. (2009) showed that commonality in liquidity mostly consists of local factors and regional sources of commonality, though also shedding light on the existence of a global component of commonality in liquidity. Moreover, Karolyi et al. (2012) conducted a large research encompassing 27,447 stocks from 40 countries, and denoted that the level of commonality in liquidity is lower in developed countries compared to emerging markets' stock exchanges. Additionally, their results gave careful evidence that commonality in liquidity effect is higher when there are large market declines in liquidity compared to large increases, implying that the commonality in liquidity effect is asymmetric and has time-variation.

Previously described results showed evidence of the existence of commonality in liquidity. In addition to those, some studies have explored the pricing dimension of commonality in liquidity. Acharya and Pedersen (2005) found that commonality in liquidity is positively priced in the US stock market with an annual premium of 0.08 %, implying a low premium required by investors from a security that is illiquid when market illiquidity is high. Kim and Lee (2014) reported a similar finding, but their estimation of the annual premium associated with commonality in liquidity was 2.28 percent. Foran et al. (2015) showed that commonality in liquidity is positively priced in the London Stock Exchange, but they did not estimate the premium associated with the commonality in liquidity.

Regarding the Finnish stock market, Butt and Virk (2015) showed that commonality in liquidity is found to be positive but not cross-sectionally priced in the Finnish stock market, based on the *Zero* measure of illiquidity by Lesmond et al. (1999). However, based on Amihud's (2002) *ILLIQ* measure, the commonality in liquidity was found to be positively and significantly priced in the Finnish stock market. On the contrary, when also using the *Zero* measure of illiquidity, Butt (2015) reported that only flight to liquidity is significantly priced in the Finnish stock market, under the same period as in Butt and Virk (2015). These contradicting results could imply that the other measure of those is more suitable for the Finnish stock market, or that the applied methodology could cause differences since the selected time period is the same in both studies.

2.3.3 Flight to Liquidity

Flight to liquidity, covariance between asset returns and market illiquidity, is probably the most extensively studied dimension of liquidity risk. This phenomenon stems from a situation where investors attempt to liquidate positions in illiquid assets and purchase more liquid asset. Intuitively, during this phenomenon, investors can see illiquid assets as uncertain and, therefore, those illiquid assets will typically decline in their implied value due to discounts for lack of liquidity. Hence, to limit their overall risk or to gain flexibility, investors may change their positions to more liquid assets. Amihud (2002) provides a prior study of this dimension of the liquidity risk when carrying out a research on stocks traded in NYSE in the years 1963–1997 and reporting market illiquidity to have significant and positive effect on stock returns, both across stocks and over time. Pástor and Stambaugh (2003) examined common stocks traded in NYSE and AMEX for the period of 1966–1999: they found evidence of systematic component and reported that stocks that are more sensitive to aggregate liquidity have measurably higher expected returns, the results being also robust to the inclusion of common risk factors such as size, value, momentum and market return. The estimated annual premium between stock with high sensitivity to market illiquidity and stocks with low sensitivity to market illiquidity were estimated by Pástor and Stambaugh (2003) as 7.5 percent. These results were later supported by Acharya and Pedersen (2005) for the US market, but their estimated annual premium for the flight to liquidity dimension was 0.16 %, significantly lower estimated by Pástor and Stambaugh (2003). In any case, later flight to liquidity, covariance between stock return and market illiquidity, was also found to be significantly priced in the US market by Liu (2006) and Korajczyk and Sadka (2008). Additionally, Baradarannia and Peat (2013) published an interesting study for covering a time period from 1926 to 2008. Likewise, their examination of all common shares of NYSE showed that systematic market liquidity risk plays a significant role in expected stock returns also in the long-run.[2] Recently, Kim and Lee (2014) explored eight measures of illiquidity and their principal component under the LCAPM framework of the stocks traded in NYSE and AMEX for the period of 1962–2008, and showed evidence of the pricing of flight to liquidity. These previous findings regarding the US market clearly showed that flight to liquidity is priced and affect stock returns. However, one should keep in mind that the US market is the most liquid market in the world, and since the purpose of this study is to investigate liquidity and asset pricing in the Finnish stock market it is fruitful to examine evidence from some other less liquid markets.

Bekaert et al. (2007) extended the scope of flight to liquidity related studies by examining 19 emerging markets under the period of 1987–2003, and reported that the local systematic risk (flight to liquidity) is empirically important and affects stock returns, interestingly, even more than the local market risk. This study pointed out that liquidity plays a key role in asset pricing in the market less liquid than the US market. However, Nguyen and Lo (2013) reported that systematic liquidity risk (flight to liquidity) is not priced and does not play a significant role in the New Zealand stock market under the period of 1996–2011. Interestingly, a closer look at the results reveals that their results showed systematic liquidity risks to be priced when using same the illiquidity measure as Pástor and Stambaugh (2003), and reported a significant effect of flight to liquidity with an annual premium of 3.55 percent. This is consistent with previous findings of Pástor and Stambaugh (2003) and Acharya and Pedersen (2005), and is economically meaningful. On the other hand, this also shows the elusive nature of liquidity, and how an illiquidity measure could be reasonably suitable in one market but not in the other.

Regarding the global evidence, Liang and Wei (2012) studied 21 exchanges by using two measures of illiquidity and reported that the systematic risk is priced, based on both measures, only for three market (France, Ireland and Japan)[3]. With respect to Finland, they discovered that

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[2] Specifically, the study of Baradarannia and Peat (2013) reports that liquidity affects stock returns cross-sectionally, but the channels for this effect are different over the two sub-periods, namely pre-1963 and post-1963. The systematic component played a significant role for the pre-1963 period, whereas for the post-1963 sample and for the period as a whole the premium with respect to the liquidity level was more prevalent. The authors explain the different results of the sub periods by flight to liquidity type of behavior.

[3] They however reported that based on at least one illiquidity measure, the systematic liquidity risk is priced in 11 countries.

the systematic liquidity risk is priced in the Finnish stock market based on Amihud's *ILLIQ* measure of illiquidity. However, a recent investigation by Saad and Samet (2015) reported that flight to liquidity does not affect stock returns in global, developed nor emerging markets.

Similar to the US evidence, flight to liquidity seem to be significantly priced in the Finnish stock market. Using monthly Finnish market data from 1987 to 2004, Vaihekoski (2009) studied whether the liquidity risk is priced in the Finnish stock market by applying two-factor Asset Pricing Model (APM) with utilization of Generalized Method of Moment (GMM). Vaihekoski (2009) used a value-weighted market-wide bid-ask spread as a measure of liquidity risk. His results support the theory and suggests that the price of the liquidity risk is negative, and the market-wide measure of illiquidity is enough to capture all liquidity related risk under the period of investigation. Recently, the phenomenon of flight to liquidity has been studied in the Finnish stock market by Butt (2015) and Butt and Virk (2015), and both of the studies show that flight to liquidity is priced and is the most important dimension of the liquidity risk in the Finnish stock market in the period of 1994–2009. Additionally, Butt and Virk (2015) report high 14.84 percent annual premium associated with the flight to liquidity risk. This should be read with caution as the premium is significantly higher than reported in other markets, and one can question whether it has an economically meaningful interpretation. In any case, these results again highlight the fact that liquidity is a multidimensional phenomenon and cannot be captured by one measure.

2.3.4 Depressed Wealth Effect

The fourth dimension of liquidity risk, the covariance between stock illiquidity and market return, is also called the depressed wealth effect. It is mainly studied in the context of LCAPM, for the first time by Acharya and Pedersen (2005), who reported that it appears to be the most important source of liquidity risk in the US market. As explained by the authors, the depressed wealth effect can be determined by concerning a selling investor holding securities that are illiquid during the declined market returns. More specifically, this problem could be magnified when the selling investor is not able to sell those (illiquid) securities, and could therefore cause wealth problems for the investor.

By using Amihud's (2002) *ILLIQ* measure, Acharya and Pedersen (2005) found that the depressed wealth effect is the most significant dimension of liquidity risks in the US market for the time period of 1963–1999 when estimating LCAPM. They reported that depressed wealth effect contributes 0.82 percent annually to the total liquidity risk premium of 1.10 percent. This implies that investors are willing to pay a premium for the stocks that remain liquid when the market return is low. Recently, these results were supported in the US market when Hagströmer et al. (2013) estimated conditional LCAPM that allows time-variation in the liquidity risks, and reported 0.68 percent annualized premium that is contributed by the depressed wealth effect. Similar evidence was found by Kim and Lee (2014) under the LCAPM framework when examining liquidity risk in the US market. They reported an annual premium of 2.42 percent for the depressed wealth effect risk, which is considerably higher than those estimated by Acharya and Pedersen (2005) and Hagströmer et al. (2013). In any case, the evidence from the US market seems to support the notion that the depressed wealth effect is the most important dimension of liquidity risk and investors are most willing to pay a premium for hedging the wealth shocks.

Outside the US market, Vu et al. (2015) investigated the Australian stock market in the period of 1995–2010. Their results suggest that different channels of liquidity are priced differently, and found that depressed wealth effect is priced in the Australian stock market. However, they did not report the premium related to depressed wealth effect, and concluded that commonality in liquidity is the most significant factor. In addition, they find that liquidity risk premium is required for both large and small stocks. An interesting discovery of Vu et al. (2015) is that they found the net liquidity risk that combines the three systematic liquidity risks to have significantly larger effect on stock return in down markets implying time-variation in illiquidity risks. On a global level, LCAPM and depressed wealth effect have been studied by Lee (2011) using data from 50 countries, and his results were consistent with the US results, showing that liquidity is persistent in most of the sample countries, and liquidity risks are priced factors, independent of market risk, in international financial markets. More specifically, while the local aggregated liquidity risk is only priced in the US and emerging market, but not in the developed and overall world markets, the global aggregated liquidity risk is priced worldwide but not in the US market. Additionally, consistent with Acharya and Pedersen (2005), Lee (2011) found that the depressed wealth effect is the most significant among three systematic liquidity risks.

Showing an annual premium of 0.66 percent for the depressed wealth effect in the global market, the results supported Acharya and Pedersen's (2005) findings. Lee (2011) not only concluded that liquidity is an important concern to investors and liquidity risk is another dimension to consider in addition to traditional market risk, but his findings also showed that the US market is a driving force in global liquidity risk. The global evidence was expanded when Saad and Samet (2015) estimated the conditional version of the LCAPM and showed also the relative importance of depressed wealth effect over the two other systematic liquidity risks. In their estimation, the contribution of depressed wealth effect risk to the overall annual liquidity risk premium was 0.71 percent in the global market.

Regarding the Finnish stock market, depressed wealth effect has been studied under the LCAPM framework. The studies conducted by Butt (2015) and Butt and Virk (2015) reported that depressed wealth effect was not priced in the Finnish stock market in the period of 1994–2009. However, their conclusions suggested that the results might have been driven by the choice of the illiquidity measure, as none of measures available can capture all the dimension of liquidity.

Similar to depressed wealth effect, the liquidity risks under different economic conditions have been studied mostly under the LCAPM framework. Hence, in this section it is reasonable to shed light on the recent studies suggesting that illiquidity risks exhibit time-variation. Vu et al. (2015) reported that that the three systematic liquidity risks have significantly larger effect on stock returns in market downturns that implied time-variation in liquidity risks in the Australian Stock Exchange. Amihud et al. (2015) and Saad and Samet (2015) found evidence that illiquidity premium is higher during market downturns in global markets, and Hagströmer et al. (2013) reported similar findings for the US market. However, Hagströmer et al. (2013) and Saad and Samet (2015) did not find decreasing trend over time neither in the US market nor globally, respectively, but reported an increase in illiquidity risks during the recent financial crises.

2.4 Liquidity-Adjusted Capital Asset Pricing Model as Theoretical Model

Acharya and Pedersen (2005) derive the liquidity adjusted capital asset pricing model from the traditional CAPM. While the traditional CAPM states that assets' returns are only affected by the systematic risk factor measured by the covariation between asset's return and market return, Acharya and Pedersen (2005) augment this by adding three systematic risk component that are interpreted as liquidity risks. Their theoretical model can be seen as a unified framework to explain the relation between stock returns and the level of illiquidity and liquidity risks. Their model is a conditional in which illiquidity betas and premium vary over time. As defined by Acharya and Pedersen (2005) in their model risk-averse agents in an overlapping economy are trading securities with varying liquidity over time. As in the standard CAPM, in the LCAPM risk-averse investors are maximizing their expected utility in a one-period framework by choosing consumption and portfolios under a wealth constraint. Hence, Acharya and Pedersen (2005) extend the traditional CAPM with its imagined frictionless economy to an economy with illiquidity costs, depicting the trading costs.

LCAPM assumes stochastic illiquidity cost that is considered to be the cost of selling a security. The frictions in the original economy are represented by this stochastic illiquidity cost which may be correlated with stochastic dividend process. Hence, Acharya and Pedersen (2005) define the expected gross and the relative illiquidity cost of an assets as follows:

$$r_t^i = \frac{P_t^i + D_t^i}{P_{t-1}^i} \tag{5}$$

$$c_t^i = \frac{C_t^i}{P_{t-1}^i} \tag{6}$$

In the equations (5) and (6) r_t^i is the expected gross return, c_t^i is the relative illiquidity cost, D_t^i is the stochastic dividend, and P_t^i is the price of an asset. Thus, the gross return is comprised of the change in price and stochastic dividend. As stated by Acharya and Pedersen (2005), the standard CAPM holds for expected net returns: $E_t\left(r_{t+1}^i - c_{t+1}^i\right)$ which follows that the conditional expected cross returns of a stock *i* are:

$$E_t\left(r^i_{t+1}\right)=r_f+E_t\left(c^i_{t+1}\right)+\lambda_t\frac{\operatorname{cov}_t\left(r^i_{t+1},r^M_{t+1}\right)}{\operatorname{var}_t\left(r^M_{t+1}-c^M_{t+1}\right)}+\lambda_t\frac{\operatorname{cov}_t\left(c^i_{t+1},c^M_{t+1}\right)}{\operatorname{var}_t\left(r^M_{t+1}-c^M_{t+1}\right)}$$
$$-\lambda_t\frac{\operatorname{cov}_t\left(r^i_{t+1},c^M_{t+1}\right)}{\operatorname{var}_t\left(r^M_{t+1}-c^M_{t+1}\right)}-\lambda_t\frac{\operatorname{cov}_t\left(c^i_{t+1},r^M_{t+1}\right)}{\operatorname{var}_t\left(r^M_{t+1}-c^M_{t+1}\right)} \tag{7}$$

In the equation (7) λ_t is the time-varying price of the risk described as:

$$\lambda_t=E_t\left(r^M_{t+1}-c^M_{t+1}-r^f\right) \tag{8}$$

In the equation r^f is the return of risk free asset. Subsequently, when assuming time-varying conditional covariances, variances, and equal risk premium among the different illiquidity risks, the equivalent formulation of equation (7) can be written as:

$$E\left(r^i_t-r^f_t\right)=E\left(c^i_t\right)+\lambda\beta^{1i}+\lambda\beta^{2i}-\lambda\beta^{3i}-\lambda\beta^{4i}, \tag{9}$$

Where

$$\beta^{i,1}_t=\frac{\operatorname{cov}_t\left(r^i_t,r^M_t\right)}{\operatorname{var}_t\left(r^M_t-c^M_t\right)}, \tag{10}$$

$$\beta^{i,2}_t=\frac{\operatorname{cov}_t\left(c^i_t,c^M_t\right)}{\operatorname{var}_t\left(r^M_t-c^M_t\right)}, \tag{11}$$

$$\beta^{i,3}_t=\frac{\operatorname{cov}_t\left(r^i_t,c^M_t\right)}{\operatorname{var}_t\left(r^M_t-c^M_t\right)}, \tag{12}$$

$$\beta^{i,4}_t=\frac{\operatorname{cov}_t\left(c^i_t,r^M_t\right)}{\operatorname{var}_t\left(r^M_t-c^M_t\right)} \tag{13}$$

In the equations (10)–(13) β^{1i} is market return adjusted for illiquidity, β^{2i} is the covariance between stock and market illiquidity, β^{3i} is covariance between stock return and market illiquidity, and β^{4i} is the covariance between the stock illiquidity and market return. C^M and c^i are the relative illiquidity costs for market and for stock i, respectively. Theoretically, the LCAPM states that expected return is a function of expected illiquidity cost plus four betas times the risk premium (Acharya and Pedersen, 2005). As depicted in the previous section this relation has also been suggested empirically. The level of illiquidity has been found to be positively priced, and investors to demand premium to compensate for an asset's illiquidity.

The second beta of the equation (9) is capturing the commonality in liquidity stemming from the covariation between an asset's illiquidity and market illiquidity. As previously described and explained by Acharya and Pedersen (2005), this phenomenon rises from the situation where an investor holding an asset that has become illiquid with the market may not choose to trade that stock. More likely, he trades similar securities at a lower cost, if the illiquidity does not co-move with the market illiquidity. In other words, the pricing implication of this risk is reflecting positive compensation for investors for holding a stock whose illiquidity increases when market illiquidity is high. Hence, investors would require a higher premium for the securities with positive covariance with individual and market illiquidity.

The covariation between a security's return and market illiquidity, flight to liquidity, is captured by the third beta in the equation (9). This co-movement between these two has a negative effect on the required return of a security, which is reflecting the investors' willingness to accept a lower expected return on a security whose return tends to be high when the market is illiquid.

Acharya and Pedersen (2005) first introduced and tested the effect of covariance between a stock's illiquidity and market return on the required rate of return. In their model, this effect is captured by the fourth beta and the effect is stemming from the investors' willingness to accept a lower expected returns on a security that is liquid in a down market. The depressed wealth effect can be determined by concerning a selling investor holding securities that are illiquid during the declined market returns. More specifically, when holding illiquid securities this problem could be magnified when the selling investor is not able to sell those (illiquid) securities, and therefore cause wealth problems for the investor. Hence, as Acharya and Pedersen (2005) explain in, a bear market investors are poor and the ability to sell a security becomes valuable. In other words, investors appreciate stocks with low illiquidity costs in a down market. Therefore, investors are willing to accept lower returns on stocks with low illiquidity costs when the market is not doing poorly, depicting the negative relation between the covariance of a stock's illiquidity with market return.

2.5 Hypotheses

The research hypotheses are drawn from the previous studies on the topic and the theoretical framework provided by Acharya and Pedersen (2005), namely the LCAPM. The first five hypotheses are related to the first research question while the sixth hypothesis concerns the second research question.

As previously has been described, the level of illiquidity and commonality in liquidity should have a positive effect on stock returns, while flight to liquidity and depressed wealth effect should affect them negatively. Hence, the first four hypotheses can be formulated as follows:

> *H1: The level of illiquidity has a positive and significant effect on stock returns in the Finnish stock market*.
>
> *H2: The co-movement between stock illiquidity and market illiquidity (commonality in liquidity) is significantly and positively related to stock returns in the Finnish stock market.*
>
> *H3: The co-movement between stock return and market illiquidity (flight to liquidity) is negatively and significantly related to stock returns in the Finnish stock market.*
>
> *H4: The co-movement between stock illiquidity and market return (depressed wealth effect) is significantly and negatively related to stock returns in the Finnish stock market.*

In addition to test the individual effects of the betas, the effect of aggregate systematic risk is tested, which means that the relative magnitudes of the individual risks determine the combined effect of the individual risks.[4] Consequently, the fifth hypothesis is stated as follows:

H5: The aggregate systematic risk is priced in the Finnish stock market.

As explained in the section 2.3, number of studies have reported that illiquidity risks vary over time, and the illiquidity premium is not constant under different market conditions (Amihud et al. 2015; Hagströmer et al. 2013; Vu et al. 2015; Saad and Samet 2015). However, the recent studies suggest that there is no systematically decreasing trend in illiquidity risks neither in the US market (Hasgströmer et al. 2013) nor globally (Saad and Samet, 2015).[5] As depicted in the section 2.2.2 there are twice the number of zero return days in the Finnish stock market compared to the US market, and as there is no evidence of decreasing liquidity risks in the US market, it can be expected that there is no decreasing trend in illiquidity risks in the Finnish stock market either. Accordingly, the sixth hypothesis is formulated as:

H6: There is no decreasing trend in illiquidity risks in the Finnish stock market.

The first five hypotheses are tested in the section 4.4, where the prices for the liquidity risks are estimated by applying fixed effect panel regression. To see whether the first five hypotheses are supported or not the significance of obtained regression coefficients are observed. If the coefficients are significant with expected signs, it means that the hypothesis are supported. The sixth hypothesis are tested in section 4.3 by applying a trend test, and to see whether the hypothesis is supported, the significance of the trend coefficient is tested. Additionally, the supporting evidence for the trend test is given by plotting the conditional liquidity risks (conditional betas). The upcoming section describe the data and methodology to be used in empirically investigating the illiquidity effect in the Finnish stock market.

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[4] Aggregate systematic risk is computed as follows: $\beta^{i,1} + \beta^{i,2} - \beta^{i3} - \beta^{i4}$, and the estimation of this is discussed in detail in the section 3.3.5.

[5] Nonetheless, Saad and Samet (2015) reported some evidence of decreasing illiquidity risks in the UK stock market.

3 DATA AND METHODOLOGY

3.1 The Finnish Stock Market

Finnish stock exchange originates in 1912, when Helsinki Stock Exchange (HSE) was established as a nonprofit cooperative organization; in 1995 it was reorganized, and became a Limited Liability Company. Later, in 1997 it was merged with the Finnish Option Exchange, and they formed together the Helsinki Security and Derivatives Exchange Limited, also known as HEX limited. Subsequently, it became part of the Swedish OMX group, and nowadays, after merger of OMX and NASDAQ, it belongs to the NASDAQ OMX exchanges. (Nasdaq OMX Nordic, 2016a) At the moment there are 151 stocks listed on the Nasdaq Helsinki stock exchange, including stocks listed on First North that is designed for small and growing companies (Nasdaq OMX Nordic, 2016b).[6] The total market capitalization at the end of July 2015 was approximately 186 billion euros (Bank of Finland 2016).

In Figure 2, the total monthly market value of the Helsinki Stock Exchange (Nasdaq Helsinki) and the turnover of shares in the Helsinki Stock Exchange are presented for the period from 1997 to July 2015. The blue area describes the total market capitalization, while the black line shows the development of the turnover of shares. They can both be seen to reflect economic conditions in Finland. As seen from Figure 2, market capitalization and the turnover of shares seem to go hand in hand. At the beginning of the period under investigation they start to rise, reaching the first pike in 2000, followed by a sharp decline, clearly depicting the IT boom and burst. The aftermaths of the dot-com bubble reach to 2003, when the economy began to recover. This growth continues, until the subprime crises and the market capitalization and turnover of shares crash after their peak in 2008. Interestingly, the turnover of shares is substantially higher before the subprime crises when compared to the IT boom, even though the market capitalization lower before the subprime crises. After 2009 the total market capitalization started steadily to rise, until in 2011 it declined again sharply, which may be due to sovereign debt crisis in Europe. Finally, after reaching the bottom of the latest decline, the market capitalization

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[6] The number of companies in the main list is at the moment 135 while in the First North there are 16 Finnish companies (Nasdaq OMX 2016b).

started to rise and seems to exhibit an upward trend. The turnover of shares can be seen to reflect something about the liquidity in the Finnish stock market, because it depicts the overall trading activity. Since financial crises, the turnover of shares have been a bit lower compared to the pre-crises period, which could affect the results in this study compared to previous studies regarding liquidity risk in the Finnish stock market.

Figure 2. Market capitalization and turnover of shares in the Finnish stock market in 1997–7/2015 (Bank of Finland 2016)

3.2 Data

The data set consist of all common stocks traded in Nasdaq Helsinki for the period of 1997–7/2015, including daily observations of closing prices, bid and ask prices, daily trading volume, and total market capitalization. Additionally, monthly book values are downloaded for calculating and controlling the value effect. There is a total number of 246 stocks in the initial sample, including also the delisted or dead stocks to avoid any survivorship bias. Only equities are extracted, and preferred shares as well as investment funds are not included into the sample. The price series are adjusted for dividends, splits and other corporate actions. While the market values are expressed in millions of euros, the volume values are in thousands of euros. In this study one month-rates for 12-month Euribor are used as a risk free rate. All the data is downloaded from Thomson Reuters Datastream.

Since the data is downloaded from Datastream, some pre-processing of the data is needed. Some other studies related to illiquidity risks have deducted the penny stock from their sample to avoid their effect in the results (e.g. Acharya and Pedersen 2005; Hagströmer et al. 2013; Kim and Lee 2014). However, due to the small number of stocks traded in the Finnish stock market, in this study the penny stocks are not filtered out. As in Lee (2014) and Kim and Lee (2014), to be included in the final sample a stock is required to have at least 100 positive trading days over the sample period. Furthermore, non-trading days are deducted from the sample, since Datastream fills a non-trading day with the price of the prior trading day. Hence, similar to Lesmond (2005**)** and Lee (2011) any day from the sample is dropped as a non-trading day if more than 90 % of the stocks have zero return on that day.[7] After this screening process the remaining data sample consist of 200 stocks with 4663 daily observations for closing prices, bid and ask prices, total trading volume and market capitalization. Hence, in total there are 932,600 stock-day observation (200*4663) of multiple variables, including missing values, to be used in the initial calculations.

As this study utilizes monthly figures of the variables under analysis, it is more convenient to take a closer look on them. However, it is needed to impose some further restrictions to calculate monthly observations for the illiquidity measures. For each stock to have monthly observation of *PQS* measure, it is required that a stock has at least 10 valid daily observations for bid and ask prices in a month. Originally, to calculate the *ILLIQ* illiquidity measure, a stock is required

[7] However, Lesmond (2005) required that 100 % of the stocks should have zero return to drop that day from the sample. This may inflate the results if only couple of stocks have non-zero return while the rest have zero returns, and thus that actual non-trading day is not captured by the 100 % rule. Hence, in this study 90 % cutoff will be applied as proposed in Lee (2011).

to have at least 15 trading days in a month (Amihud 2002). However, since this study utilizes adjusted version of Amihud's *ILLIQ* (*AdjILLIQ*) illiquidity measure, such restriction is not needed. However, to calculate the *AdjILLIQ*, a stock should have at least 5 trading days in a month. Otherwise the calculation of the measure may not be meaningful. In total, the monthly sample is constructed based on the pre-processed daily observations, which consists altogether of 44,600 stock-month observations, including missing values. The summary statistics of the monthly data across the stocks is presented in the table 1.

Table 1. Descriptive statistics of monthly observations
Table provides descriptive statistics of the constructed monthly sample. All the series are presented in percentages.

	AdjILLIQ (%)	*PQS* (%)	Returns (%)
Number of valid observations	27415	27624	36886
Number of missing observations	17185	16976	7514
Mean	12.879	3.555	0.599
Standard error of mean	0.822	0.214	0.039
Median	11.756	1.769	0.000
Minimum value	0.000	0.000	-86.047
Maximum value	42.142	115.952	1257.143
Range	42.142	115.952	1343.189
Mean variance	15.343	19.870	177.917
Minimum variance	0.099	0.009	5.476
Maximum variance	204.582	649.708	7479.413
Mean standard deviation	3.917	4.458	13.339
Minimum standard deviation	0.315	0.097	2.340
Maximum standard deviation	14.303	25.489	86.484

As depicted in the table 1, the number of valid observations is the highest for returns series, while the *AdjILLIQ* has the lowest number of valid observations. The number of valid observations for the *PQS* and *AdjILLIQ* are almost the same, approximately 27,500 stock-month observations. Monthly returns have the highest range with minimum value of -86 percent and maximum of 1257 percent, and the mean stands at 0.6 percent. The range of *PQS* spans from zero to 115, with mean value of approximately 3.7 percent. For the *AdjILLIQ* measure, the mean value is approximately 13, and it has the smallest range, which is probably due to logarithm transformation. Monthly stock returns have the highest mean standard deviation with the value of a bit below 13 percent, whereas the corresponding values for *PQS* and *AdjILLIQ* are approximately 4.5 percent and 3.9, respectively. An eye-catching value is the maximum value of *PQS* that could be caused by some small stock, since the mean and median values are below 4 percent. In summary, return series has the highest deviation which is approximately three times as much as *PQS* and *AdjILLIQ*. Logarithmic transformation of the *AdjILLIQ* may explain the smallest values for range, variance and standard deviation.

3.3 Methodology

To estimate the conditional version of LCAPM, the dynamic conditional correlation generalized conditional autoregressive heteroscedasticity, DCC-GARCH (1,1) method is applied to estimate time-varying conditional illiquidity risks, as in Kim (2013) and Saad and Samet (2015). However, in contrast with those studies, this study utilizes individual stocks as test assets instead of portfolios when estimating the price of the liquidity risk. Portfolios are used only when testing time trend in liquidity risks. Additionally, while many of the studies concerning illiquidity risk estimate the price of the risk by using the conventional Fama-MacBeth (1973) procedure, in this study the fixed effect panel regression is used as in Vu et al. (2015) to avoid the statistical biases of Fama-MacBeth that are discussed more detailed in the section 3.3.5.

Generally, the estimation procedure is to form quintile portfolios by calculating pre-ranking liquidity betas for each stock each year based on the equations (10–(13), and each year stocks are sorted on the portfolios based on the pre-ranking liquidity betas implying a one-year holding period. Then conditional liquidity betas are estimated for the portfolios, and subsequently the estimated portfolio conditional betas are assigned to individual stocks in the portfolios. To see whether there is a significant trend in the illiquidity risks, the simple linear trend is conducted for the most liquid and illiquid portfolio quintiles. Finally, by following Vu et al. (2015), the fixed effect panel regressions are utilized using individual stocks. Next, the methodology will be discussed in detail. Section 3.3.1 and 3.3.2 describe the first two steps, while section 3.3.3 specifies the estimation of the conditional time-varying illiquidity risks. Finally, section 3.3.4

and 3.3.5 depict the final empirical estimation specifications for the trend test and the pricing of illiquidity risk, respectively.

3.3.1 Innovations in Illiquidity

Market portfolio is defined to include all the stocks that are retained in the market; to avoid bias towards large liquid stocks, previous studies (e.g. Amihud, 2002; Chordia et al., 2000; Acharya and Pedersen, 2005; Saad and Samet, 2015) are followed, and equally weighted return and illiquidity for market portfolio are formed. Because liquidity has been shown to be highly persistence, meaning that liquidity is predictable, the illiquidity measures are adjusted for innovations. This adjustment is done to reduce the autocorrelation problem that has been reported in the previous literature (e.g. Acharya and Pedersen, (2005); Goyenko et al. (2009)). Basically, this means that the monthly illiquidity measures will be transformed by using an autoregressive (AR) model. Specifically, the innovations in illiquidity series are accessed by regressing a monthly illiquidity measure against their own previous lags, and the residuals attained from the regression are used to estimate the illiquidity betas. Similar to Acharya and Pedersen (2005) and Vu et al. (2015) innovations are obtained through AR(2) filtering of monthly illiquidity series as depicted below:

$$c_t^i = a_i + \rho_i c_{t-1}^i + \rho_i c_{t-2}^i + \varepsilon_t^i \tag{14}$$

In the equation (14) c_t^i is a measure of illiquidity for stock *i* at month *t*, and ε_t^i is the residuals in liquidity for stock *i* at month *t.* This AR(2) filtering is done for all the stocks and market illiquidity series, and the residuals of the regressions are interpreted as the innovation in illiquidity and are subsequently used to calculate pre-ranking betas for the individual stocks.

3.3.2 Betas Estimation for Individual Stocks

Following Lee (2011), Kim and Lee (2014) and Vu et al. (2015) this study utilizes individual stocks as test assets. However, due to error-in-variable problem, i.e. the higher noises in estimated betas, liquidity risks will be estimated at the portfolio level, and the individual stocks are used as test asset at the regression stage. Choosing to use individual stocks as test asset provides both benefits and costs compared to use of portfolios. First, spurious result potentially arising when using characteristic-based portfolios can be avoided by using individual stocks (Brennan et al. 1998). Second, when using individual stocks to conduct empirical analysis, the potential loss of information can be avoided. Third, an increase in the power of the test can be achieved by using individual stocks, since there are more observations compared to portfolios. This is particularly important in the Finnish stock market because there are only very limited number of stocks, and some widely applied method in larger market may not be directly applied in the Finnish stock market. Lastly, using individual stocks is suitable for controlling individual stock characteristics, like book-to-market ratio and size (Lee, 2011). The costs of using individual stocks is that they might cause higher noise in the estimates. Taking into account these costs and benefits, this study utilizes a one-dimensional portfolio sorting to estimate liquidity risk, and then assigns these loadings to individual stocks following a similar approach as in Lee (2011) and in Kim and Lee (2014).

This one-dimensional sorting methodology, similar to Fama and French (1992), has many advantages over the characteristic-based sorting methodology. As depicted in Lee (2011) and in Kim and Lee (2014), portfolio sorting based on pre-ranking betas is widely-used in asset pricing research, since the estimation of the post-ranking betas for portfolios sorted on pre-ranking betas can reduce the bias that could arise from using some characteristic based sorting, for instance sorting based on illiquidity level or market capitalization. Additionally, portfolio formation based on pre-ranking betas can help to minimize the loss of information, potentially caused by portfolio formation, by providing a wide dispersion of estimates across portfolios (Lee 2011, 143).

Similar to Lee (2011) and Saad and Samet (2015), the portfolios are formed based on three pre-ranking illiquidity betas depicted in the equations (11)–(13). Relying on a 5-year window that rolls forward on an annual basis, the three illiquidity betas are estimated based on the previous 36 monthly observations. More specifically, for each stock i, pre-ranking illiquidity beta k (k=1,…,3) of year t will be calculated as depicted in the equations (11)–(13), using the monthly returns and innovations in illiquidity over the years t - 5 to t - 1. The window rolls forward on an annual basis, and to have a pre-ranking beta a stock must have at least 36 monthly observations of returns and innovations in illiquidity within the 5-year window. Then at the beginning of each year t, stocks are sorted into quintile portfolios based on the three pre-ranking betas.[8] Quintile portfolios are used to ensure a sufficient amount of stocks in each portfolio due to the small number of equities listed in the Finnish stock market (see detailed information in the section 3.1), and they are designed to include stocks with extreme liquidity risk, as in Saad and Samet (2015).[9] Subsequently, for each portfolio equally weighted returns, r_t^p, and illiquidity, c_t^p, are calculated as follows:

$$r_t^p = \frac{1}{n}\sum_{i=1}^{n} r_t^i, \tag{15}$$

$$c_t^p = \frac{1}{n}\sum_{i=1}^{n} c_t^i \tag{16}$$

where r_t^i is the return of stock i from portfolio p in month t, c_t^i is the illiquidity of stock i, from portfolio p in month t, and n is the number of stocks in portfolio p. Before estimating conditional illiquidity betas, it will be checked whether the portfolios' quintiles are successfully created with dispersed and monotonic illiquidity betas, by calculating full-sample post-ranking betas (Lee, 2011; Kim and Lee, 2014; Saad and Samet, 2015). Subsequently, on a monthly basis, conditional post-ranking illiquidity beta k of portfolio p will be estimated for each of the three sets of quintile portfolios (p=1,…,5), and is assigned to individual stock i, that belongs to portfolio p in a given year.

To clarify, this process produces three sets of quintile portfolios based on the calculated pre-ranking liquidity betas. Thus, the first set is based on the commonality in liquidity beta sorting, the second set on flight to liquidity beta sorting, and the third set on depressed wealth effect beta sorting. All of these sets contain five portfolios that have equally weighted monthly returns and illiquidity; then the four conditional betas, based on the equations (10)–(13), are estimated for

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[8] It is worth noting that according to LCAPM the commonality beta is positive, while the two other liquidity risk betas are negative, meaning that when sorting stocks, the 1st quintile portfolio is the most liquid when sorted commonality beta, but is the most illiquid when sorted on flight to liquidity and depressed wealth effect betas (Saad and Samet, 2015).
[9] To be precise, Saad and Samet (2015) formed decile portfolios, but in this study quintile portfolios will be used due to small number of stocks in the Finnish stock market.

each of the portfolios, and finally the conditional betas are assigned to individual stocks that belong in a particular portfolio. For instance, first stocks are sorted based on the commonality in liquidity pre-ranking betas into quintile portfolios that have equally weighted returns and illiquidity. Then for all of these quintile portfolios, the four conditional betas are estimated, and then these portfolio conditional betas are assigned to stocks that belong to a particular portfolio in a given year. Similar procedure is followed for all the three sets of portfolios, and hence this methodology allows for examining results based on the three different portfolio sorting for both of the measures.

3.3.3 Time-varying Illiquidity Risks

It is well-known fact that financial markets can be characterized by random fluctuations over time, which is fundamental for asset pricing since value of shares depends on the risk. Therefore, the concept of conditional heteroscedasticity as explained by Bollerslev (1986), is essential in the context of asset pricing. Moreover, as all the investments are risky, risk-averse investors compares the expected return to exposed risk. Since assumption of a constant level of the risk of an asset is a very strong assumption, it is important to estimate time-varying risks. In addition to traditional market risk, this study considers three other sources of risks, namely illiquidity risks as depicted in the LCAPM. Unlike the other studies dealing with the LCAPM framework in the Finnish stock market, this research estimates a conditional version of LCAPM. To estimate conditional covariances as depicted in the equations (10)–(13), this study follows Saad and Samet (2015) and Kim (2013) and relies on DCC-GARCH (1,1), a multivariate GARCH model, proposed by Engle (2002), which can be seen as a generalization of the Bollerslev (1990) constant conditional correlation (CCC) estimator.[10] The DCC-GARCH method has also been used in asset pricing framework by Bali and Engle (2010) when estimating intertemporal CAPM. The clear advantage of the DCC-GARCH model is that it avoids computational complexities as the model can be estimated easily even when the conditional variance-

[10] The DCC-GARCH(1,1) is estimated by using Kevin Sheppard's MFE toolbox: https://www.kevinsheppard.com/MFE_Toolbox

covariance matrices are large (Engle 2002, 342). However, it does not take into account asymmetries in the estimation.

Considering

$$Y_t = \left(c_t^i, c_t^M, r_t^i, r_t^M\right)' \text{ for } t = 1,\ldots,T, \text{ with} \tag{17}$$

$$E\left(y_t \mid F_{t-1}\right) = 0 \text{, and} \tag{18}$$

$$Var\left(y_t \mid F_{t-1}\right) = H_t \tag{19}$$

where Y_t depicts the variables among which conditional covariances are estimated, F_{t-1} is the information available up to time (t - 1), H_t is the conditional variance-covariance matrix, and T is the total number of observations for each variable. The general idea of the DCC-GARCH is to decompose the covariance matrix into conditional standard deviations, D_t, and conditional correlation matrix, R_t, both of which are designed to be time-varying (Engle, 2002). In other words, as presented in Engle (2002), the model parametrizes the volatilities and correlations separately, even though they are estimated jointly. Assuming that the variance-covariance matrix follows a quadvariate DCC-GARCH (1,1) as presented in Engle (2002), the conditional LCAPM parametrization for the conditional variance-covariance matrix is:

$$H_t = D_t R_t D_t \tag{20}$$

Where D_t is the diagonal matrix of time varying standard deviations from univariate GARCH processes:

$$D_t = \begin{bmatrix} \sqrt{h_{1t}} & 0 & \cdots & 0 \\ 0 & \sqrt{h_{2t}} & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 0 & \ldots & 0 & \sqrt{h_{nt}} \end{bmatrix} \tag{21}$$

where conditional variances are modelled through GARCH(1,1) specification as follows:

$$h_{i,t} = c_i + a_i e_{i,t-1}^2 + b_i h_{i,t-1}, \qquad i = 1,\ldots,K \tag{22}$$

Where $h_{i,t}$ is the conditional variance of variable i at month t, $e_{i,t-1}^2$ and $h_{i,t-1}$ are previous month's squared innovation and variance of variable i, respectively, with the restrictions of $\alpha_i > 0$, $\beta_i > 0$, and $\alpha_i + \beta_i < 1$, to insure non-negativity and stationarity.

R_t is the matrix of standardized disturbances of conditional correlations with diagonal elements equal to one:

$$R_t = \begin{bmatrix} 1 & \rho_{12,t} & \rho_{13,t} & \cdots & \rho_{1n,t} \\ \rho_{12,t} & 1 & \rho_{23,r} & \cdots & \rho_{2n,t} \\ \rho_{13,t} & \rho_{23,t} & 1 & \ddots & \vdots \\ \vdots & \vdots & \ddots & \ddots & \rho_{n-1,n,t} \\ \rho_{1n,t} & \rho_{2n,t} & \cdots & \rho_{n-1,n,t} & 1 \end{bmatrix} \tag{23}$$

It should be noted that R_t has to fulfill two requirements. First, since H_t is a covariance matrix it should be positive definite. In addition, all the elements of conditional correlation matrix have to be equal or less than one. Since H_t is a quadratic form based on R_t it follows from basics in linear algebra that R_t has to be positive definite to ensure that H_t is positive definite. Hence, to guarantee both of these requirements Engle (2002) decomposes the conditional correlation matrix is into:

$$R_t = diag\left\{Q_t^*\right\}^{-1/2} Q_t \, diag\left\{Q_t^*\right\}^{-1/2} \tag{24}$$

Where Q_t is assumed to have following dynamics:

$$Q_t = (1 - \alpha - \beta)\overline{Q} + \alpha\left(\varepsilon_{t-1}\varepsilon_{t-1}^{'}\right) + \beta Q_{t-1} \tag{25}$$

In the formulas (24) and (25) $\bar{Q}$ is the unconditional covariance matrix of standardized residuals, while Q_t is the conditional covariance matrix of standardized residuals. *Diag*(.) refers to a matrix comprising the main diagonal elements of (.), and Q_t^* is a diagonal matrix that takes the square roots of each element in *Q*. This rescales the elements in *Q* to guarantee the requirement of all elements of conditional correlation matrix to be equal or less than one. To fulfill the requirement that covariance is positive definite, scalars α and β needs to be non-negative and satisfy the condition $\alpha + \beta < 1$.

The model parameters of DCC-GARCH(1,1) are estimated using quasi-maximum likelihood in two steps, as in Engle (2002). First, each variable of the quadvariate DCC-GARCH(1,1) is modelled separately as a univariate GARCH process. Then, in the second step, the conditional likelihood is maximized with respect to unknown parameters in the correlation matrix. The joint log-likelihood estimator can be expressed as:

$$\log L(\theta, \alpha, \beta) = -0.5 \sum_{t=1}^{T} \left(K \ln(2\pi) + \ln|H_t| + \varepsilon_t' H_t^{-1} \varepsilon_t \right) \qquad (26)$$

Where Θ, α and β are the unknown parameters that are to be estimated, *T* is the number of periods, *ln* refers to natural logarithm, and *K* is the number of cross-sectional dimensions, which is four in this quadvariate DCC-GARCH (1,1). (Saad and Samet, 2015)

For each of the quintile portfolios the following conditional covariances will be estimated: $\operatorname{cov}(r_t^i, r_t^M)$, $\operatorname{cov}(c_t^i, c_t^M)$, $\operatorname{cov}(r_t^i, c_t^M)$, $\operatorname{cov}(c_t^i, r_t^M)$ by using innovation series to assure condition of stationarity. These four conditional covariances depict the four systematic risks specified by LCAPM and correspond to the numerators in the equations (10)–(13). After this, conditional variance of the market return (adjusted for illiquidity) is estimated, since it is needed as divisor to calculate conditional betas, as depicted in the equations (10)–(13)**.** The conditional variance of market returns (adjusted for illiquidity) is estimated through exponential GARCH model (EGARCH), which accounts for asymmetries in the series (Brooks 441, 2014).[11] Finally, the

[11] The unreported results for EGARCH tests show that asymmetric effect is found to be negative and significant in the case of both measures which support the use of EGARCH over the GARCH model in the estimation of conditional variance for market returns.

conditional betas are assigned to individual stocks in a portfolio in a given year. Then these stock level conditional betas are used in the panel regression analysis to explain individual stock returns. The specifications of the final regression analysis are discussed in the section 3.3.5.

3.3.4 Test for Time Trend in Illiquidity Risks

Previous studies have shown that illiquidity risk is higher during market downturn, implying time-variation in illiquidity risk, as pointed out in the section 2.3.4. Due to this time-varying element of illiquidity risk, time trend of the estimated illiquidity betas are tested. Similar to Saad and Samet (2015), the dynamics of conditional illiquidity betas are investigated by running simple linear time trend test for the most illiquid and liquid portfolio quintiles of the three illiquidity pre-ranking beta sorted portfolios. The significant time trends are tested by using Vogelsang's (1998, 125) simple linear time trend as follows:

$$\beta_t = \delta_0 + \delta_1 t + \mu_t \tag{27}$$

In the formula (27) β_t is one of the three conditional illiquidity betas of the most liquid or illiquid portfolio quintile, while δ_1 is the time trend coefficient. Following Saad and Samet (2015), the significance of the time trend coefficient is tested by utilizing Vogelsang's (1998) t-PS1 and Bunzel and Vogelsang's (2005) t-DAN tests. The t-PS1 test tackles the problems of nonstationary and serial correlation and does not need any prior information about the form of autocorrelation in the series Vogelsang (1998, 144). This means that the test statistic is robust when serial correlation is severe or there is a unit root in the errors (Vogelsang 1998, 144). Thus, it does not suffer from over-rejection of the null hypothesis when the serial correlation is high (Vogelsang, 1998). The t-DAN test by Bunzel and Vogelsang (2005) can be seen as development of the t-PS1 test that keeps the good size properties of t-PS1 test but has better power, both asymptotically and in finite samples. The t-DAN test is denoted as DAN since it uses Daniell kernel to non-parametrically estimate error variance that is needed by the test. The detailed econometric specifications and derivations for the t-PS1 can be found in Vogelsang (1998) and t-DAN test in Bunzel and Vogelsang (2005).

3.3.5 Pricing of the Liquidity Risks

In the spirit of Acharya and Pedersen (2005), Lee (2011) and Vu et al. (2015), in this study seven specification of LCAPM will be estimated. The previously described conditional betas are used at the individual stock level to see whether they have explanatory power in explaining stock returns. First, as in Acharya and Pedersen (2005), imposing the model-implied constrain of equal price of the liquidity risk, that is $\lambda^1 = \lambda^2 = -\lambda^3 = -\lambda^4$, the aggregate systematic risk beta ($\beta^{i,6}$) is defined.[12] Furthermore, likewise in Acharya and Pedersen (2005), the net illiquidity risk beta ($\beta^{i,5}$) is defined to separate liquidity risk as follows:

$$\beta_t^{i,5} = \beta_t^{i,2} - \beta_t^{i,3} - \beta_t^{i,4} \tag{28}$$

$$\beta_t^{i,6} = \beta_t^{i,1} + \beta_t^{i,2} - \beta_t^{i,3} - \beta_t^{i,4} \tag{29}$$

The aggregate systematic risk beta is defined to avoid the multicollinearity problem which arises from the high correlation between the explanatory variables. Perfect multicollinearity occurs when there is an exact relationship between two or more explanatory variables. However, this is rare with real-world data, where near multicollinearity is more plausible. Ignoring the near multicollinearity may cause a bunch of problems. First, the regression looks good as a whole but individual coefficients are not significant, meaning that R^2 of regression will be high but the individual coefficients have high standard errors. Second, adding or removing one beta from the regression leads to a large change in the coefficient values. Third, the confidence intervals for the parameters will be high. (Brooks 2014, 217–218) Hence, before any analysis, the correlation between all the explanatory variables (including control variables) is conducted.

As previously mentioned seven specifications of the LCAPM will be estimated. Each liquidity risk is presented at a time to avoid the multicollinearity problem. Firm size, and book-to-market values are used as control variables similar to Vu et al. (2015). Addition to those Vu et al. (2015)

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[12] Specifically, in their paper, Acharya and Pedersen (2005) call this beta as “net beta”.

used momentum but it is not incorporated in this study. The seven alternative specifications of LCAPM are outlined in the equations (30)–(36) below:

$$E\left(r_t^i - r_f^i\right) = \alpha_t + kE\left(c_t^i\right) + \lambda_1 \beta_t^{i,1} + \varphi_1 BM_t + \varphi_2 Size_t + \mu_t \tag{30}$$

$$E\left(r_t^i - r_f^i\right) = \alpha_t + kE\left(c_t^i\right) + \lambda_1 \beta_t^{i,1} + \lambda_2 \beta_t^{i,2} + \varphi_1 BM_t + \varphi_2 Size_t + \mu_t \tag{31}$$

$$E\left(r_t^i - r_f^i\right) = \alpha_t + kE\left(c_t^i\right) + \lambda_1 \beta_t^{i,1} - \lambda_3 \beta_t^{i,3} + \varphi_1 BM_t + \varphi_2 Size_t + \mu_t \tag{32}$$

$$E\left(r_t^i - r_f^i\right) = \alpha_t + kE\left(c_t^i\right) + \lambda_1 \beta_t^{i,1} - \lambda_4 \beta_t^{i,4} + \varphi_1 BM_t + \varphi_2 Size_t + \mu_t \tag{33}$$

$$E\left(r_t^i - r_f^i\right) = \alpha_t + kE\left(c_t^i\right) + \lambda_1 \beta_t^{i,1} + \lambda_5 \beta_t^{i,5} + \varphi_1 BM_t + \varphi_2 Size_t + \mu_t \tag{34}$$

$$E\left(r_t^i - r_f^i\right) = \alpha_t + kE\left(c_t^i\right) + \lambda_6 \beta_t^{i,6} + \varphi_1 BM_t + \varphi_2 Size_t + \mu_t \tag{35}$$

$$E\left(r_t^i - r_f^i\right) = \alpha_t + kE\left(c_t^i\right) + \lambda_1 \beta_t^{i,1} + \lambda_2 \beta_t^{i,2} - \lambda_2 \beta_t^{i,3} - \lambda_2 \beta_t^{i,4} + \varphi_1 BM_t + \varphi_2 Size_t + \mu_t \tag{36}$$

In the equations (30)–(36), $r_t^i - r_t^f$ represents individual stock excess return at month *t*, *kE(* c_t^i *)* is the expected illiquidity cost, measured as the previous month illiquidity, $\beta_t^{i,1}$ to $\beta_t^{i,6}$ are the liquidity risks (conditional betas) at month *t*, BM_t is the natural logarithm of book-to-market ratio of a stock at the beginning of the month *t*, $Size_t$ is the natural logarithm of market capitalization of a stock at month *t*, and μ_t is the error term. Logarithms are taken over the book-to-market values and market capitalizations to account for extreme values because the penny stocks are incorporated in this study and their large values could have affect the results. Since, the portfolio sorting and re-balancing is done on a yearly basis, monthly returns of the 12-month Euribor rates are used as a risk-free rate. The first four specifications allow for exploring the effect of each liquidity risk separately, while the equations (34) and (35) permit the examination of net liquidity risk and aggregate systematic risk, and the last equation is depicting the full model and the joint effect of the illiquidity betas. In the equations (30)–(36), *k* is depicting the holding period that is assumed to be 1 in this study, implying that illiquidity costs are incurred once each model period (Acharya and Pedersen 2005, 392–393). Because the panel regression uses monthly figures as estimation period it may not represent a typical investor's holding period. To solve this, Acharya and Pedersen (2005, 393) calibrated *k* to better represent investors' holding period in the US market, but since there is no estimated holding period for the Finnish stock market, this study estimates the regressions with *k* as a free parameter (*k=1)*.

The estimation of the specified regressions is conducted by applying firm fixed effect regression, as in Vu et al. (2015). Significant coefficients indicate that the conditional illiquidity betas are priced risk factors with predictive power in explaining stock returns. Fixed effect panel regression is used instead of widely applied Fama-MacBeth (1973) procedure, since Petersen (2009) shows that Fama-MacBeth method is subject to statistical biases and does not account for serial correlation. Furthermore, Petersen (2009) continues that Fama-MacBeth results are biased even when corrected for serial correlation, as depicted by Newey and West (1987). Hence, following Vu et al. (2015), the firm fixed effect panel regression is used to estimate the price of the liquidity risks.

4 RESULTS

4.1 Innovations in Illiquidity

As depicted in the previous section liquidity has been shown to be highly persistent, implying that liquidity is predictable, and hence the focus is on the innovations in liquidity. However, before calculating innovations in liquidity the autocorrelations are checked by the Breusch-Godfrey serial correlation LM test (Brooks 2014, 197–198). Specifically, Breusch-Godfrey serial correlation LM test is performed first with one lag and two lags for both illiquidity and return series for all the stocks as well as market return and illiquidity. Table 14 in the Appendix 1 reports results for market illiquidity and return series and their innovations.[13] The table shows that both market illiquidity and return series exhibit first and second order autocorrelation. Hence, the innovations in illiquidity and market return are obtained through AR(2) process, as depicted in the section 3.3.1. After this processing the table shows that none of the series exhibit first or second order serial correlation, and the illiquidity betas for the stocks can be calculated as in equations (11)–(13) by using innovation series.

Figure 3 describes the dynamics of innovations in market illiquidity for both *PQS* and *AdjILLIQ* measures. Both of the innovation series seem to share similar kind of dynamics, while *AdjILLIQ* shows a bit larger a magnitude. The series are more dispersed in the beginning of the period under investigation, and after 2003 series exhibit lower dispersion, except the spikes in the series. This correspond to the figure 2 in the section 3.1, where it was noticed that during the years 2003 to 2008 Finland faced economic growth and the trading volume increased. This could mean that in Finland illiquidity risk is not constant in different market conditions, but varies over time, which has been reported in other markets (e.g. Karolyi et al., 2012; Vu et al., 2015), and supports the use of conditional betas in LCAPM estimations.

The upper spikes in the figure 3 show the events associated with liquidity leakages. For instance, period from late 1999 to the beginning of 2002 includes events related to the dot-com bubble, as well as the terrorists' attack (9/11) in the US in 2001 that we can see as spikes in the figure.

[13] The results for Breusch-Godfrey serial correlation LM tests for individual stocks are not presented for brevity.

As mentioned previously, from the 2003 onwards the innovations series seem to be relatively stable and exhibit smaller magnitude, which could reflect the economic growth in Finland and globally.

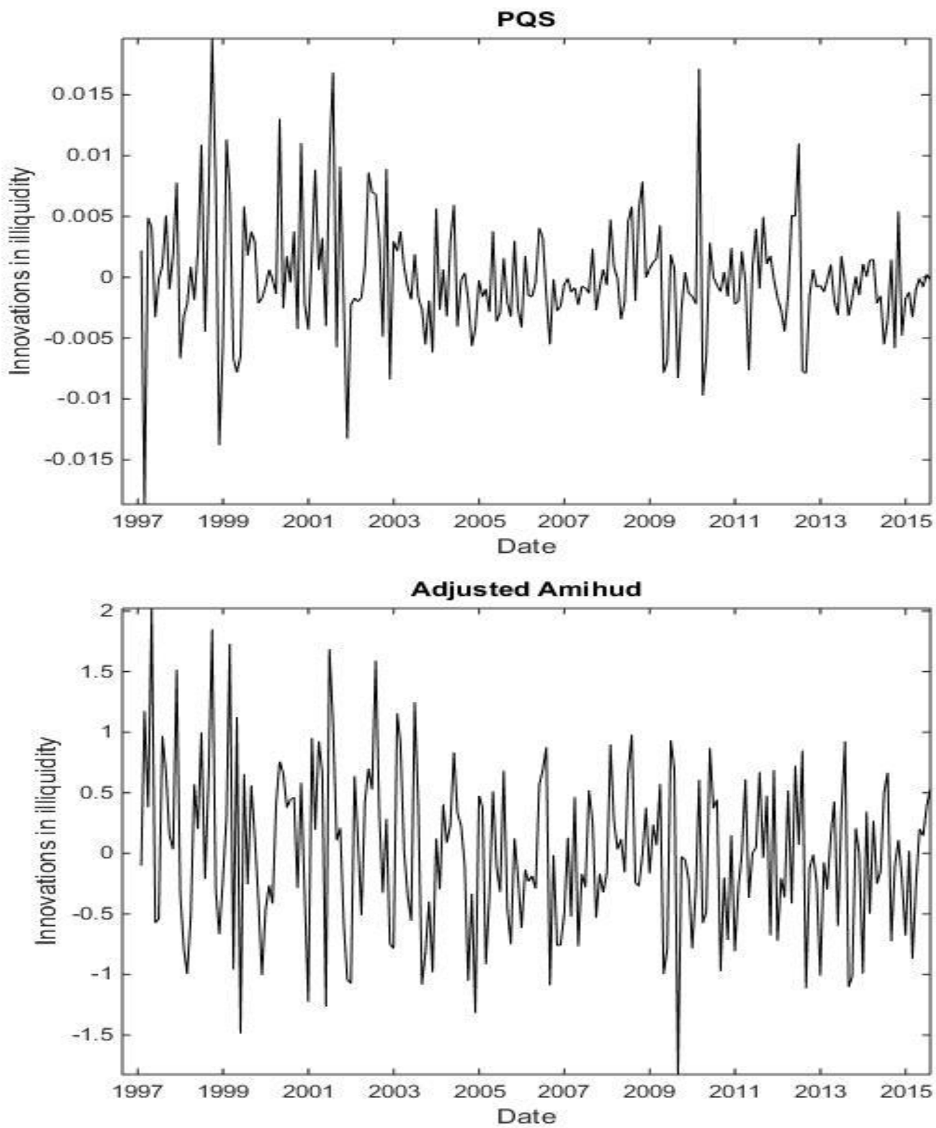

Figure 3. Innovations in market illiquidity

However, as we all know the whole world suffered from the consequences of the subprime crises and the economic growth sharply declined globally and in Finland in 2007 and 2008. Surprisingly, we cannot see any clear spikes in the figure until in 2010 in *PQS* series that may be due to European sovereign debt crises and especially revelation of untruthful government debt levels and deficits of Greece, which caused increased lack of confidence, and eventually led to economic adjustment programs in order to get financing from other EU states and International Monetary Fund (*IMF*). Similar peaks can be seen in the *AdjILLIQ* innovations series, even though the magnitude is smaller and peaks are not that easily recognized.

4.2 Illiquidity Beta Sorted Portfolios

Pre-ranking betas are calculated for the stocks as depicted in the section 3.3.2, and the post-ranking betas over the sample period are calculated to see whether the portfolio quintiles are created successfully with dispersed and monotonic illiquidity betas, which should be the case by design. Table 2 reports these full-sample post-ranking betas, and it can be seen that the signs of the illiquidity betas are consistent with those estimated by Acharya and Pedersen (2005). Additionally, as intended, the post-ranking betas are sufficiently dispersed and monotonic across portfolios. For instance, the commonality in liquidity beta for the most liquid portfolio is 0.002 and increases to 0.025 when reaching the most illiquid portfolio quintile, for the *PQS* measure. Similarly, flight to liquidity and depressed wealth effect betas decrease monotonically from -0.043 and -0.031 to -0.080 and -0.094, respectively. Likewise, for the *AdjILLIQ* measure, monotonic increasing for commonality in liquidity betas and decreasing for the flight to liquidity betas and depressed wealth effect betas can be seen. Interestingly, the difference between the most illiquid and liquid portfolio quintiles are almost the same for both of the measure, and are identical with regards to flight to liquidity beta. The absolute magnitudes are generally the largest in the case of flight to liquidity beta, while the commonality in liquidity betas have the lowest magnitudes, according to both measures. This could imply that flight to liquidity contributes the most to the overall liquidity risk in Finnish stock market, as it has been found to be significant and negatively priced in Finland (Butt, 2015; Butt and Virk, 2015). However, the differences between the most liquid and illiquid portfolio quintiles are largest for the depressed wealth effect betas. Overall, it can be concluded that the aim of forming portfolio quintiles including stocks with extreme liquidity risk and dispersed and monotonic illiquidity betas is fairly achieved.

Table 2. Post-ranking illiquidity betas of the illiquidity sorted portfolios

This table reports the full-sample post-ranking illiquidity beta *k*, for the five portfolios sorted on the corresponding pre-ranking beta, i.e., beta *k*. For instance, β^2 depicts the post ranking betas for the portfolio quintiles sorted on β^2 over the time period of 2002–7/2015. β^2, β^3, and β^4 refer to commonality in liquidity, flight to liquidity, and depressed wealth effect betas, respectively. Panel A describes the post-ranking betas for the quintile portfolios based on *PQS* illiquidity measure while Panel B shows the post-ranking betas for the quintile portfolios based on *AdjILLIQ* measure. Numbers on the left refer to portfolio quintiles where 1 is the most liquid portfolio when sorted on β^2 and the most illiquid portfolio when sorted on β^3 and β^4. IML refers to the difference in the post-ranking betas for the most illiquid and the most liquid portfolios.

Portfolio rank	β^2	β^3	β^4
Panel A. Closing Percent Quoted Spread (*PQS*)			
1	0.002	-0.080	-0.094
2	0.004	-0.068	-0.046
3	0.006	-0.062	-0.029
4	0.010	-0.059	-0.022
5	0.025	-0.043	-0.031
IML	0.023	-0.036	-0.063
Panel B. Adjusted Amihud (*AdjILLIQ*)			
1	0.008	-0.092	-0.077
2	0.013	-0.081	-0.058
3	0.023	-0.062	-0.067
4	0.026	-0.064	-0.031
5	0.035	-0.056	-0.023
IML	0.027	-0.036	-0.054

In addition to calculating post-ranking betas over the sample period, the portfolios' characteristics are calculated. Specifically, for each portfolio quintile the average monthly return and illiquidity, and standard deviation of return and illiquidity are estimated. Table 3 shows the characteristics of the portfolios based on the *PQS* measure and table 4 for the portfolios based on *AdjILLIQ* measure. Regarding the *PQS* measure, based on all the three illiquidity betas sorting, the portfolios with highest liquidity risks have higher returns and level of illiquidity on average (except flight to liquidity sorted portfolios) compared to the portfolios with the least liquidity risk, which implies that the illiquid stocks earn higher returns than the liquid stocks, as literature suggest. Additionally, standard deviations of the illiquidity level increase when moving from the most liquid portfolio to the most illiquid. However, standard deviations of the portfolio return seem to be lower for the most illiquid portfolio compared with the most liquid portfolio when sorted on commonality in liquidity and depressed wealth effect betas.

Table 3. Illiquidity sorted portfolios' characteristics based on the *PQS* measure

The table shows mean values of portfolios' monthly returns $\mu(r^p)$ and illiquidity $\mu(c^p)$ as well as monthly standard deviations of the portfolios' returns $\sigma(r^p)$ and illiquidity $\sigma(c^p)$. β^2, β^3, and β^4 refer to commonality in liquidity, flight to liquidity, and depressed wealth effect betas, respectively. For the portfolios that are sorted based on β^2 portfolio number 1 is the most liquid and 5 is the most illiquid while for the portfolios that are sorted based on $\beta^3$and β^4 portfolio number 1 is the most illiquid and 5 the most liquid. IML refers to the difference between the most illiquid and the most liquid portfolios.

Portofolio	1	2	3	4	5	IML
Panel A: Commonality in liquidity (β^2) sorted portfolios						
$\mu(r^p)$	0.007	0.003	0.007	0.006	0.009	0.002
$\sigma(r^p)$	0.054	0.052	0.051	0.043	0.052	-0.002
$\mu(c^p)$	0.006	0.012	0.023	0.031	0.068	0.062
$\sigma(c^p)$	0.004	0.004	0.011	0.014	0.033	0.029
Panel B: Flight to liquidity (β^3) sorted portfolios						
$\mu(r^p)$	0.008	0.008	0.005	0.004	0.007	0.001
$\sigma(r^p)$	0.068	0.050	0.048	0.045	0.034	0.034
$\mu(c^p)$	0.004	0.004	0.011	0.014	0.033	-0.029
$\sigma(c^p)$	0.019	0.014	0.008	0.014	0.019	0.000
Panel C: Depressed wealth effect (β^4) sorted portfolios						
$\mu(r^p)$	0.011	0.005	0.005	0.007	0.004	0.006
$\sigma(r^p)$	0.050	0.049	0.048	0.051	0.051	-0.001
$\mu(c^p)$	0.065	0.028	0.018	0.013	0.016	0.049
$\sigma(c^p)$	0.027	0.013	0.006	0.010	0.013	0.015

Likewise, table 4 depicts the portfolios' characteristics when pre-ranking beta calculations are based on the *AdjILLIQ* measure. Regarding the portfolios' returns only commonality in liquidity sorted portfolios have higher return when moving from the most illiquid quintile to the most liquid quantile. However, standard deviation is smaller for the most illiquid portfolio than for the most liquid portfolio. As intended, portfolios show a higher level of illiquidity when moving from the most illiquid to more liquid portfolios, except in the case of flight to liquidity sorted portfolios. Similar to the *PQS* measure based portfolio sorting, portfolios that have a higher liquidity risk exhibit higher returns, even though the flight to liquidity sorted portfolios seem to be an exception again.

Table 4. Illiquidity sorted portfolios' characteristics based on the *AdjILLIQ* measure

The table shows mean values of portfolios' monthly returns $\mu(r^p)$ and illiquidity $\mu(c^p)$ as well as monthly standard deviations of the portfolios' returns $\sigma(r^p)$ and illiquidity $\sigma(c^p)$. β^2, β^3, and β^4 refer to commonality in liquidity, flight to liquidity, and depressed wealth effect betas, respectively. For the portfolios that are sorted based on β^2 portfolio number 1 is the most liquid and 5 is the most illiquid while for the portfolios that are sorted based on $\beta^3$and β^4 portfolio number 1 is the most illiquid and 5 the most liquid. IML refers to the difference between the most illiquid and the most liquid portfolios.

Portofolio	1	2	3	4	5	IML
Panel A: Commonality in liquidity (β^2) sorted portfolios						
$\mu(r^p)$	0.007	0.003	0.006	0.007	0.009	0.002
$\sigma(r^p)$	0.052	0.050	0.048	0.050	0.047	-0.006
$\mu(c^p)$	0.073	0.090	0.117	0.140	0.161	0.088
$\sigma(c^p)$	0.023	0.011	0.015	0.017	0.022	-0.002
Panel B: Flight to liquidity (β^3) sorted portfolios						
$\mu(r^p)$	0.006	0.005	0.007	0.005	0.009	-0.003
$\sigma(r^p)$	0.064	0.052	0.047	0.040	0.041	0.023
$\mu(c^p)$	0.095	0.109	0.109	0.126	0.143	-0.048
$\sigma(c^p)$	0.018	0.017	0.019	0.016	0.018	0.000
Panel C: Depressed wealth effect (β^4) sorted portfolios						
$\mu(r^p)$	0.006	0.007	0.008	0.004	0.006	0.000
$\sigma(r^p)$	0.045	0.051	0.054	0.052	0.042	0.002
$\mu(c^p)$	0.151	0.128	0.107	0.081	0.113	0.038
$\sigma(c^p)$	0.026	0.020	0.015	0.009	0.017	0.009

Serial correlation. Similar to individual stocks, serial correlation for illiquidity betas sorted portfolios are tested. Table 15 and 16 in the Appendix 2 indicate high first and second order serial correlation in portfolio's illiquidity series, and hence, the AR(2) model is used to capture the innovations in the illiquidity series. Table 17 and 18 in Appendix 2 report the results for the serial correlation test for portfolio return and innovations in illiquidity; what can be noted is the absence of serial correlation in the innovation in illiquidity series, while some of the return series exhibit first and second order serial correlation. However, most of the return series show no serial correlation.[14]

[14] Since the DCC-GARCH(1,1) estimation by using Kevin Sheppard's MFE toolbox requires zero-mean series (i.e. innovations) as inputs the innovations in return series are also captured via AR(2) process that are used to run the model similar approach as in Saad and Samet (2015).

Stationarity. To ensure that the portfolio return and illiquidity series can be validly used in time-varying illiquidity risk estimation, the condition of stationarity needs to be tested, which is done by conducting the Augmented Dickey-Fuller (*ADF*) test for unit root and Kwiatkowski-Phillips-Schmidt-Shin (*KPSS*) test (Kwiatkowski et al., 1992) for stationarity. The *ADF* test for unit root is conducted by using 12 as the maximum number of lags. The tables 19 and 20 in the Appendix 3 show the results for ADF and KPSS tests, and the test for unit root is rejected in all cases. Furthermore, the KPSS test shows that the condition of stationary is fulfilled. Hence, the DCC-GARCH(1,1) estimation can be conducted for the illiquidity risk sorted portfolios.

4.3 Time-varying Illiquidity Risks

As depicted in the section 3.3.3, the time-varying illiquidity risks (covariances) are calculated by using the DCC-GARCH(1,1) method on portfolio level as in Saad and Samet (2015), while the market return adjusted for illiquidity is captured by EGARCH(1,1) model. Then the conditional illiquidity betas that are calculated for the portfolios are subsequently assigned to individual stocks. However, before assigning the illiquidity betas for the individual stocks, the significance of time trend, as depicted in the equation (27), is examined through Vogelsang's (1998) PS1 test and Bunzel and Vogelsang's (2005) DAN test. Table 5 reports the results for the tests. The second and third columns show the result for PS1 and DAN tests based on the *PQS* measure, while the fourth and fifth columns show the corresponding results with respect to the *AdjILLIQ* measure.

As seen from the table 5, there seems to be no evidence of decreasing, or any kind of a significant trend in illiquidity risks in the Finnish stock market. For the PS1 test, only the most illiquid portfolio quintile sorted on β^4 is significant at 10 % level, with a positive trend coefficient value indicating a decreasing trend. However, the DAN test indicates that there is no decreasing or increasing trend at all.

Table 5. Testing significant time trend in illiquidity risks

The table depicts the results for the time trend tests as depicted in the section 3.3.4. The first column shows the portfolio quintile that is under investigation. β^2, β^3, and β^4 refer to commonality in liquidity, flight to liquidity, and depressed wealth effect betas, respectively. t-PS1 and t-DAN are time trend coefficient (δ_1), as depicted in the equation (27), with the test statistics at 5 % level below them in the parenthesis. Critical values for the PS1 test are 2.647, 2.152 and 1.720 at 1%, 5% and 10% level, respectively. Corresponding critical values for the DAN test are 1.710, 2.052 and 2.462. ***,** and * denote significance at 1%, 5% and 10% level, respectively.

Portfolio	*PQS*		*AdjILLIQ*	
	t-PS1	t-DAN	t-PS1	t-DAN
The most liquid β^2 portfolio	0.0001	0.0000	-0.0001	0.0000
	(-1.051)	(-0.864)	(-0.103)	(-0.009)
The most illiquid β^2 portfolio	0.0000	0.0001	0.0001	0.0001
	(0.443)	(1.297)	(0.098)	(0.162)
The most liquid β^3 portfolio	0.0000	-0.0001	-0.0002	-0.0002
	(-0.135)	(-0.475)	(-0.190)	(-0.204)
The most illiquid β^3 portfolio	-0.0001	-0.0002	0.0000	-0.0002
	(-0.300)	(-1.070)	(-0.019)	(-0.079)
The most liquid β^4 portfolio	0.0000	0.0000	-0.0007	-0.0006
	(0.205)	(-0.028)	(0.000)	(0.000)
The most illiquid β^4 portfolio	0.0000	0.0000	0.0003*	0.0002
	(0.117)	(-0.453)	(1.754)	(0.998)

Figure 4 plots the three time-varying illiquidity betas for the most (red line) and the least liquid (blue line) quintile portfolios of the portfolios sorted on the corresponding illiquidity beta. In other words, in the figure, for instance, time-varying commonality in liquidity betas are the most and the least liquid quintile portfolios' betas based on the commonality in liquidity (β^2) sorting. The figure confirms the previous results from the trend tests. Only the most liquid portfolio sorted on depressed wealth effect beta (β^4) based on the *AdjILLIQ* measure seems to exhibit a trend. However, the test statistics in the table 5 clearly indicates that there is no linear trend. This could be due to the fact that PS1 test does not suffer from over-rejection of the null hypothesis when serial correlation is strong, as explained in the section 3.3.4. As expected, illiquidity risks are higher for the most illiquid portfolios, while the largest difference is found for the depressed wealth effect and commonality in liquidity betas when using the *PQS* and *AdjILLIQ* measure, respectively. The flight to liquidity time-varying beta has the lowest difference, and similar pattern between the illiquidity measures can be seen. In addition, the conditional commonality in liquidity betas have positive signs, while flight to liquidity and depressed wealth effect betas have negative signs, as anticipated. From the figure 4 it can also be noticed that the liquidity risk varies substantially over time, and for instance the commonality in liquidity and flight to liquidity risks increase during the recent financial crises according to both illiquidity measures. Furthermore, the depressed wealth effect risk increases for the most illiquid portfolio with respect to the *PQS* measure, but such behavior cannot bet seen as clear with regard to the *AdjILLIQ* measure. Moreover, the most illiquid portfolios have more and larger variation in the conditional betas, which means that they react more aggressively to the changes in market conditions, as anticipated. Also, it can be seen that illiquidity risks start increasing at the beginning of the period under investigation, and just before the burst of the subprime crisis the illiquidity risks fall at a low level, and during the crisis they start rising reaching generally the highest level during the investigated period.

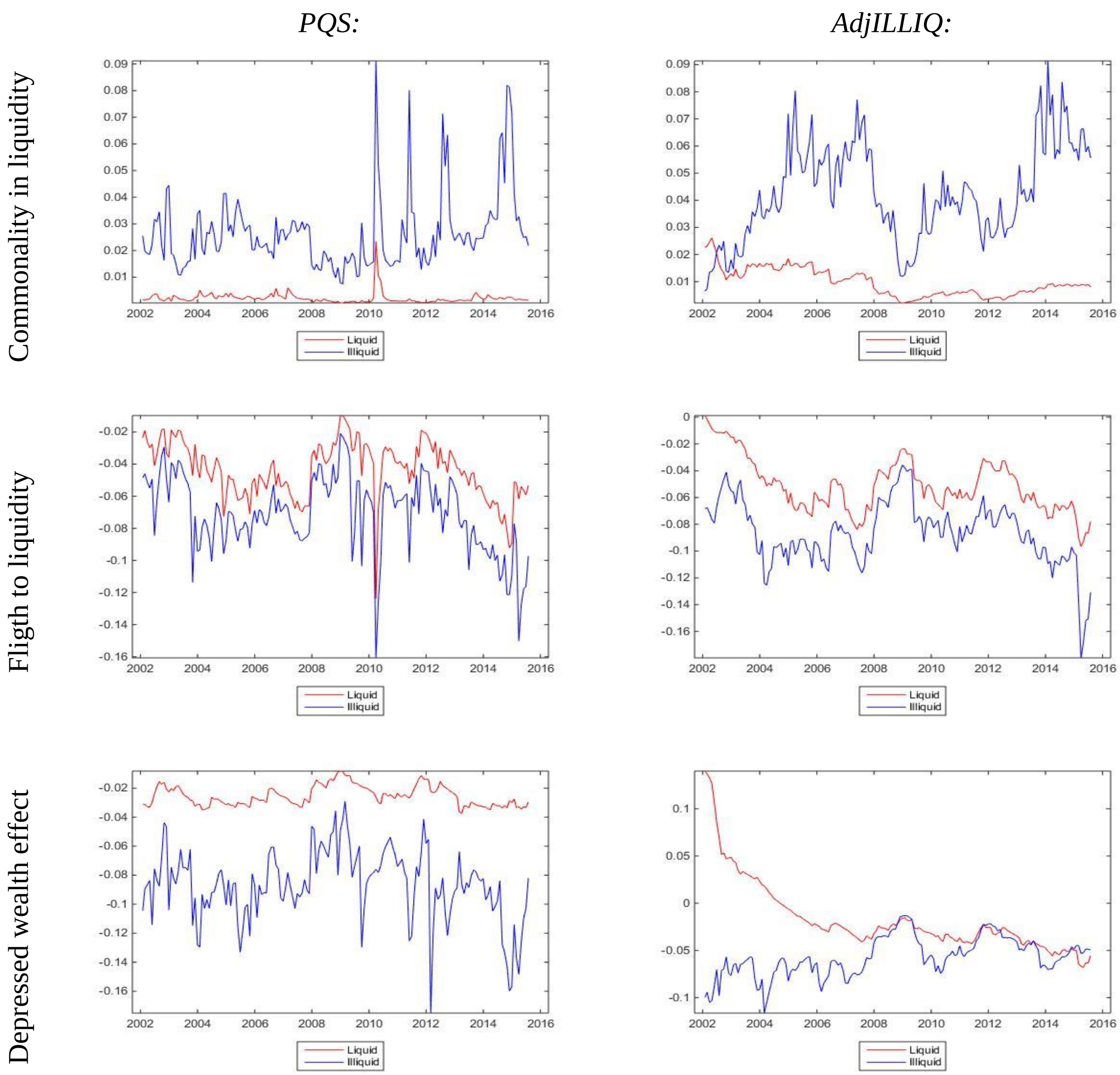

Figure 4. Time-varying conditional illiquidity betas

Quantitatively, the standard deviations of the most liquid and illiquid portfolios based on the *PQS* measure are 0.002 and 0.014, respectively. For the flight to liquidity and depressed wealth effect, the corresponding values are 0.018 and 0.007 for the liquid portfolios, and 0.024 and 0.025 for the illiquid portfolios. Concerning the *AdjILLIQ* measure, the corresponding values are 0.005 and 0.018 for commonality in liquidity sorted, 0.020 and 0.024 for flight to liquidity sorted, and 0.038 and 0.021 for depressed wealth effect sorted portfolios. Surprisingly, the standard deviation for depressed wealth effect is larger for the most liquid portfolio quintile than for the most illiquid portfolio quintile. The largest difference between the most illiquid and the most liquid portfolio quintiles in absolute terms is for the depressed wealth effect, with the mean difference of 0.062 in terms of the *PQS* measure. For the commonality in liquidity and flight to liquidity, the mean differences are 0.024 and 0.028, respectively. For the *AdjILLIQ* measure, the mean difference between the most illiquid and the most liquid portfolio quintiles is also the largest for the depressed wealth effect risk with the mean value of 0.040, while the mean differences for the commonality and flight to liquidity risks are 0.033 and 0.035, respectively. These variations in illiquidity risks conform to the stylized fact that illiquidity risks indicate time variation, and give justification to use a conditional version of the LCAPM for the estimation of the price of the illiquidity risk. Overall, the figure 4 and the results from the trend tests indicate that there is no decreasing trend in illiquidity risks in the Finnish stock market, and the hypothesis *H6*, which stated: *"There is no decreasing trend in illiquidity risk in the Finnish stock market"*, can be accepted.

4.4 Pricing of the Liquidity Risks

This section evaluates whether the liquidity risks are priced in the Finnish stock market by estimating fixed effect panel regressions, as specified in the section 3.3.5. However, as explained in the section 3.3.5, highly correlated explanatory variables may cause collinearity problems, which affect the results of the regression. Hence, the correlations between all the explanatory variables are estimated. Table 6 presents the correlations between each of the *PQS* based conditional liquidity betas and control variables (book-to-market values and market capitalization) that are used in the panel regression analysis. Surprisingly, the correlations between the illiquidity betas are not as large as anticipated, except the correlation between β^1

and β^3, and β^2 and β^4 that have correlations of -0.681 and -0.799, respectively. Interestingly, none of the explanatory variables that are used in the regression simultaneously have high correlations, except the correlation between β^4 and market value for the conditional betas estimated based on commonality in liquidity pre-beta sorting, which can be considered moderately high. Additionally, the correlation between β^1 and β^6 is extremely high having almost perfect positive correlation. A similar magnitude of correlation between the explanatory variables can be seen for the conditional beta estimation based on flight to liquidity and depressed wealth effect pre-ranking betas portfolio sorting.

Table 6. Correlations between the explanatory variables based on the *PQS* measure

Table shows correlations between all the used explanatory variables. β^2, β^3, and β^4 refer to commonality in liquidity, flight to liquidity, and depressed wealth effect betas, respectively. β^5 and β^6 are the net liquidity beta and the aggregate systematic risk beta, while *BM* and *MV* are natural logarithms of a stock's book-to-market ratios and market capitalizations. Panels A, B and C describe the results based on commonality in liquidity, flight to liquidity and depressed wealth effect portfolios sorting in estimation of conditional illiquidity betas, respectively.

	E(c)	β^1	β^2	β^3	β^4	β^5	β^6	*BM*	*MV*
Panel A: Commonality in liquidity (β^2) sorting									
E(c)	1.000	-0.206	0.290	0.141	-0.311	0.176	-0.166	0.284	-0.481
β^1		1.000	0.002	-0.681	-0.042	0.356	0.990	-0.084	0.217
β^2			1.000	-0.297	-0.799	0.829	0.127	0.056	-0.451
β^3				1.000	0.192	-0.664	-0.738	0.043	-0.122
β^4					1.000	-0.850	-0.168	-0.067	0.570
β^5						1.000	0.485	0.030	-0.371
β^6							1.000	-0.074	0.146
BM								1.000	-0.243
MV									1.000
Panel B: Flight to liquidity (β^3) sorting									
	E(c)	β^1	β^2	β^3	β^4	β^5	β^6	*BM*	*MV*
E(c)	1.000	-0.133	0.001	0.134	0.029	-0.096	-0.137	0.284	-0.481
β^1		1.000	-0.120	-0.699	0.049	0.376	0.995	-0.031	0.079
β^2			1.000	-0.283	-0.812	0.760	-0.037	-0.009	-0.015
β^3				1.000	0.221	-0.765	-0.747	0.031	-0.085
β^4					1.000	-0.790	-0.035	0.024	-0.004
β^5						1.000	0.463	-0.032	0.051
β^6							1.000	-0.033	0.081
BM								1.000	-0.243
MV									1.000
Panel C: Depressed wealth effect (β^4) sorting									
	E(c)	β^1	β^2	β^3	β^4	β^5	β^6	*BM*	*MV*
E(c)	1.000	-0.178	0.249	0.111	-0.287	0.164	-0.142	0.284	-0.481
β^1		1.000	0.040	-0.683	-0.079	0.378	0.990	-0.084	0.133
β^2			1.000	-0.356	-0.870	0.875	0.168	0.069	-0.314
β^3				1.000	0.226	-0.676	-0.739	0.054	-0.043
β^4					1.000	-0.865	-0.203	-0.070	0.426
β^5						1.000	0.503	0.029	-0.292
β^6							1.000	-0.074	0.080
BM								1.000	-0.243
MV									1.000

Similarly, table 7 depicts the correlations between explanatory variables based on the *AdjILLIQ* measure, and there cannot be seen a high correlation between variables that are used simultaneously in the regression, apart from the correlation between expected illiquidity and market capitalization, that is highly negative with the value of -0.797. This implies that when market capitalization rises the expected illiquidity declines, and the level of illiquidity and the size of a firm are negatively related. This makes sense because larger companies are usually considered to be more interesting as their trading volumes are, which increases the liquidity.

Table 7. Correlations of the explanatory variables based on the *AdjILLIQ* measure

Table shows correlations between all the used explanatory variables. β^2, β^3, and β^4 refer to commonality in liquidity, flight to liquidity, and depressed wealth effect betas, respectively. β^5 and β^6 are the net liquidity beta and the aggregate systematic risk beta, while *BM* and *MV* are natural logarithms of a stock's book-to-market ratios and market capitalizations. Panels A, B and C describe the results based on commonality in liquidity, flight to liquidity and depressed wealth effect portfolios sorting in estimation of conditional illiquidity betas, respectively.

Panel A: Commonality in liquidity (β^2) sorting									
	E(c)	β^1	β^2	β^3	β^4	β^5	β^6	*BM*	*MV*
E(c)	1.000	-0.232	0.348	0.314	-0.278	0.131	-0.189	0.167	-0.797
β^1		1.000	0.123	-0.714	-0.209	0.451	0.989	-0.058	0.114
β^2			1.000	-0.280	-0.695	0.814	0.250	0.001	-0.440
β^3				1.000	0.252	-0.644	-0.761	0.097	-0.251
β^4					1.000	-0.868	-0.338	-0.017	0.337
β^5						1.000	0.581	-0.031	-0.219
β^6							1.000	-0.058	0.067
BM								1.000	-0.237
MV									1.000
Panel B: Flight to liquidity (β^3) sorting									
	E(c)	β^1	β^2	β^3	β^4	β^5	β^6	*BM*	*MV*
E(c)	1.000	-0.274	0.090	0.280	0.088	-0.176	-0.272	0.162	-0.797
β^1		1.000	-0.094	-0.820	-0.442	0.644	0.996	-0.084	0.164
β^2			1.000	-0.193	-0.388	0.556	-0.022	-0.073	-0.104
β^3				1.000	0.467	-0.837	-0.853	0.091	-0.160
β^4					1.000	-0.821	-0.503	0.123	-0.034
β^5						1.000	0.710	-0.127	0.079
β^6							1.000	-0.092	0.161
BM								1.000	-0.234
MV									1.000
Panel C: Depressed wealth effect (β^4) sorting									
	E(c)	β^1	β^2	β^3	β^4	β^5	β^6	*BM*	*MV*
E(c)	1.000	-0.210	0.188	0.255	-0.109	-0.012	-0.191	0.167	-0.797
β^1		1.000	0.159	-0.709	-0.394	0.579	0.991	-0.073	0.081
β^2			1.000	-0.380	-0.607	0.746	0.262	-0.049	-0.254
β^3				1.000	0.376	-0.755	-0.759	0.076	-0.155
β^4					1.000	-0.866	-0.493	0.037	0.229
β^5						1.000	0.681	-0.067	-0.115
β^6							1.000	-0.077	0.054
BM								1.000	-0.237
MV									1.000

Following Vu et al. (2015), to estimate the price of the illiquidity risks firm fixed effect panel regression is applied to avoid statistical biases of the conventional Fama-MacBeth (1973) procedure, as depicted in the section 3.3.5. However, Brooks (2014, 529–530; 543–547) points out that it should be tested whether the panel approach is needed at all or whether the data could be simply pooled together and Ordinary Least Squares (OLS) employed. This can be done by observing the significance of F-test statistics of the fixed effect panel regression, which will tell whether all the regression coefficients are zero, meaning that independent variables do not cause any statistical inference on the dependent variable (Brooks 2014, 530–543). The results in the table 21 in Appendix 4 reject the null for all the different panel regression specifications of the LCAPM, and hence the pooled sample could not be used, which supports the use of the fixed effect model. Furthermore, to test the validity of the chosen fixed effect model, and whether the random effect model should be applied instead, the Hausman test is performed (Brooks 2014, 545–546). The results in the table 22 in Appendix 4 indicate that the null is rejected in all the cases, which implies that the random effects model is not appropriate and the fixed effect model is to be preferred.

Table 8 gives the results for firm fixed effect panel regression, when using *PQS* as the measure of illiquidity. The first column depicts the estimation equations (30)–(36), as specified in the section 3.3.5, while the panels A, B and C show the results for the commonality in liquidity, flight to liquidity and depressed wealth effect sorted portfolios, respectively. The top row specifies the variables used in the regression, where *E(c)* expected illiquidity, while the different betas represent the illiquidity risk betas as depicted in the equations (10)–(13) and (28)–(29). *LnBM* and *lnMV* are the natural logarithms of book-to-market value and market capitalization of a stock at the beginning of the month, respectively, that are used as control variables.

Table 8. Panel regressions with fixed effects using the *PQS* measure

The table presents firm fixed effect panel regression results using individual stocks as test assets. The numbers in the first column corresponds the estimation specification presented in equations (30)–(36). *a* is the intercept of the regression, *E(c)* is the expected illiquidity, and β^2, β^3, and β^4 refer to commonality in liquidity, flight to liquidity, and depressed wealth effect betas, respectively. β^5 and β^6 are net liquidity beta and aggregate systemic risk beta while *lnBM* and *lnMV* are natural logarithms of a stock's book-to-market ratios and market capitalizations at beginning of the month. Individual excess stock return is the dependent variable in all of the models. The values in the parenthesis represent t-statistics of the estimated coefficients. ***, **, and * denote significance at 1%, 5%, and 10% level, respectively.

	a	*E(c)*	β^1	β^2	β^3	β^4	β^5	β^6	*lnBM*	*lnMV*
Panel A: Commonality in liquidity (β^2) sorting										
1	-0.264***	0.251***	0.013***						-0.015***	0.013***
	(-7.935)	(8.182)	(3.964)						(-9.793)	(7.093)
2	-0.269***	0.251***	0.012***	0.222**					-0.014***	0.013***
	(-8.064)	(8.182)	(3.591)	(2.037)					(-9.685)	(7.204)
3	-0.268***	0.251***	0.016***		0.054				-0.014***	0.013***
	(-7.999)	(8.179)	(3.664)		(1.029)				(-9.745)	(7.161)
4	-0.275***	0.249***	0.011***			-0.105**			-0.014***	0.013***
	(-8.170)	(8.135)	(3.160)			(-2.167)			(-9.558)	(7.308)
5	-0.266***	0.250***	0.011***				0.029		-0.014***	0.013***
	(-7.979)	(8.170)	(2.757)				(1.131)		(-9.739)	(7.124)
6	-0.265***	0.251***						0.012***	-0.014***	0.013***
	(-7.955)	(8.188)						(4.068)	(-9.771)	(7.100)
7	-0.284***	0.250***	0.017***	0.270	0.130**	-0.051			-0.014***	0.014***
	(-8.351)	(8.151)	(3.826)	(1.584)	(2.160)	(-0.742)			(-9.426)	(7.499)
Panel B: Flight to liquidity (β^3) sorting										
1	-0.263***	0.246***	0.008***						-0.015***	0.013***
	(-7.877)	(8.032)	(2.698)						(-9.948)	(7.196)
2	-0.263***	0.246***	0.008***	0.007					-0.015***	0.013***
	(-7.877)	(8.025)	(2.697)	(0.046)					(-9.927)	(7.190)
3	-0.264***	0.246***	0.008**		0.011				-0.015***	0.013***
	(-7.860)	(8.029)	(2.159)		(0.200)				(-9.942)	(7.176)
4	-0.263***	0.246***	0.007***			-0.003			-0.015***	0.013***
	(-7.876)	(8.020)	(2.684)			(-0.056)			(-9.923)	(7.184)
5	-0.264***	0.246***	0.008**				-0.002		-0.015***	0.013***
	(-7.871)	(8.020)	(2.454)				(-0.060)		(-9.944)	(7.174)
6	-0.263***	0.246***						0.007***	-0.015***	0.013***
	(-7.864)	(8.037)						(2.679)	(-9.939)	(7.168)
7	-0.265***	0.246***	0.008**	0.036	0.017	0.001			-0.015***	0.013***
	(-7.850)	(8.022)	(2.026)	(0.131)	(0.267)	(0.011)			(-9.885)	(7.169)
Panel C: Depressed wealth effect (β^4) sorting										
1	-0.269***	0.250***	0.013***						-0.014***	0.013***
	(-8.085)	(8.171)	(3.976)						(-9.704)	(7.249)
2	-0.273***	0.250***	0.012***	0.250*					-0.014***	0.013***
	(-8.200)	(8.146)	(3.651)	(1.959)					(-9.617)	(7.336)
3	-0.268***	0.250***	0.012***		-0.019				-0.014***	0.013***
	(-0.268)	(0.250)	(2.756)		(-0.320)				(-9.708)	(7.189)
4	-0.278***	0.249***	0.011***			-0.117**			-0.014***	0.013***
	(-8.315)	(8.118)	(3.304)			(-2.513)			(-9.494)	(7.431)
5	-0.271***	0.249***	0.009**				0.053**		-0.014***	0.013***
	(-8.153)	(8.134)	(2.459)				(1.997)		(-9.617)	(7.278)
6	-0.269***	0.251***						0.013***	-0.014***	0.013***
	(-8.098)	(8.185)						(4.181)	(-9.675)	(7.234)
7	-0.279***	0.249***	0.012**	0.008	0.019	-0.118			-0.014***	0.013***
	(-8.285)	(8.118)	(2.452)	(0.032)	(0.257)	(-1.395)			(-9.473)	(7.410)

Panel A in table 8 reports the prices of illiquidity risks for the conditional betas estimated based on commonality in liquidity beta sorting. Results show that the expected illiquidity is significant and positive, supporting the first hypothesis of positive relationship between expected illiquidity and stock returns. Additionally, market beta (β^1) is found to be positive and significant in all the cases, as intended. Commonality in liquidity (β^2) and depressed wealth effect (β^4) are also found to be significant with the prices of 0.222 and -0.105 and expected signs. These support the hypotheses two and four of a positive influence of commonality in liquidity on stock returns and a negative relation between stock illiquidity and market return on stock return. Flight to liquidity (β^3) is not found to be significant, implying rejection of the third hypothesis of negative relation between flight to liquidity and stock returns. Furthermore, control variables are highly significant. Regarding the two net betas, the aggregate systematic risk (β^6) is highly significant with a positive sign and price of 0.012, while the net liquidity beta is insignificant for the commonality in liquidity sorted portfolios. The positive and significant coefficient of aggregate systematic risk supports the hypothesis five that the aggregate systematic risk is priced in the Finnish stock market.

In the panel B on table 8 it is shown that only the aggregated systematic risk is significant with the price of 0.007, while other illiquidity related systematic risks are insignificant for the flight to liquidity sorted portfolios. However, the level of illiquidity is positive and significant, indicating the positive relationship between expected stock returns and the level of illiquidity. These results support the hypothesis one and six. Additionally, market beta (β^1) remains positive and significant, as expected by the model. Control variables seem to be significant as well.

For the results based on the depressed wealth effect sorting there can be seen similar results in the liquidity risks as for the commonality in liquidity based sorting, as depicted in the panel C. All the liquidity risks except flight to liquidity are significant with expected signs. Importantly, the aggregate systematic risk is found to be significant with the price of 0.013, which is similar in magnitude to that based on commonality in liquidity sorting. Estimated prices for the commonality in liquidity and depressed wealth effect betas are 0.250 and -0.117, respectively, which are also very similar to those estimated when using commonality in liquidity based portfolio sorting. As for the commonality in liquidity and flight to liquidity based portfolio sorting, the expected illiquidity is positive and significant in all the cases, supporting the positive relation between expected returns and illiquidity in the Finnish stock market. These results support the hypothesis one, two, four, and five while hypothesis three is not supported.

The results based on the *PQS* measure strongly support the hypotheses one, two, four, and five, while there seems to be no support for the third hypothesis. This could indicate that flight to liquidity dimension does not play a significant role in the Finnish stock market (section 5 discusses the economic interpretation of the results in more detail).

The results for the firm fixed effect panel regression when using the *AdjILLIQ* illiquidity measure are reported in the table 9, and similarly to results based on the *PQS* measure, the first column shows the regression equation as specified in the equations (30)–(36), while the panels A, B and C show the results for the commonality in liquidity, flight to liquidity and depressed wealth effect portfolio sorting to estimate conditional betas, respectively. From the panel A it can be noticed that all the illiquidity risk betas are significant. However, flight to liquidity has a negative sign and the economic significance is not appropriate, while the signs for the other betas are as expected by the LCAPM. The prices for the commonality in liquidity and depressed wealth effect are 0.410 and -0.230, respectively. Corresponding prices for the net liquidity risk and aggregate market risk are 0.086 and 0.013, respectively. It should be noticed that the market beta (β^1) and flight to liquidity beta (β^3) have high correlation (-0.714), as shown in the table 7 which could affect the results in the third model specification. Market beta (β^1) is found to be positive and significant for the first three model specifications. When testing the significance of depressed wealth effect and net liquidity risk, the market beta turns out to be insignificant, while the sign remains as expected. Similar to the results based on the *PQS* measure, the expected illiquidity is positive and significant. Additionally, the control variables are significant in all model specifications. The results based on the *AdjILLIQ* measure and commonality in liquidity portfolio sorting support the hypotheses one, two, four, and five while there seems to be no support for the hypothesis three.

Table 9. Panel regressions with fixed effects using the *AdjILLIQ* measure

The table presents firm fixed effect panel regression results using individual stocks as test assets. The numbers in the first column corresponds the estimation specification presented in equations (30)–(36). *a* is the intercept of the regression, *E(c)* is the expected illiquidity, and β^2, β^3, and β^4 refer to commonality in liquidity, flight to liquidity, and depressed wealth effect betas, respectively. β^5 and β^6 are net liquidity beta and aggregate systemic risk beta while *lnBM* and *lnMV* are natural logarithms of a stock's book-to-market ratios and market capitalizations at beginning of the month. Individual excess stock return is the dependent variable in all of the models. The values in the parenthesis represent t-statistics of the estimated coefficients. ***, **, and * denote significance at 1%, 5%, and 10% level, respectively.

	a	*E(c)*	β^1	β^2	β^3	β^4	β^5	β^6	*lnBM*	*lnMV*
Panel A: Commonality in liquidity (β^2) sorting										
1	-0.341***	0.293***	0.012***						-0.012***	0.015***
	(-9.301)	(8.169)	(3.370)						(-8.386)	(8.318)
2	-0.367***	0.320***	0.008**	0.401***					-0.011***	0.016***
	(-9.933)	(8.854)	(2.095)	(5.203)					(-7.492)	(8.811)
3	-0.365***	0.275***	0.026***		0.258***				-0.012***	0.017***
	(-9.796)	(7.618)	(4.923)		(3.589)				(-8.364)	(8.915)
4	-0.363***	0.307***	0.006			-0.230***			-0.011***	0.016***
	(-9.850)	(8.563)	(1.478)			(-5.169)			(-7.529)	(8.775)
5	-0.347***	0.310***	0.005				0.086***		-0.012***	0.016***
	(-9.457)	(8.566)	(1.042)				(3.382)		(-7.863)	(8.341)
6	-0.343***	0.298***						0.013***	-0.012***	0.015***
	(-9.350)	(8.287)						(3.786)	(-8.289)	(8.301)
7	-0.446***	0.302***	0.032***	0.579***	0.589***	-0.136***			-0.010***	0.021***
	(-11.624)	(8.338)	(5.969)	(5.503)	(7.108)	(-2.472)			(-6.592)	(10.682)
Panel B: Flight to liquidity (β^3) sorting										
1	-0.332***	0.270***	0.001						-0.013***	0.016***
	(-9.045)	(7.585)	(0.226)						(-8.576)	(8.333)
2	-0.369***	0.275***	-0.002	0.214**					-0.012***	0.018***
	(-9.879)	(7.577)	(-0.648)	(2.282)					(-7.931)	(9.149)
3	-0.347***	0.255***	0.014***		0.227***				-0.012***	0.017***
	(-9.388)	(7.099)	(2.654)		(3.225)				(-8.572)	(8.750)
4	-0.335***	0.273***	-0.002			-0.106*			-0.012***	0.016***
	(-9.124)	(7.653)	(-0.608)			(-1.741)			(-8.023)	(8.386)
5	-0.360***	0.260***	-0.002				-0.002		-0.013***	0.017***
	(-9.692)	(7.201)	(-0.435)				(-0.050)		(-8.533)	(9.062)
6	-0.360***	0.260***						-0.002	-0.013***	0.017***
	(-9.692)	(7.260)						(-0.604)	(-8.684)	(9.068)
7	-0.416***	0.264***	0.023***	0.502***	0.462***	-0.035			-0.011***	0.020***
	(-10.882)	(7.268)	(3.839)	(4.185)	(5.638)	(-0.509)			(-10.882)	(7.268)
Panel C: Depressed wealth effect (β^4) sorting										
1	-0.337***	0.286***	0.009**						-0.012***	0.016***
	(-9.204)	(7.987)	(2.451)						(-8.314)	(8.332)
2	-0.345***	0.302***	0.006*	0.327***					-0.011***	0.016***
	(-9.404)	(8.370)	(1.659)	(3.497)					(-7.655)	(8.386)
3	-0.346***	0.277***	0.015***		0.118**				-0.012***	0.016***
	(-9.377)	(7.691)	(3.141)		(1.978)				(-8.261)	(8.541)
4	-0.340***	0.287***	0.006*			-0.069			-0.012***	0.016***
	(-9.266)	(8.018)	(1.636)			(-1.561)			(-7.896)	(8.388)
5	-0.337***	0.290***	0.006				0.026		-0.012***	0.015***
	(-9.194)	(8.048)	(1.406)				(1.017)		(-8.093)	(8.283)
6	-0.337***	0.288***						0.008**	-0.012***	0.015***
	(-9.207)	(8.018)						(2.558)	(-8.248)	(8.311)
7	-0.370***	0.293***	0.020***	0.564***	0.274***	0.033			-0.011***	0.017***
	(-9.946)	(8.097)	(3.983)	(4.550)	(4.061)	(0.617)			(-7.189)	(8.970)

The results for the flight to liquidity sorted portfolios are depicted in panel B of table 9. Neither the net liquidity risk nor the aggregate systematic risk is priced, while commonality in liquidity, flight to liquidity and depressed wealth effect are significant when used in separate regressions. The price for commonality in liquidity and depressed wealth effect are 0.214 and -0.106, respectively, while the flight to liquidity beta has a positive sign, implying that economic interpretation is not meaningful. Consistent with the results from the *PQS* measure, the expected illiquidity is found to be positive and significant in all the regression specifications, confirming a positive relationship between the expected returns and illiquidity. Surprisingly, the market beta is significant only when used simultaneously with flight to liquidity beta (β^3). These results support the hypotheses one, two, and four while other hypotheses are not supported.

For the depressed wealth effect portfolio sorting based conditional betas, panel C in table 9 depicts that the aggregate systematic risk is significant with the price of 0.008, while the commonality in liquidity beta (β^2) is positive and significant with the price of 0.327. Other illiquidity related betas are not significant or the economic interpretation is not meaningful. The market beta (β^1) is positive and significant in all the model specifications, except in model 5. Expected illiquidity remains to be positive and significant for all the model specifications, as already implied by other regressions. Book-to-market value and market capitalization are significant, as well. Concerning these results, the hypotheses one, two, and five are supported whereas the rest of the hypotheses are not supported.

Similar to results based on *PQS* measure, panel regression analysis based on *AdjILLIQ* measure shows strong support for the hypotheses one, two, four, and five. Additionally, the results based on the *AdjILLIQ* measure also indicate that β^3 is significant implying the pricing of flight to liquidity effect. However, the sign of the β^3 is positive and then the economic interpretation is not meaningful. It follows that no evidence is found for the third hypothesis.

Concerning the results presented in the tables 8 and 9, it can be seen that the expected illiquidity affects positively the expected excess stock returns in the Finnish stock market, with a fairly similar magnitude of coefficients for both the *PQS* and *AdjILLIQ* measures. The hypothesis *H1* stated that: "*The level of illiquidity has positive and significant effect on stock returns in the Finnish stock market*". This hypothesis can be accepted, since all the model specifications show positive and statistically highly significant coefficients. This confirms the previous findings of Swan and Westerholm (2002) who reported a negative relationship between the excess stock returns and the level of liquidity (i.e. positive relations with the level of illiquidity).

Interestingly, commonality in liquidity appears to be positively priced and significant in all the cases except the flight to liquidity sorted portfolios based on the *PQS* illiquidity measure. The hypothesis *H2* stated: *"The co-movement between stock illiquidity and market illiquidity (commonality in liquidity) is significantly and positively related to stock returns in the Finnish stock market"*. From the results depicted earlier in this section, it can be concluded that this hypothesis can be accepted. Previous studies of Butt and Butt and Virk (2015) have found commonality in liquidity to be significantly priced based on Amihud's (2002) *ILLIQ* measure and this study supports that finding. However, Butt and Virk (2015) and Butt (2015) reported that commonality in liquidity is not priced in the Finnish stock market based on *Zero* measure of illiquidity by Lesmond et al. (1999), contradicting with the findings of this paper, which suggests that commonality in liquidity to be positively priced in the Finnish stock market.

Another interesting finding from the results is that flight to liquidity (β^3) effect is not priced negatively or it is insignificant. Hypothesis *H3* stated that *"the co-movement between stock return and market illiquidity (flight to liquidity) is negatively and significantly related stock returns in the Finnish stock market*" but the results obtained from the fixed effect panel regressions show no support for this hypothesis, and hence it is rejected. From the *PQS* based results it was reported that flight to liquidity is not significant in any case, even though the price of that risk was found to be negative. On the other hand, the results from the *AdjILLIQ* measure indicates that the third beta is positively and significantly priced. However, this is suggested neither by the theory nor the previous findings regarding the Finnish stock market. Vaihekoski (2009) reported that the systematic component (flight to liquidity) is negatively and significantly priced in the Finnish stock market. Later, this got supported by Butt (2015) and Butt and Virk (2015) who reported that the flight to liquidity is the most significant effect among the risks specified by the LCAPM. In any case, one should bear in mind that this study utilizes new illiquidity measures that have been reported to have a high correlation with their intraday counterparts (see section 2.2). The economic significance and interpretation of the results are discussed in detail in the section 5.

The depressed wealth effect is found to be negatively priced in most of the cases with respect to both measures; this supports the main findings of Acharya and Pedersen (2005), who reported that the depressed wealth effect is the most significant risk, implying that investors are willing to accept lower returns for the stocks that are liquid in market downturn. As stated in the hypothesis *H4*: *"The co-movement between stock illiquidity and market return (depressed wealth effect) is significantly and negatively related to stock returns in the Finnish stock market"*. It can be concluded, based on the results, that this hypothesis is also accepted. Despite the vast international supportive evidence for this result (e.g. Lee, 2011; Kim & Lee, 2014; Vu et al., 2015; Saad & Samet, 2015), the previous findings concerning the Finnish stock market under the LCAPM framework by Butt (2015) and Butt and Virk (2015) have reported depressed wealth effect to remain insignificant. Butt and Virk (2015) even argue that the significance of the depressed wealth effect is more a dimensional effect of the chosen proxy for illiquidity than the systematic effect of risk. Definitely, it is clear that each illiquidity measure can capture only a certain dimension of the elusive concept of liquidity, and no single measure can capture all the dimensions. However, one should be cautious when interpreting the results of Butt and Virk (2015), since many other studies has shown that the depressed wealth effect is significant, when using the same measure of illiquidity as they.

Regarding the fifth hypothesis that states: "*The aggregate systematic risk is priced in the Finnish stock market"*, the evidence from the fixed effect panel regressions show that this hypothesis can also be accepted. In conclusion, the results show evidence for the hypothesis one, two, four, five and six while there seems to be no support for the third hypothesis. These results are mainly supported by previous findings concerning markets other than Finland, as previously depicted. On the other hand, the results do not support the significance of flight to liquidity effect, that has been reported the most significant in the Finnish stock market (Butt, 2015; Butt and Virk, 2015).

4.5 Robustness Tests

Robustness tests are conducted to see whether the results described in the previous section hold. In the section 2.3, it was shown that differences in the results can be driven by methodological issues. Especially, the studies by Butt (2015) and Butt and Virk (2015) proved that the chosen methodology can influence on the results. Even though they used the same measure of illiquidity and exactly the same time period, their results were partly different. The only difference was the chosen methodology. Hence, it is important to test whether the main results in this study are driven by the chosen estimation methodology, or whether they hold when using different estimation methods. Additionally, some studies argue that the liquidity effect and liquidity risk are only priced for the smallest stocks. For example, Chordia et al. (2009) suggest that the illiquidity of large firms seems to have a larger response to market-wide changes in illiquidity, thus implying that commonality in liquidity is more of a large firm phenomenon. This was also found by Fabre and Frino (2004) to be the case for the Australian stock market. These results imply that liquidity and firm size are closely related. Therefore, it should be tested whether the results are driven by the size effect in this study.

The test of whether the results for the pricing of the liquidity risk hold when using different estimation methods is conducted by applying conventional Fama-MacBeth (1973) method, since it is widely applied in the literature of empirical finance and studies concerning liquidity and liquidity risk. Importantly, it is also applied by the original paper of Acharya and Pedersen (2005), where they introduced the LCAPM. The general idea of Fama-MacBeth (1973) is to run cross-sectional regressions at each time point, and then calculate the time-series average of the cross-sectional coefficients. The test statistics for statistical inference can be obtained from a time-series sample of the cross-sectional coefficients. The results for the Fama-Macbeth (1973) regressions are presented in the tables 10 and 11 for the *PQS* and *AdjILLIQ* measure, respectively.

Table 10. Fama-MacBeth regressions based on the *PQS* measure

The table presents Fama-Macbeth regression results using individual stocks as test assets. The numbers in the first column corresponds the estimation specification presented in equations (30)–(36). *a* is the intercept of the regression, *E(c)* is the expected illiquidity, and β^2, β^3, and β^4 refer to commonality in liquidity, flight to liquidity, and depressed wealth effect betas, respectively. β^5 and β^6 are net liquidity beta and aggregate systemic risk beta while *lnBM* and *lnMV* are natural logarithms of a stock's book-to-market ratios and market capitalizations at beginning of the month. Individual excess stock return is the dependent variable in all of the models. The values in the parenthesis represent t-statistics of the estimated coefficients. ***, **, and * denote significance at 1%, 5%, and 10% level, respectively.

	a	*E(c)*	β^1	β^2	β^3	β^4	β^5	β^6	*lnBM*	*lnMV*
Panel A: Commonality in liquidity (β^2) sorting										
1	-0.066***	0.123**	0.016						-0.005***	0.002***
	(-3.849)	(1.964)	(1.460)						(-6.236)	(3.290)
2	-0.090***	0.112*	0.021**	0.424*					-0.005***	0.003***
	(-4.675)	(1.772)	(2.004)	(1.872)					(-5.973)	(4.001)
3	-0.095***	0.118*	-0.041		-1.368*				-0.005***	0.003***
	(-4.717)	(1.879)	(-1.282)		(-1.759)				(-5.917)	(4.050)
4	-0.095***	0.120*	0.010			-0.187**			-0.005***	0.004***
	(-4.496)	(1.891)	(0.871)			(-2.257)			(-5.847)	(4.668)
5	-0.093***	0.116*	0.006				0.152***		-0.005***	0.004***
	(-4.812)	(1.834)	(0.525)				(2.870)		(-5.862)	(4.643)
6	-0.077***	0.118*						0.019*	-0.005***	0.003***
	(-4.199)	(1.886)						(1.868)	(-6.129)	(3.563)
7	-0.173***	0.125*	-0.327*	3.048	-8.582*	0.609			-0.005***	0.004***
	(-2.857)	(1.953)	(-1.948)	(1.362)	(-1.927)	(1.236)			(-5.862)	(4.670)
Panel B: Flight to liquidity (β^3) sorting										
1	-0.041***	0.131**	-0.004						-0.005***	0.002***
	(-2.737)	(2.166)	(-0.759)						(-5.955)	(2.920)
2	-0.036*	0.131**	-0.008	0.184					-0.005***	0.002***
	(-1.948)	(2.183)	(-0.900)	(0.337)					(-5.959)	(3.018)
3	-0.058***	0.138**	-0.020*		-0.414				-0.005***	0.002***
	(-3.661)	(2.290)	(-1.769)		(-1.447)				(-6.068)	(2.888)
4	-0.043**	0.135**	-0.005			-0.030			-0.005***	0.002***
	(-2.485)	(2.237)	(-0.691)			(-0.326)			(-6.032)	(3.085)
5	-0.043**	0.137**	-0.005				0.003		-0.005***	0.002***
	(-2.378)	(2.267)	(-0.807)				(0.041)		(-6.110)	(3.081)
6	-0.041***	0.132**						-0.004	-0.005***	0.002***
	(-2.732)	(2.184)						(-0.737)	(-5.980)	(2.951)
7	-0.089	0.143**	0.104	5.708	2.515	-0.039			-0.006***	0.002***
	(-0.322)	(2.358)	(0.733)	(0.232)	(0.368)	(-0.008)			(-6.099)	(3.045)
Panel C: Depressed wealth effect (β^4) sorting										
1	-0.055***	0.122**	-0.004						-0.005***	0.003***
	(-3.361)	(1.984)	(-0.416)						(-6.054)	(3.597)
2	-0.089***	0.112*	0.011	0.308					-0.005***	0.003***
	(-4.032)	(1.807)	(0.665)	(0.864)					(-6.043)	(4.093)
3	-0.078***	0.126**	-0.048*		-0.842				-0.005***	0.004***
	(-3.336)	(2.068)	(-1.837)		(-1.475)				(-5.717)	(4.194)
4	-0.104***	0.113*	0.019			-0.203***			-0.005***	0.004***
	(-4.799)	(1.822)	(1.381)			(-2.602)			(-6.052)	(4.333)
5	-0.101***	0.113*	0.006				0.131**		-0.005***	0.004***
	(-4.614)	(1.826)	(0.429)				(2.273)		(-5.991)	(4.409)
6	-0.060***	0.121**						0.000	-0.005***	0.003***
	(-3.367)	(1.966)						(0.023)	(-6.113)	(3.663)
7	0.338	0.123**	-0.847	2.933	-10.550	2.783			-0.005***	0.004***
	(1.386)	(1.977)	(-1.325)	(0.491)	(-0.831)	(0.862)			(-5.959)	(4.793)

From the table 10 it can be observed that the positive relation between expected illiquidity and expected returns holds, while the (β^1) appears to be negative and insignificant in most of the cases in the Fama-MacBeth regressions for the *PQS* based results. The Fama-MacBeth results find commonality in liquidity (β^2) to be positive and significant for the commonality in liquidity sorted portfolios, which supports the main findings from the panel regression analysis. While the main findings report that flight to liquidity (β^3) is not significant in any case, the Fama-MacBeth test shows that is negative and significant for the commonality in liquidity beta sorted portfolios. Similar to main findings, the depressed wealth effect (β^4) remains to be negative and highly significant, supporting the panel regression estimations. However, the significance of the aggregate systematic risk (β^6) is not that robust as being significantly priced under Fama-MacBeth procedure only in one case. The net liquidity risk (β^5) is significant for the Fama-MacBeth regressions. Overall, the main results do not change very significantly and only some differences between the fixed effect panel regressions and Fama-MacBeth regressions can be seen, which supports the robustness of the main results for the *PQS* measure.

Regarding the results based *AdjILLIQ* measure under the Fama-MacBeth procedure β^4 and net liquidity risk beta (β^5) remain to be significant, while all the other betas turn out to be insignificant. Expected illiquidity is positive and highly significant in all the cases, supporting the robustness of the results. Compared the robustness of the results based on the *PQS* measure, these results are not that robust. However, the robustness tests show that depressed wealth effect (β^4) is significant based on the both illiquidity measures.

Table 11. Fama-MacBeth regressions based on the *AdjILLIQ* measure

The table presents Fama-Macbeth regression results using individual stocks as test assets. The numbers in the first column corresponds the estimation specification presented in equations (30)–(36). *a* is the intercept of the regression, *E(c)* is the expected illiquidity, and β^2, β^3, and β^4 refer to commonality in liquidity, flight to liquidity, and depressed wealth effect betas, respectively. β^5 and β^6 are net liquidity beta and aggregate systemic risk beta while *lnBM* and *lnMV* are natural logarithms of a stock's book-to-market ratios and market capitalizations at beginning of the month. Individual excess stock return is the dependent variable in all of the models. The values in the parenthesis represent t-statistics of the estimated coefficients. ***, **, and * denote significance at 1%, 5%, and 10% level, respectively.

	a	*E(c)*	β^1	β^2	β^3	β^4	β^5	β^6	*lnBM*	*lnMV*
Panel A: Commonality in liquidity (β^2) sorting										
1	-0.077***	0.133***	-0.013						-0.425***	0.419***
	(-2.604)	(3.526)	(-0.952)						(-12.611)	(12.609)
2	-0.113***	0.109***	-0.004	0.366					-0.061***	0.005***
	(-3.404)	(2.822)	(-0.197)	(1.462)					(-12.610)	(12.611)
3	-0.082**	0.138***	-0.002		0.222				-0.433***	0.467***
	(-2.483)	(3.632)	(-0.138)		(1.195)				(-12.611)	(12.610)
4	-0.119***	0.112***	0.002			-0.257***			-0.416***	-0.504***
	(-3.799)	(2.947)	(0.154)			(-2.716)			(-12.611)	(12.611)
5	-0.120***	0.109***	-0.001				0.180***		-0.408***	0.475***
	(-3.747)	(2.868)	(-0.046)				(2.743)		(-12.610)	(12.610)
6	-0.109***	0.132***						0.015	-0.422***	0.421***
	(-3.637)	(3.536)						(1.298)	(-12.611)	(12.609)
7	-1.044	0.115***	0.499	30.535	-5.298	16.583			-0.417***	0.557***
	(-1.201)	(2.958)	(0.979)	(1.008)	(-1.073)	(0.971)			(-12.611)	(12.611)
Panel B: Flight to liquidity (β^3) sorting										
1	-0.083***	0.136***	-0.007						-0.004***	0.004***
	(-3.114)	(3.567)	(-1.131)						(-4.181)	(3.560)
2	-0.083***	0.130***	-0.006	0.183					-0.004***	0.004***
	(-2.610)	(3.395)	(-0.475)	(0.384)					(-4.273)	(3.635)
3	-0.082***	0.136***	0.002		0.207				-0.004***	0.004***
	(-3.074)	(3.547)	(0.128)		(0.995)				(-4.464)	(3.525)
4	-0.069**	0.134***	-0.012			0.380			-0.004***	0.004***
	(-2.318)	(3.477)	(-1.583)			(1.358)			(-4.408)	(3.479)
5	-0.099***	0.129***	-0.006				0.117		-0.004***	0.004***
	(-3.267)	(3.361)	(-0.734)				(0.791)		(-4.573)	(3.379)
6	-0.080***	0.135***						-0.008	-0.004***	0.004***
	(-3.036)	(3.551)						(-1.471)	(-4.314)	(3.574)
7	-0.035	0.130***	-0.008	-0.274	0.356	0.561			-0.004***	0.004***
	(-0.529)	(3.362)	(-0.241)	(-0.259)	(1.165)	(1.116)			(-4.664)	(3.620)
Panel C: Depressed wealth effect (β^4) sorting										
1	-0.095***	0.144***	0.001						-0.004***	0.004***
	(-3.707)	(3.846)	(0.115)						(-4.417)	(3.721)
2	-0.111***	0.140***	0.001	0.108					-0.004***	0.005***
	(-3.945)	(3.722)	(0.074)	(0.233)					(-4.241)	(3.944)
3	-0.108***	0.143***	0.021		0.188				-0.004***	0.004***
	(-4.025)	(3.801)	(1.446)		(1.142)				(-4.416)	(3.988)
4	-0.105***	0.143***	-0.008			-0.291***			-0.004***	0.005***
	(-3.828)	(3.799)	(-0.768)			(-2.983)			(-4.309	(4.090)
5	-0.104***	0.141***	-0.007				0.107		-0.004***	0.004***
	(-3.706)	(3.754)	(-0.757)				(1.467)		(-4.308)	(3.939)
6	-0.101***	0.146***						0.003	-0.004***	0.004***
	(-3.857)	(3.882)						(0.447)	(-4.406)	(3.812)
7	-0.081	0.140***	-0.106	-3.007	-0.056	-1.772			-0.004***	0.005***
	(-0.539)	(3.684)	(-0.645)	(-0.961)	(-0.067)	(-1.628)			(-4.284)	(4.172)

To test whether the results are driven by the size effect, a method similar to Vu et al. (2015) is followed. Specifically, stocks are sorted each year based on their market capitalization, and divided into three size groups based on 30-40-30 split. Then, an analysis similar to the one for the main results is carried out, and results for the size groups are reported in the tables 12 and 13.

These results mainly support the findings and, for instance, shows that the aggregate systematic risk is significantly priced in all size groups regarding the *PQS* measure. However, commonality in liquidity (β^2) seems to be priced only for the medium sized stocks for *PQS* based results, while it is priced in all the cases based on the *AdjILLIQ* measure. Additionally, the significance of depressed wealth effect (β^4) is supported, which is more robust for the *AdjILLIQ* measure. However, it should be noted that, based on the *PQS* measure, for the large stocks only aggregate systematic risk (β^6) is priced, besides the traditional market risk (β^1). Interestingly, flight to liquidity seems to be priced for the small and medium sized stocks, based on the *AdjILLIQ* measure, even though it was not found to be significant in the main results. Expected illiquidity are positively priced in all the regression specifications, supporting the main results, and implying that expected returns are increasing with the expected illiquidity in all sized stocks. Generally, fixed effect panel regression results for the size group seem to be more robust when using the *AdjILLIQ* illiquidity measure. In summary, there seems to be some differences in pricing of the liquidity risk among the different size groups, but further investigation is left for future research.

Overall, it can be concluded that the main results from the panel estimations are fairly robust. Even though the illiquidity measures are designed to capture different dimensions of illiquidity, the main results show that the commonality in liquidity and depressed wealth effect betas (β^2 and β^4) seem to be the most significant. Finally, all the results are highly robust for the positive relationship between expected illiquidity and expected returns.

Table 12. Panel regressions with fixed effects for size groups based on the *PQS* measure

The table presents firm fixed effect panel regression results using individual stocks as test assets. The numbers in the first column corresponds the estimation specification presented in equations (30)–(36). *a* is the intercept of the regression, *E(c)* is the expected illiquidity, and β^2, β^3, and β^4 refer to commonality in liquidity, flight to liquidity, and depressed wealth effect betas, respectively. β^5 and β^6 are net liquidity beta and aggregate systemic risk beta while *lnBM* and *lnMV* are natural logarithms of a stock's book-to-market ratios and market capitalizations at beginning of the month. Individual excess stock return is the dependent variable in all of the models. The values in the parenthesis represent t-statistics of the estimated coefficients. ***, **, and * denote significance at 1%, 5%, and 10% level, respectively.

	a	*E(c)*	β^1	β^2	β^3	β^4	β^5	β^6	*lnBM*	*lnMV*
Panel A: Small stocks										
1	-0.485***	0.286***	0.021***						-0.016***	0.027***
	(-7.409)	(7.129)	(3.346)						(-4.619)	(6.970)
2	-0.484***	0.287***	0.019**	0.112					-0.016***	0.027***
	(-7.390)	(7.146)	(2.709)	(0.546)					(-4.614)	(6.932)
3	-0.480***	0.288***	0.011		-0.208				-0.016***	0.027***
	(-7.337)	(7.170)	(1.040)		(-1.285)				(-4.592)	(6.872)
4	-0.477***	0.290***	0.004			-0.216**			-0.016***	0.027***
	(-7.294)	(7.222)	(0.419)			(-2.359)			(-4.682)	(6.820)
5	-0.479***	0.289***	0.008				0.092*		-0.016***	0.027***
	(-7.315)	(7.204)	(0.801)				(1.829)		(-4.631)	(6.836)
6	-0.483***	0.287***						0.019***	-0.016***	0.027**
	(-7.390)	(7.164)						(3.526)	(-4.611)	(6.929)
7	-0.477***	0.289***	0.003	-0.279	0.018	-0.300**			-0.016***	0.027***
	(-7.291)	(7.192)	(0.244)	(-0.853)	(0.058)	(-2.158)			(-4.711)	(6.839)
Panel B: Medium size stocks										
1	-0.497***	0.377***	0.025***						-0.018***	0.025***
	(-9.009)	(4.079)	(6.900)						(-7.343)	(8.428)
2	-0.482***	0.357***	0.022***	0.421***					-0.018***	0.024***
	(-8.705)	(3.858)	(6.049)	(2.820)					(-7.355)	(8.104)
3	-0.475***	0.383***	0.013**		-0.294**				-0.018***	0.024***
	(-8.500)	(4.142)	(2.013)		(-2.333)				(-7.389)	(7.862)
4	-0.493***	0.376***	0.024***			-0.029			-0.018***	0.025***
	(-8.807)	(4.070)	(5.194)			(-0.375)			(-7.352)	(8.210)
5	-0.482***	0.374***	0.020***				0.062		-0.018***	0.024***
	(-8.636)	(4.043)	(4.090)				(1.618)		(-7.384)	(8.022)
6	-0.491***	0.377***						0.023***	-0.018***	0.025***
	(-8.911)	(4.079)						(7.015)	(-7.354)	(8.312)
7	-0.534***	0.323***	0.037***	1.927***	-0.389*	1.087***			-0.017***	0.027***
	(-9.425)	(3.445)	(4.070)	(5.097)	(-1.687)	(5.527)			(-6.873)	(8.860)
Panel C: Large stocks										
1	-0.316***	0.650***	0.024***						-0.013***	0.014***
	(-4.920)	(3.053)	(6.440)						(-5.740)	(4.423)
2	-0.313***	0.618***	0.022***	0.575					-0.013***	0.013***
	(-4.863)	(2.875)	(5.877)	(1.165)					(-5.725)	(4.370)
3	-0.346***	0.662***	0.031***		0.192*				-0.012***	0.015***
	(-5.191)	(3.107)	(5.423)		(1.676)				(-5.578)	(4.717)
4	-0.316***	0.655***	0.024***			0.044			-0.013***	0.014***
	(-4.920)	(3.061)	(5.788)			(0.233)			(-5.744)	(4.423)
5	-0.327***	0.665***	0.027***				-0.065		-0.012***	0.014***
	(-5.008)	(3.114)	(5.298)				(-0.938)		(-5.704)	(4.520)
6	-0.313***	0.644***						0.022***	-0.013***	0.013***
	(-4.863)	(3.024)						(6.384)	(-5.749)	(4.366)
7	-0.431***	0.433**	0.068***	9.561***	1.060***	2.352***			-0.011***	0.019***
	(-6.273)	(2.001)	(8.241)	(6.132)	(5.559)	(4.918)			(-5.174)	(5.873)

Table 13. Panel regressions with fixed effects for size groups based on the *AdjILLIQ* measure

The table presents firm fixed effect panel regression results using individual stocks as test assets. The numbers in the first column corresponds the estimation specification presented in equations (30)–(36). *a* is the intercept of the regression, *E(c)* is the expected illiquidity, and β^2, β^3, and β^4 refer to commonality in liquidity, flight to liquidity, and depressed wealth effect betas, respectively. β^5 and β^6 are net liquidity beta and aggregate systemic risk beta while *lnBM* and *lnMV* are natural logarithms of a stock's book-to-market ratios and market capitalizations at beginning of the month. Individual excess stock return is the dependent variable in all of the models. The values in the parenthesis represent t-statistics of the estimated coefficients. ***, **, and * denote significance at 1%, 5%, and 10% level, respectively.

	a	*E(c)*	β^1	β^2	β^3	β^4	β^5	β^6	*lnBM*	*lnMV*
Panel A: Small stocks										
1	-0.569***	0.230***	0.293***						-0.010***	0.031***
	(-8.061)	(4.544)	(6.502)						(-2.991)	(7.501)
2	-0.570***	0.240***	0.197***	0.049**					-0.009***	0.030***
	(-8.084)	(4.722)	(3.208)	(2.303)					(-2.859)	(7.267)
3	-0.568***	0.244***	-0.014		-8.151***				-0.009***	0.030***
	(-8.058)	(4.813)	(-0.135)		(-8.151)				(-2.718)	(7.266)
4	-0.553***	0.236***	0.035			-0.037**			-0.010***	0.029***
	(-7.811)	(4.664)	(0.317)			(-2.573)			(-3.015)	(7.130)
5	-0.558***	0.240***	0.051				0.027***		-0.010***	0.029***
	(-7.903)	(4.731)	(0.527)				(2.788)		(-2.936)	(7.103)
6	-0.557***	0.241***						0.029***	-0.010***	0.029***
	(-7.914)	(4.768)						(7.076)	(-2.932)	(7.135)
7	-0.562***	0.244***	-0.059	-0.001	-6.890**	-0.014			-0.009***	0.029***
	(-7.924)	(4.806)	(-0.478)	(-0.029)	(-2.047)	(-0.735)			(-2.762)	(7.144)
Panel B: Medium size stocks										
1	-0.646***	0.215***	0.227***						-0.019***	0.032***
	(-10.308)	(3.587)	(10.751)						(-7.817)	(9.982)
2	-0.643***	0.251***	0.103***	0.156***					-0.018***	0.030***
	(-10.328)	(4.200)	(4.063)	(8.529)					(-7.588)	(9.461)
3	-0.645***	0.243***	0.097**		-2.778***				-0.018***	0.031***
	(-10.299)	(4.032)	(2.487)		(-3.978)				(-7.716)	(9.852)
4	-0.639***	0.230***	0.141***			-0.019***			-0.019***	0.031***
	(-10.196)	(3.825)	(4.286)			(-3.425)			(-7.808)	(9.756)
5	-0.637***	0.239***	0.101***				0.024***		-0.019***	0.031***
	(-10.176)	(3.979)	(3.088)				(5.061)		(-7.771)	(9.628)
6	-0.626***	0.251***						0.032***	-0.018***	0.030***
	(-10.040)	(4.188)						(11.708)	(-7.738)	(9.463)
7	-0.651***	0.259***	0.094**	0.169***	-2.192*	0.023**			-0.018***	0.030***
	(-10.432)	(4.300)	(2.402)	(7.824)	(-1.682)	(2.106)			(-7.493)	(9.556)
Panel C: Large stocks										
1	-0.751***	0.819***	0.189***						-0.014***	0.032***
	(-9.886)	(8.296)	(9.420)						(-6.396)	(9.221)
2	-0.828***	0.790***	0.111***	0.374***					-0.009***	0.035***
	(-10.863)	(8.046)	(4.903)	(7.528)					(-4.199)	(10.023)
3	-0.760***	0.811***	0.240***		0.925				-0.014***	0.032***
	(-9.980)	(8.209)	(6.441)		(1.616)				(-6.412)	(9.335)
4	-0.760***	0.817***	0.175***			-0.007			-0.014***	0.032***
	(-9.787)	(8.276)	(5.448)			(-0.568)			(-6.004)	(9.137)
5	-0.783***	0.812***	0.140***				0.022***		-0.013***	0.033***
	(-10.100)	(8.230)	(4.441)				(2.053)		(-5.544)	(9.448)
6	-0.813***	0.806***						0.049***	-0.011***	0.035***
	(-10.557)	(8.161)						(9.182)	(-4.893)	(9.929)
7	-0.814***	0.768***	0.325***	0.601***	2.370***	0.066***			-0.010***	0.034***
	(-10.453)	(7.830)	(7.787)	(9.560)	(3.879)	(4.231)			(-4.404)	(9.535)

5 DISCUSSION

This part discusses the economic significance of the results. Not only the economic interpretation is described, but also the limitations of the LCAPM are considered. The economic significance of each illiquidity risk is discussed separately, and the total illiquidity premium associated with three illiquidity risks are calculated. This part also discusses further issues that could be studied in the future.

Even though there are some minor differences between the results with regard to the *PQS* and *AdjILLIQ* measures, some unified conclusions can be derived. First, the level of illiquidity is significantly priced in Finnish stock market, supporting the theory that illiquid stocks should earn higher returns. Secondly, it can be concluded that the market return premium is also significantly priced in the Finnish stock market while the flight to liquidity plays an insignificant role in the Finnish stock market. Finally, the results for both illiquidity measures provide fairly similar results; the commonality in liquidity and depressed wealth effect are both significantly priced. The *AdjILLIQ* finds a bit stronger support for the commonality in liquidity effect, while the *PQS* shows stronger evidence for the depressed wealth effect. In any case, these differences are only slight and both of them are priced with respect to both measures.

As explained in the section 2.3.2, commonality in liquidity is the covariance between a stock illiquidity and market illiquidity. This phenomenon stems from the situation where an investor holding an asset that has become illiquid with market may not choose to trade that stock, but more likely trades similar securities at a lower cost, if the liquidity of this security does not co-move with the market liquidity, as explained by Acharya and Pedersen (2005). Hence, the pricing implication of this risk is reflecting a positive compensation for investors for holding a stock whose illiquidity increases when the market illiquidity is high. Regarding the results obtained in this study, the investors in Finnish stock market are compensated and earn higher premium for stocks with positive covariance with market illiquidity. In other words, those investors who are willing to hold stocks that become illiquid when the Finnish stock market becomes illiquid earn a premium for holding those stocks. However, some investors may prefer stocks that remain liquid when stock market becomes illiquid, and are able to sell those stocks during the liquidity leakages when illiquid stocks are not sellable.

While Butt (2015) and Butt and Virk (2015) found flight to liquidity being the most important illiquidity risk in the Finnish stock market, this study shows contradicting results. As depicted in the section 2.3.3 flight to liquidity stems from investors' willingness to accept lower return on a security whose return tends to be high when the market is illiquid. Regarding both of the illiquidity measures, the flight to liquidity effect is found to be insignificant. Economically this means that investors in the Finnish stock market are not compensated for this kind of risk.

As Acharya and Pedersen (2005) found the depressed wealth effect to be the most significant among the three dimensions of illiquidity risks, and this study shows supporting evidence. As depicted in the section 2.3.4, this risk could be magnified during the declined market returns when a selling investor is trying to liquidate position in illiquid stocks but is unable to do that, and hence cause wealth problems for the investor. In other words, investors appreciate stocks with low illiquidity costs in a down market. This implies that investors are willing to accept lower returns on stocks with low illiquidity costs, when the market is doing well. Thus, in the Finnish stock market the important aspect of illiquidity risk is having stocks that are less liquid in bad times. This result is supported and founded not only by Acharya and Pedersen (2005) in the US market, but also globally by Lee (2011) and Saad and Samet (2015). Both of these studies show that the depressed wealth effect is the most important aspect of illiquidity risks. During the market declines, investors' marginal utility of consumption is higher due to wealth and consumption decline, and if investors have to pay more for trading the stocks, it aggravates the investors' situation. It seems that in Finnish stock market this kind of risk is priced, and investors get compensated for having stocks that are illiquid during market declines, and bearing the potential reduction in wealth.

To further discuss the economic significance of the illiquidity risks, the annual premiums associated with them are calculated. Annual premiums associated with the three liquidity risks are computed with respect to both of the illiquidity measure. Since the measures are designed to capture different aspects of liquidity, this gives an opportunity to explore differences that possible arise. To avoid multicollinearity problem, the calculation is done based on aggregate systematic risk beta (β^6). The annual premiums for different illiquidity risks are obtained from depressed wealth effect beta (β^4) sorted portfolios. Since the magnitudes of the aggregate systematic risk coefficients are fairly similar, there should not be any large differences.

However, the annual premiums are also calculated based on commonality in liquidity (β^2) sorting to see whether there are differences.

The difference in annualized expected returns between the most illiquid and liquid portfolios attributable to commonality in liquidity is $\lambda(\beta^{2,l,P5}-\beta^{2,l,P1})*12 = 0.38\%$ for the *PQS* based illiquidity measure. Similarly, the estimated annualized illiquidity risk premiums for the flight to liquidity and depressed wealth effect are 0.43% and 0.96%, respectively, with the total illiquidity risk premium of 1.77%. The corresponding illiquidity risk premiums for the *AdjILLIQ* based illiquidity measure are 0.31%, 0.34%, and 0.39% for the commonality in liquidity, flight to liquidity, and depressed wealth effect, respectively, with the total annual illiquidity risk premium of 1.04%. The two different measures seem to provide a bit different illiquidity risk premiums, with the *AdjILLIQ* being closer to that of estimated by Acharya and Pedersen (2005), who reported 1.10% of total annual illiquidity risk premium.[15] Commonality in liquidity contributes the least to the total annual illiquidity premium, while the depressed wealth effect contributes the most. Even though flight to liquidity has contribution to the total illiquidity premium, it was found to be insignificant and not priced. Hence, the results regarding flight to liquidity should be interpreted with caution. The estimated conditional illiquidity premiums are higher than previously found for the developed markets. Hagströmer et al. (2013) report a 0.46–0.83% annual illiquidity risk premium, depending on the conditional LCAPM specification for the US market, while the recent study of Saad and Samet (2015) estimated the conditional illiquidity risk premium of 0.73% for the developed markets. However, as described earlier in this study, the Finnish stock market exhibit thin trading and has twice the number of zero return trading days compared to the US market and, thus the results can also be compared to premiums estimated for emerging markets. Saad and Samet (2015) estimated a conditional illiquidity risk premium of 1.91% for emerging markets, which is closer to that estimated in this study when using the *PQS* measure.

[15] The annual illiquidity premiums based on commonality in liquidity beta sorting for the *PQS* measure are 0.35%, 0.40%, and 0.89% for commonality in liquidity, flight to liquidity and depressed wealth effect, respectively, with the total annual illiquidity premium of 1.64%. Corresponding values for *AdjILLIQ* measure are 0.51%, 0.55%, and 0.63% with the total annual illiquidity premium of 1.69%.

Since there are differences in the illiquidity risk premiums between the two measures utilized in this study, it is important to revise the economic intuition behind the models to form further economic interpretations for different investor groups. Institutional investors who tend to execute large transaction might be more interested in the results obtained from the *AdjILLIQ* measure, since it is a cost-per-volume. Hence, it captures the price response to large trading volumes and is more related to the resiliency dimension of liquidity. From this perspective it can be said that risks related to price response changes affect significantly stock returns in the Finnish stock market. The total annual illiquidity risk premium associated with *AdjILLIQ* measure is 1.04%, which is distributed pretty smoothly among the three illiquidity risks.

When concerning smaller individual investors, the results from the *PQS* measure should be given more value since the measure is a spread proxy that evaluates the cost of a single trade. While *AdjILLIQ* can be considered emphasizing on market resiliency *PQS* give more importance on market tightness. The total annual illiquidity risk premium of 1.77% is substantially higher compared to that associated with the *AdjILLIQ* measure, underlining the relative importance of depressed wealth effect. The findings regarding the *PQS* measure indicate that illiquidity level and illiquidity risks significantly affect the stock returns.

In this study the results seem to be consistent with the previous researches on LCAPM estimated risk premium. The results indicate the relative importance of depressed wealth effect over the commonality in liquidity and flight to liquidity in the Finnish stock market. This means that the highest illiquidity risk that comprises the total premium in the Finnish stock market is liquidity dry-ups when market returns are declined (β^4). This is followed by the risk of liquidity dry-up when market illiquidity is high (β^2). Additionally, this study suggest that investors are not willing to pay premium for stocks that have high returns when markets are illiquid (β^3). In other words, investors in the Finnish stock market are willing to pay more premium for hedging wealth shocks than to have liquid assets during the declined market liquidity, while they are not willing to pay premium for stocks with higher returns during declined market liquidity.

The differences between previous findings in the Finnish stock market and this study could be arising for a various of reasons. As discussed in the section 2.3, the different results could be caused by the chosen methodology. To the knowledge of the author, this study utilizes the conditional version of the LCAPM for the first time in the Finnish stock market, which allows for the investigation of time-varying liquidity risk and does not have a strong assumption of constant liquidity risk over time. Hence, the methodology used in this study can be seen a step towards a more realistic model and improvement compared to those used by Butt (2015) and Butt and Virk (2015). Additionally, the data selection is depicted very poorly in Butt (2015) and Butt and Virk (2015), and a reader cannot, for instance, know whether the penny stocks are included in the sample or not. One issue that may cause the difference is obviously the estimation time period. This study uses six-year newer data compared to Butt (2015) and Butt and Virk (2015). During that time the economic growth has been very low or nonexistent in Finland, which could have been reflected to investors' behavior and pricing of the liquidity risks. These uncertain market conditions may affect the investors' required premium for the stocks. However, it is more difficult to find reasoning why flight to liquidity is not found to be significant dimension of systematic risk in this study, but depressed wealth effect is the most significant dimension. One explanation could be that during the good economic conditions the investors are not worried about their wealth, but when the economic is doing poorly, wealth effect is amplified. This leads to the explanation that the effect of the three systematic liquidity risks plays different role during the economic growth and a down market. In other words, when markets and an economy are doing good, investors are not worried about their wealth but want earn higher returns, and hence they are not willing to pay premium for stocks that earn higher returns during declined market returns. More detailed explanation would require information about investors behavior and types in the Finnish stock market, since institutional and individual investors most likely have different preferences.

Even though the results support the international evidence regarding the LCAPM and show the relative significance of the depressed wealth effect in the Finnish stock market, the author wants to make some critical observations with respect to the estimated model. First, the LCAPM assumes expected illiquidity incorporated in the model to be measuring the cost of selling. In this respect, the *PQS* measure can be seen more direct to measure the cost of selling since it is a percent-cost measure, while the *AdjILLIQ* measure is an indirect measure capturing price impact associated with some volume of a transaction. However, the analysis shows that both measures provide fairly similar results, and both of the measures seem to be appropriate for the

Finnish stock market. Additionally, as depicted in Acharya and Pedersen (2005), the full model specification in equation (9) is troublesome to estimate efficiently due to collinearity between the illiquidity betas exploited in the model. Because of this, the model imposes a restriction of equal risk premiums, $\lambda^1 = \lambda^2 = -\lambda^3 = -\lambda^{4,}$ in the regression stage to estimate aggregate effect of liquidity risks. It follows that individual effect of each illiquidity risks cannot be investigated effectively simultaneously, but they have to be examined in separate regressions. Furthermore, the LCAPM specification by Acharya and Pedersen (2005) considers the average holding period of the investors to estimate how often the expected illiquidity costs occurs. The average holding period is captured in the *k* parameter in the model, and Acharya and Pedersen (2005) estimated also the LCAPM with fixed holding period. However, in this study the average holding period is assumed to equal 1 meaning that the illiquidity costs incur once a month because monthly figures are used in the regression stage. Since this might be a strong assumption, it can be seen as a weakness of the model. Nevertheless, it must be stated that no studies regarding average holding period were available for the Finnish stock market, and hence it should have been estimated. Finally, the estimation of conditional version of LCAPM is an improvement to the previous research regarding the Finnish stock market, and complements the research base with respect to the LCAPM.

Results show that empirical estimation of conditional LCAPM in the Finnish stock market with newly proposed illiquidity measure performs rather well. On the one hand the international evidence is supported by emphasizing the relative importance of depressed wealth effect, on the other hand the results are contradicting with previous research regarding Finnish stock market. Hence, there are some further issues that could be studied to develop the discussion around liquidity and illiquidity risks. Since the conditional LCAPM seems to be proper model to investigate illiquidity risk in the Finnish stock market, it can be complemented by incorporating the average holding period into the model. However, the average holding period should not be implemented as fixed but allowing time-variation for it. To the knowledge of the author Hagströmer et al. (2013) is the only study to consider this time-variation under the LCAPM framework when using reciprocal of average annual turnover rate of the market as the average holding period. A similar method could be applied not only in the Finnish stock market but also in any market globally. As earlier pointed out by Butt and Virk (2015), the depressed wealth effect may be more dimensional effect depending on the choice of the illiquidity measure. Hence, to further investigate illiquidity risks in the Finnish stock market, one option is to include multiple illiquidity measures and obtain their common component, and use that in the context of LCAPM. For instance, a global study of Kim and Lee (2014) used eight different proxies for illiquidity, and used their first principal component to estimate LCAPM. Not only do their results suggest that there is a systematic and common component across the measures, but they also show that there is strong evidence of the pricing of illiquidity risk. This could be applied in the Finnish stock market as well to reduce the potential noise across different proxies. While previously presented remarks to extend the discussion around the illiquidity and illiquidity risks are more methodological issues, some viewpoints that can be considered to extend the current scope and discussion around LCAPM are drawn. Concerning the Finnish stock market, it could be fruitful to investigate the sources of time variations of different LCAPM illiquidity risks, as in Saad and Samet (2015), who explored the determinants of illiquidity risk premium by using a wide set of macroeconomic variables. This could provide lucrative insights, for instance, for investors to forecast more accurately illiquidity risk due to changes in macroeconomic environment, and help them with their portfolio allocations.

6 CONCLUSIONS

The purpose of the study was to examine whether the systematic liquidity risks are priced in the Finnish stock market, and whether there is a decreasing time trend in liquidity risks. In addition to those, one purpose was to investigate whether different measures of illiquidity affect the results. To test whether the illiquidity level and illiquidity risks are priced in the Finnish stock market, this study estimated the conditional version of the LCAPM developed by Acharya and Pedersen (2005) for the first time in the Finnish stock market. Two different measures of illiquidity, namely *PQS* and *AdjILLIQ*, were used to see whether different dimensions of liquidity can be captured and are they priced in the Finnish stock market. Both of these measures were utilized for the first time in the Finnish stock market under the LCAPM framework. To research the topic three questions were asked: (1) Is the asset specific level of illiquidity priced in the Finnish stock market, and are systematic co-movements in liquidity priced in the Finnish stock market? (2) Is there a decreasing trend in liquidity risk? (3**)** Does the choice of liquidity measure affect the relationship between liquidity risk and stock returns?

Analyzing 200 common shares during the period of 1997–July 2015 in the Finnish stock market, this study shows that both expected illiquidity and illiquidity risk are priced and affect significantly the cross-section of stock returns. The market risk adjusted for illiquidity costs was also found to be significant. Importantly, the results hold when controlling for size and book-to-market value, and are generally robust for different size groups. Furthermore, no decreasing trend was found in the Finnish stock market under the period of investigation.

The conditional estimation of the LCAPM, by using individual stocks as test assets, found the commonality in liquidity and depressed wealth effect to be the most significant in the Finnish stock market, supporting the international evidence. However, this is in contrast with previous studies regarding the Finnish stock market, where the flight to liquidity have been recognized as the most significant dimension. The total annual illiquidity risk premium for holding the most illiquid portfolio was found to be 1.77% for the *PQS* measure and 1.04% for the *AdjILLIQ* measure. Similar to international evidence, the depressed wealth effect is found to contribute the most to the total annual illiquidity risk premium. Regarding the two illiquidity measures incorporated into this, study they both seem to provide similar results with meaningful economic interpretations. Hence, the results are significant for both individual investors with small trading volumes as well as for large institutional investors with large trading volumes.

This study contributes the previous research by estimating the conditional version of the LCAPM, utilizes two recently developed well-performing illiquidity proxies, and tests linear trends in illiquidity risks in the Finnish stock market. The model specification found commonality in liquidity and depressed wealth effect to be significant, while flight to liquidity was not significant. The model did not account for average holding period in the Finnish stock market but it could be incorporated in the model to further investigate illiquidity risks in the Finnish stock market. However, this would require some information about the investors' holding period, and therefore is left for future research.

Overall, the results indicate that investors should not only consider traditional market risk when diversifying their portfolios, but also account for covariation between stock illiquidity and market return, as well as covariation between stock illiquidity and market illiquidity. To answer the research questions, it can be concluded that two systematic illiquidity risks are priced in the Finnish stock market and they affect stock returns, while there is no evidence of decreasing trend in illiquidity risk.

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APPENDICES

APPENDIX 1. SERIAL CORRELATION TESTS FOR MARKET PORTFOLIOS

Table 14. Serial correlation test for market return and illiquidity

Table presents result for Breusch-Godfrey serial correlation LM test for market return and illiquidity, as well as their innovations. Table shows test statistics of the LM test up to two lags, and the corresponding p-values are presented below the test statistics. Second column presents the results based on the *PQS* measure of illiquidity, while third column depicts the results based on the *AdjILLIQ* measure. * denotes significance at 5 % level, and insignificant statistic means that the null hypothesis is not rejected and there is no serial correlation in the series.

	PQS	*AdjILLIQ*
Return		
Lag 1	9.164*	9.164*
	(0.002)	(0.002)
Lag 2	8.311*	8.311*
	(0.016)	(0.016)
Innovations (return)		
Lag 1	0.094	0.094
	(0.759)	(0.759)
Lag 2	0.397	0.397
	(0.820)	(0.820)
Illiquidity		
Lag 1	160.655*	229.800*
	(0.000)	(0.000)
Lag 2	177.640*	245.844*
	(0.000)	(0.000)
Innovations (illiquidity)		
Lag 1	0.002	0.001
	(0.966)	(0.974)
Lag 2	3.225	0.238
	(0.199)	(0.888)

LM test – H0: There is no serial correlation in the series

APPENDIX 2. SERIAL CORRELATION TESTS FOR ILLIQUIDITY BETAS SORTED PORTFOLIOS

Table 15. Serial correlation test for portfolios' illiquidity based on the *PQS* measure

Table presents result for Breusch-Godfrey serial correlation LM test for portfolios' illiquidity sorted on the *PQS* measure. Table shows test statistics of the LM test up to two lags and the corresponding p-values are presented below the test statistics. * denotes significance at 5 % level, and insignificant statistic means that the null hypothesis is not rejected and there is no serial correlation in the series.

Portfolio	1	2	3	4	5
Panel A: Commonality in liquidity (β^2) sorted portfolios					
Lag 1	69.521*	71.216*	64.255*	53.665*	91.010*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Lag 2	72.050*	71.802*	64.834*	53.432*	92.668*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Panel B: Flight to liquidity (β^3) sorted portfolios					
Lag 1	33.742*	37.918*	83.718*	81.335*	79.796*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Lag 2	33.019*	38.552*	93.263*	82.420*	101.277*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Panel C: Depressed wealth effect (β^4) sorted portfolios					
Lag 1	87.862*	34.733*	50.517*	19.044*	73.651*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Lag 2	89.243*	34.352*	75.280*	19.217*	74.245*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

LM test – H0: There is no serial correlation in the series

Table 16. Serial correlation test for portfolios' illiquidity based on the *AdjILLIQ* measure

Table presents result for Breusch-Godfrey serial correlation LM test for portfolios' illiquidity sorted on the *AdjILLIQ* measure. Table shows test statistics of the LM test up to two lags and the corresponding p-values are presented below the test statistics. * denotes significance at 5 % level, and insignificant statistic means that the null hypothesis is not rejected and there is no serial correlation in the series.

Portfolio	1	2	3	4	5
Panel A: Commonality in liquidity (β^2) sorted portfolios					
Lag 1	31.873*	31.271*	56.015*	50.516*	57.345*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Lag 2	32.027*	33.143*	59.548*	51.812*	61.916*
	(0.000)	0.000)	(0.000)	(0.000)	(0.000)
Panel B: Flight to liquidity (β^3) sorted portfolios					
Lag 1	48.422*	76.238*	46.849*	74.801*	50.957*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Lag 2	48.972*	76.676*	47.383*	83.856*	51.454*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Panel C: Depressed wealth effect (β^4) sorted portfolios					
Lag 1	41.553*	30.406*	33.871*	69.856*	70.358*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Lag 2	41.535*	29.704*	33.148*	69.560*	71.454*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

LM test – H0: There is no serial correlation in the series

Table 17. Serial correlation test for portfolios' returns and illiquidity innovations based on the *PQS* measure

Table shows result for Breusch-Godfrey serial correlation LM test for portfolios' returns and innovations in illiquidity based on the *PQS* liquidity measure. Table shows test statistics of the LM test up to two lags, and the corresponding p-values are presented below the test statistics. * denotes significance at 5 % level, and insignificant statistic means that the null hypothesis is not rejected and there is no serial correlation in the series.

Portfolio	1	2	3	4	5
Panel A: Commonality in liquidity (β^2) sorted portfolios					
Returns					
Lag1	2.933	4.820*	5.124*	4.713*	0.406
	(0.087)	(0.028)	(0.024)	(0.030)	(0.524)
Lag2	3.917	4.699	5.342	4.946	1.258
	(0.141)	(0.095)	(0.069)	(0.084)	(0.533)
Illiquidity innovations					
Lag 1	0.095	0.000	0.008	0.047	0.000
	(0.757)	(0.990)	(0.927)	(0.829)	(0.997)
Lag 2	1.337	1.109	0.084	6.021	0.063
	(0.512)	(0.574)	(0.959)	(0.049)	(0.969)
Panel B: Flight to liquidity (β^3) sorted portfolios					
Returns					
Lag 1	2.906	6.598*	3.882*	2.472	7.159*
	(0.088)	(0.010)	(0.049)	(0.116)	(0.007)
Lag 2	3.139	6.937*	3.929	2.568	7.249*
	(0.208)	(0.031)	(0.140)	(0.277)	(0.027)
Illiquidity innovations					
Lag 1	0.000	0.012	0.128	0.000	0.002
	(0.984)	(0.912)	(0.721)	(0.984)	(0.968)
Lag 2	0.710	1.415	1.698	0.011	0.878
	(0.701)	(0.493)	(0.428)	(0.994)	(0.645)
Panel C: Depressed wealth effect (β^4) sorted portfolios					
Returns					
Lag 1	0.303	5.416*	5.837*	3.403	3.566
	(0.582)	(0.020)	(0.016)	(0.065)	(0.059)
Lag 2	2.825	5.467	5.810	3.318	3.627
	(0.243)	(0.065)	(0.055)	(0.190)	(0.163)
Illiquidity innovations					
Lag 1	0.000	0.005	0.028	0.010	0.022
	(0.997)	(0.945)	(0.867)	(0.921)	(0.882)
Lag 2	0.000	1.702	3.016	2.980	1.618
	(1.000)	(0.427)	(0.221)	(0.225)	(0.445)

LM test – H0: There is no serial correlation in the series

Table 18. Serial correlation test for portfolios' returns and illiquidity innovations based on the *AdjILLIQ* measure

Table shows result for the Breusch-Godfrey serial correlation LM test for portfolios' returns and innovations in illiquidity based on the *AdjILLIQ* illiquidity measure. Table shows test statistics of the LM test up to two lags, and the corresponding p-values are presented below the test statistics. * denotes significance at 5 % level, and insignificant statistic means that the null hypothesis is not rejected and there is no serial correlation in the series.

Portfolio	1	2	3	4	5
Panel A: Commonality in liquidity (β^2) sorted portfolios					
Returns					
Lag1	3.660	4.976*	3.183	1.922	2.173
	(0.056)	(0.026)	(0.074)	(0.166)	(0.140)
Lag2	4.459	4.919	3.278	2.098	2.323
	(0.108)	(0.085)	(0.194)	(0.350)	(0.313)
Illiquidity innovations					
Lag 1	0.001	0.008	0.193	0.072	0.020
	(0.981)	(0.931)	(0.660)	(0.789)	(0.888)
Lag 2	0.017	1.175	1.955	1.821	0.932
	(0.992)	(0.556)	(0.376)	(0.402)	(0.627)
Panel B: Flight to liquidity (β^3) sorted portfolios					
Returns					
Lag 1	4.306*	4.694*	3.343	3.794	4.188*
	(0.038)	(0.030)	(0.067)	(0.051)	(0.041)
Lag 2	4.396	4.656	3.790	4.044	4.560
	(0.111)	(0.098)	(0.150)	(0.132)	(0.102)
Illiquidity innovations					
Lag 1	0.001	0.000	0.124	0.003	0.595
	(0.981)	(0.998)	(0.725)	(0.955)	(0.440)
Lag 2	0.756	0.026	3.491	0.097	3.661
	(0.685)	(0.987)	(0.175)	(0.953)	(0.160)
Panel C: Depressed wealth effect (β^4) sorted portfolios					
Returns					
Lag 1	3.606	3.518	3.978*	4.560*	2.100
	(0.058)	(0.061)	(0.046)	(0.033)	(0.147)
Lag 2	3.750	3.951	4.278	4.442	2.116
	(0.153)	(0.139)	(0.118)	(0.109)	(0.347)
Illiquidity innovations					
Lag 1	0.007	0.027	0.004	0.001	0.105
	(0.933)	(0.869)	(0.951)	(0.980)	(0.746)
Lag 2	0.201	0.795	0.072	0.075	1.599
	(0.904)	(0.672)	(0.965)	(0.963)	(0.449)

LM test – H0: There is no serial correlation in the series

APPENDIX 3. STATIONARY TESTS FOR THE ILLIQUDITY BETAS SORTED PORTFOLIOS

Table 19. Stationary test of illiquidity beta sorted portfolios based on the *PQS* measure

Table reports results from the ADF and KPSS tests for all the portfolios sorted based on the *PQS* measure of illiquidity. Results are provided for the portfolios' returns and illiquidity innovations. Test statistics are reported for both ADF and KPSS tests, and the corresponding critical values at 5 % level are in the parenthesis below each test statistic. * denotes significance at 5 % level. Significant ADF value means that there is not a unit root in the series, while insignificant KPSS test statistic means that the series is stationary.

Portfolio	1	2	3	4	5
Panel A: Commonality in liquidity (β^2) sorted portfolios					
ADF returns	-10.843*	-4.871*	-10.119*	-10.282*	-5.481*
	(-2.942)	(-2.942)	(-2.942)	(-2.942)	(-2.942)
KPSS returns	0.093	0.170	0.250	0.154	0.283
	(0.463)	(0.463)	(0.463)	(0.463)	(0.463)
ADF illiquidity	-13.243*	-13.131*	-12.816*	-11.180*	-12.632*
	-(3.479)	(-3.479)	(-3.479)	(-3.479)	(-3.479)
KPSS illiquidity	0.039	0.024	0.037	0.037	0.101
	(0.146)	(0.146)	(0.146)	(0.146)	(0.146)
Panel B: Flight to liquidity (β^3) sorted portfolios					
ADF returns	-10.670*	-9.712*	-10.355*	-10.792*	-9.911*
	(-2.942)	(-2.942)	(-2.942)	(-2.942)	(-2.942)
KPSS returns	0.087	0.132	0.237	0.298	0.792*
	(0.463)	(0.463)	(0.463)	(0.463)	(0.463)
ADF illiquidity	-12.695*	-12.869*	-13.157*	-12.726*	-12.574*
	(-3.479)	(-3.479)	(-3.479)	(-3.479)	(-3.479)
KPSS illiquidity	0.055	0.049	0.075	0.081	0.112
	(0.146)	(0.146)	(0.146)	(0.146)	(0.146)
Panel C: Depressed wealth effect (β^4) sorted portfolios					
ADF returns	-6.013*	-9.987*	-10.066*	-4.898*	-10.706*
	(-2.942)	(-2.942)	(-2.942)	(-2.943)	(-2.942)
KPSS returns	0.164	0.181	0.276	0.186	0.091
	(0.463)	(0.463)	(0.463)	(0.463)	(0.463)
ADF illiquidity	-12.665*	-10.116*	-10.965*	-12.628*	-12.904*
	(-3.479)	(-3.479)	(-3.479)	(-3.479)	(-3.479)
KPSS illiquidity	0.101	0.042	0.058	0.064	0.075
	(0.146)	(0.146)	(0.146)	(0.146)	(0.146)

ADF – H0: There is a unit root in the series
KPSS – H0: Series is stationary

Table 20. Stationary test of illiquidity beta sorted portfolios based on the *AdjILLIQ* measure

Table reports results from the ADF and KPSS test for all the portfolios sorted based on the *AdjILLIQ* measure of illiquidity. Results are provided for the portfolios' returns and illiquidity innovations. Test statistics are reported for both ADF and KPSS tests, and the corresponding critical values at 5 % level are in the parenthesis below each test statistic. * denotes significance at 5 % level. Significant ADF value means that there is not a unit root in the series while insignificant KPSS test statistic means that the series is stationary.

Portfolio	1	2	3	4	5
Panel A: Commonality in liquidity (β^2) sorted portfolios					
ADF returns	-10.249*	-4.954*	-10.420*	-11.096*	-11.001*
	(-2.942)	(-2.943)	(-2.942)	(-2.942)	(-2.942)
KPSS returns	0.099	0.190	0.167	0.179	0.229
	(0.463)	(0.463)	(0.463)	(0.463)	(0.463)
ADF illiquidity	-12.741*	-13.008*	-7.071*	-10.183*	-12.841*
	(-3.479)	(-3.479)	(-3.481)	(-3.479)	(-3.479)
KPSS illiquidity	0.024	0.032	0.047	0.104	0.094
	(0.146)	(0.146)	(0.146)	(0.146)	(0.146)
Panel B: Flight to liquidity (β^3) sorted portfolios					
ADF returns	-10.246*	-9.952*	-10.768*	-10.598*	-10.323*
	(-2.942)	(-2.942)	(-2.942)	(-2.942)	(-2.942)
KPSS returns	0.081	0.192	0.263	0.277	0.425
	(0.463)	(0.463)	(0.463)	(0.463)	(0.463)
ADF illiquidity	-12.367*	-12.699*	-11.303*	-12.712*	-13.657*
	(-3.479)	(-3.479)	(-3.479)	(-3.479)	(-3.479)
KPSS illiquidity	0.060	0.074	0.048	0.094	0.080
	(0.146)	(0.146)	(0.146)	(0.146)	(0.146)
Panel C: Depressed wealth effect (β^4) sorted portfolios					
ADF returns	-10.531*	-10.612*	-10.393*	-10.140*	-10.894*
	(-2.942)	(-2.942)	(-2.942)	(-2.942)	(-2.942)
KPSS returns	0.356	0.219	0.096	0.150	0.186
	(0.463)	(0.463)	(0.463)	(0.463)	(0.463)
ADF illiquidity	-12.758*	-12.784*	-12.886*	-12.796*	-13.183*
	(-3.479)	(-3.479)	(-3.479)	(-3.479)	(-3.479)
KPSS illiquidity	0.077	0.048	0.032	0.035	0.062
	(0.146)	(0.146)	(0.146)	(0.146)	(0.146)

ADF – H0: There is a unit root in the series
KPSS – H0: Series is stationary

APPENDIX 4. MODEL SPECIFICATION TESTS

Table 21. F-test for fixed effects

The table shows the results for the F-test for fixed effects. The numbers from 1 to 7 correspond to estimation specifications as in equations (30)–(36). Test statistics are reported with the p-values under them. Panel A reports the results based on the *PQS* illiquidity measure while panel B shows the results based on the *AdjILLIQ* illiquidity measure. Beta 2, beta 3, and beta 4 describes the results based on commonality, flight to liquidity and depressed wealth effect portfolios sorting in estimation of conditional illiquidity betas, respectively. * denotes significance at 1 % level, and significant value means that the null is rejected, and favors the choice of fixed effect model over pooled OLS.

Model	1	2	3	4	5	6	7
Panel A: *PQS* measure							
Beta 2	2.588*	2.600*	2.577*	2.603*	2.579*	2.594*	2.603*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Beta 3	2.529*	2.511*	2.512*	2.511*	2.511*	2.528*	2.478*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Beta 4	2.558*	2.597*	2.596*	2.692*	2.586*	2.545*	3.051*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Panel B: *AdjILLIQ* measure							
Beta 2	2.524*	2.694*	2.571*	2.612*	2.598*	2.600*	2.580*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Beta 3	2.445*	2.572*	2.501*	2.450*	2.536*	2.553*	2.758*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Beta 4	2.487*	2.555*	2.497*	2.487*	2.477*	2.491*	2.635*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

H0: All the independent variables are zero.

Table 22. Hausman test for random effects.

The table reports the results for the Hausman test for random effects. The numbers from 1 to 7 correspond to estimation specifications as in equations (30)–(36). Chi-square test statistics are provided with the corresponding p-values below them. Panel A reports the results based on the *PQS* illiquidity measure while panel B shows the results based on the *AdjILLIQ* illiquidity measure. Beta 2, beta 3, and beta 4 describes the results based on commonality, flight to liquidity and depressed wealth effect portfolios sorting in estimation of conditional illiquidity betas, respectively. * denotes significance, and significant value means that the null is rejected, and tells that the random effect model is not appropriate and fixed effect model should be applied.

Model	1	2	3	4	5	6	7
Panel A: *PQS* measure							
Beta 2	114.357*	113.491*	116.617*	110.755*	111.735*	113.033*	116.567*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Beta 3	120.821	120.508	121.550	119.157	119.966	120.061	123.830*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Beta 4	114.294	112.924	114.505	111.032	110.745	112.281	118.027*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Panel B: *AdjILLIQ* measure							
Beta 2	103.141*	108.167*	110.496*	103.741*	100.647*	101.373*	134.475*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Beta 3	119.850*	107.894*	116.356*	102.753*	117.770*	119.850*	131.310*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Beta 4	101.546*	100.912*	104.335*	101.607*	101.098*	99.617*	122.017*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

H0: The slope coefficients between fixed effect and random effect model do not differ.